ESSAYS ON FINANCIAL ANOMALIES

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ABSTRACT OF THE THESISS

Essays on Financial Anomalies

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This dissertation studies two pervasive financial anomalies: price momentum and accrual anomaly.

The first essay establishes a robust link between momentum and accruals (the difference between accounting earnings and cash flow). I find that momentum profitability is statistically significant and economically large only among firms with high accruals. The cross-sectional characteristics of momentum previously documented do not subsume the effect of accruals on momentum profits, and the effect also holds in different market states. To understand the source of momentum, I analyze the predictive power of accruals for stock returns based on two hypotheses: earnings manipulation and earnings overestimation. I find that loser stocks with high accruals experience significant decreases in industry-adjusted sales growth and the largest amount of income-decreasing special items in subsequent years. Most of momentum profitability among high-accrual

firms is attributable to the high discretionary accrual group. My findings indicate that, primarily due to the effect of earnings manipulation, the downward payoff of loser stocks with high accruals largely drives the accrual-based momentum profit.

The second essay investigates the relationship between financial distress and accrual anomaly. I investigate whether the continued existence of the accrual anomaly is due to the failure to account for the compensation for distress risk. I find a U-shape pattern of distress risks across accrual portfolios. The accrual profit is mostly concentrated in firms with high distress, suggesting that the abnormal returns to the accrual trading strategy may result from the high distress-risk exposures. Market frictions such as idiosyncratic stock return volatility, illiquidity, and short-sale constraints do not generate the accrual anomaly, but they prevent stock prices from adjusting once financial distress triggers the abnormal returns to the accrual trading strategy.

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Chapter 1

Introduction

Price momentum and accrual anomalies are two well-documented financial phenomena (see, Jegadeesh and Titman, 1993; and Sloan, 1996). Fama and French (2008) highlight the pervasive effect of accruals and momentum. They demonstrate that the returns associated with accruals and momentum remain strong and robust in all size groups, cross-sectional regressions, and tests based on different portfolio sorting methods. To date, no attempt has been made to empirically connect these two anomalies.

Jegadeesh and Titman (1993) first document that momentum trading strategies of buying past winners and selling past losers generate statistically significant and economically large profits. Fama and French (1996) show that their three-factor model (Fama and French, 1993) does not explain momentum. The robustness of momentum profitability has attracted a variety of explanations, both risk based and behavioral. Several works demonstrate the significance of momentum for stocks with certain characteristics in both cross-sectional and time series analyses.

Accruals are defined as the difference between accounting earnings and cash flows. Sloan (1996) first documents the accrual anomaly: firms with high accruals underperform firms with low accruals. He suggests that investors are overly optimistic about the future prospects of firms with high accruals and overly pessimistic about the future prospects of firms with low accruals. The literature has broadly used accrual-based variables as proxies for managerial manipulation, or for market misvaluation.

Recent studies show that financial distress predicts low future stock returns. Researchers explore different characteristics and explanations for the low returns of distressed firm. This finding challenges the basic concept in finance that high non-diversifiable risk is compensated by high returns, and is termed "distress anomaly". Campbell, et al. (2008) recommend an explanation of distress anomaly related to the preferences of institutional investors for low distress risk stocks, with the demand driving up the subsequent returns for low distress risk stocks and the lack of demand driving down the subsequent returns for high distress risk stocks.

This dissertation contains two essays on these two pervasive financial anomalies: price momentum and accrual anomaly. The first essay, Chapter 2, establishes a robust link between momentum and accruals (the difference between accounting earnings and cash flow). I find that momentum profitability is statistically significant and economically large only among firms with high accruals. The cross-sectional characteristics of momentum previously documented do not subsume the effect of accruals on momentum profits, and the effect also holds in different market states. To understand the source of momentum, I analyze the predictive power of accruals for stock returns based on two hypotheses: earnings manipulation and earnings overestimation. I find that loser stocks with high accruals experience significant decreases in industry-adjusted sales growth and the largest amount of income-decreasing special items in subsequent years. Most of momentum profitability among high-accrual firms is attributable to the high discretionary accrual group. My findings indicate that, primarily due to the effect of earnings manipulation, the downward payoff of loser stocks with high accruals largely drives the accrual-based momentum profit.

The second essay, Chapter 3, investigates the relationship between financial distress and accrual anomaly. I investigate whether the continued existence of the accrual anomaly is due to the failure to account for the compensation for distress risk. I find a U-shape pattern of distress risks across accrual portfolios. The accrual profit is mostly concentrated in firms with high distress, suggesting that the abnormal returns to the accrual trading strategy may result from the high distress-risk exposures. Market frictions such as idiosyncratic stock return volatility, illiquidity, and short-sale constraints do not generate the accrual anomaly, but they prevent stock prices from adjusting once financial distress triggers the abnormal returns to the accrual trading strategy.

Both essays provide possible rational and/or behavioral explanation about price momentum and accrual anomaly. Finally, Chapter 4 summarizes the results and concludes.

Chapter 2

The Effect of Accruals on Momentum

2.1 Introduction

Price momentum and accrual anomalies are two well-documented financial phenomena (see, Jegadeesh and Titman, 1993; and Sloan, 1996). Fama and French (2008) highlight the pervasive effect of accruals and momentum. They demonstrate that the returns associated with accruals and momentum remain strong and robust in all size groups, cross-sectional regressions, and tests based on different portfolio sorting methods. To date, no attempt has been made to empirically connect these two anomalies.[1] This paper fills in this gap in the literature by investigating the effect of accruals on momentum to understand the profitability of momentum strategies. I raise three important empirical questions. First, do accruals have a relation to momentum? Second, if so, can I use accrual-based variables to explain momentum profits? Third, why is it important to examine how accruals impact the profitability of momentum strategies?

Jegadeesh and Titman (1993) first document that momentum trading strategies of buying past winners and selling past losers generate statistically significant and economically large profits. Fama and French (1996) show that their three-factor model

[1] Chan, Jegadeesh, and Lakonishok (1996) show that past earnings surprises and past stock returns have independent explanatory power for future returns. Chordia and Shivakumar (2006) indicate that price momentum is captured by the systematic component of earnings momentum. Collins and Hribar (2000) find that the accrual mispricing is distinct from post-earnings announcement drift.

(Fama and French, 1993) does not explain momentum. The robustness of momentum profitability has attracted a variety of explanations, both risk based and behavioral. Several works demonstrate the significance of momentum for stocks with certain characteristics in both cross-sectional and time series analyses.[2]

Accruals are defined as the difference between accounting earnings and cash flows. Dechow (1994) states that the primary role of accruals is to overcome problems with measuring firm performance when firms are in continuous operation. However, the use of accruals introduces a new set of problems, such as managerial discretion over the recognition of accruals. Managers can use accruals to signal their private information or to opportunistically manipulate earnings. Because investors fixate on reported earnings, they might be temporarily misled and induced to misvalue stocks.[3] Sloan (1996) first documents the accrual anomaly: firms with high accruals underperform firms with low accruals. He suggests that investors are overly optimistic about the future prospects of firms with high accruals and overly pessimistic about the future prospects of firms with low accruals. The literature has broadly used accrual-based variables as proxies for managerial manipulation, or for market misvaluation.[4]

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[2] Risk-based explanations include Berk, Green and Naik (1999), Ahn, Conrad and Dittmar (2003), Grinblatt and Moskowitz (2004), Korajczyk and Sadka (2004), Lesmond, Schill and Zhou (2004), Sagi and Seasholes (2007), Chen, Novy-Marx and Zhang (2011), and Wang and Wu (2011). Behavioral explanations include Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999). Characteristics-based analyses include Asness (1997), Hong, Lim and Stein (2000), Lee and Swaminathan (2000), Chordia and Shivakumar (2002), Cooper, Gutierrez and Hameed (2004), Zhang (2006), Sadka (2006), Avramov, et al. (2007), Antoniou, Doukas and Subrahmanyam (2011), and Garlappi and Yan (2011).

[3] For instance, the second largest accounting fraud in US history – the WorldCom scandal, is a case of earnings manipulation through adjusting accruals. WorldCom's improper accounting includes two principal types: reduced reported line costs and exaggerated reported revenues. From the second quarter of 1999 through the first quarter of 2002, WorldCom improperly reduced its reported line costs (and increased pretax income) by over $7 billion. (http://www.worldcomnews.com).

[4] See, e.g., Subramanyam (1996), Teoh, Welch and Wong (1998a, b), Collins and Hribar (2000), Xie (2001), Richardson, et al. (2005), Thomas and Zhang (2002), Chan, et al. (2006), Kothari, Loutskina and Nikolaev (2008), and Gong, Louis and Sun (2008).

This paper argues that accruals may have a distinctively predictive power for future stock returns because they contain information on both earnings manipulation and misvaluation. In this way, I can offer both rational and behavioral explanations for momentum through the effect of accruals. Recent research considers accruals as an important indicator related to earnings quality that is useful for equity valuation (see, e.g., Richardson, et al., 2005; and Chan, et al., 2006). Earnings increases usually go along with high accruals that suggest low earnings quality followed by poor future returns. My paper focuses on how price continuation following the release of public earnings information varies with accruals. I demonstrate that higher accruals lead to relatively lower future returns for loser stocks but higher accruals do not lead to relatively higher future returns for winner stocks, suggesting that accruals might only delay the incorporation of certain information (mostly bad news) into stock prices. The significant accrual-based momentum profit implies the robust effect of accruals and sheds light on the contribution of accruals to momentum profitability.

I find that momentum profitability is statistically significant and economically large only among high-accrual firms but is nonexistent for firms with low- and medium-levels of accruals. More specifically, the strategies that sequentially sort on accruals and then on past six-month returns yield momentum payoff that increases monotonically with accruals; the equally-/value-weighted average (EW/VW) payoffs increase from an insignificant 0.26%/0.45% per month for the low-accrual group to a significant 1.37%/1.29% per month for the high-accrual group. The discrepancy in EW/VW payoffs from the loser stocks among the three accrual groups (1.29%/0.83%, 1.11%/0.72% and 0.13%/-0.03% per month for low-, medium- and high-accrual groups, respectively) implies that the downward payoff of loser stocks with high accruals largely drives the accrual-based momentum profit. The effect of accruals on momentum is robust after I control for the time-varying beta, the Fama-French three factors, and Carhart's (1997) four factors. The cross-sectional characteristics of momentum previously documented do not subsume the interaction between accruals and momentum, and the interaction also holds in different market states.

In order to understand the source of accrual-based momentum, I analyze the predictive power of accruals for stock returns based on two hypotheses -- earnings overestimation and earnings manipulation. Chan, et al. (2006) indicate that changes in accounts receivable, inventories, and accounts payable are three items that contribute most to differentiating accruals across firms. These three dominant components in accruals imply that managers of growing firms with high accruals might extrapolate the fast-growing trend of the past into the future. Because managers overestimate the persistence in sales growth, they build up inventories and other working capital items. Moreover, high accruals can reflect increases in current assets when managers overstate accounts receivable, or decreases in current liabilities when managers understate accounts payable. Investors, analysts, and the media usually pay more attention to firms' short-term earnings performance. Under these circumstances, there are more incentives for managers to inflate a firm's earnings prospects than to lower current earnings and defer them to the future prospects. Therefore, earnings overestimation and/or traces of manipulation are more likely to be found in firms with high accruals. Given this asymmetric effects of high and low accruals, I focus on the fundamental performance of firms with high accruals. I employ three tests to examine the earnings manipulation and earnings overestimation hypotheses. I find that the effect of accruals on momentum is mainly due to earnings manipulation; earnings overestimation also has some explanatory power for accrual-based momentum, but it does not play a major role.

First, I examine the operating performance (proxied by industry-adjusted sales growth) of the loser and winner stocks in three accrual groups before and after the portfolio formation. Over the holding periods, the sales growth of high-accrual losers declines significantly while that of the high-accrual winners improves; there is no significant decrease in sales growth for loser stocks with low or medium accruals. This implies that managers of growing firms with high accruals may extrapolate their past fast growing trend into the future and supports the earnings overestimation hypothesis. In addition, I cannot rule out the existence of earnings manipulation because this misvaluation might be induced by managerial efforts to manipulate earnings and stock prices. Second, I track special items in pre- and post-formation periods to check the existence of earnings manipulation. Special items are intended to capture the impact of unusual or nonrecurring events on a firm's income statement, such as inventory writedowns. If managers manipulate earnings, the effects will not sustain indefinitely, and corrections are expected to be reported as special items in the following years. In subsequent years, the amount of income-decreasing special items relative to total assets is the largest for the loser firms with high accruals. This test implies that earnings manipulation affects the accrual-based momentum profit. Third, I decompose accruals into nondiscretionary and discretionary components and distinguish the effect of earnings overestimation and manipulation. I find that most accrual-based momentum profitability is contributable to the high discretionary accrual group. This evidence provides strong support for the earnings manipulation hypothesis, but weaker support for the overestimation hypothesis.

The remainder of this paper is organized as follows. Section 2.2 details the data and summary statistics. Section 2.3 presents the empirical results of testing the momentum effect in combination with past returns and accruals. Section 2.4 proposes the hypotheses and explores possible explanations for accrual-based momentum profit. Section 2.5 summarizes the results and concludes.

2.2 Data and Summary Statistics

The sample includes all non-financial firms listed on NYSE/AMEX with monthly return data on the Center for Research in Security Prices (CRSP) and annual accounting data on Compustat from January 1965 to December 2008. My sample excludes firms that are a foreign firm, a closed-end fund, a real estate investment trust (REIT), and an American Depository Receipt (ADR). I extract monthly returns on all NYSE and AMEX stocks from CRSP database, subject to several selection criteria.[5] The annual financial data required to construct *accruals* are obtained from Compustat. The accrual component of earnings is computed using information from the balance sheet and income statement, consistent with the existing literature on earnings management (see, e.g., Dechow, Sloan, and Sweeney, 1995; and Sloan, 1996):[6]

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[5] Both Jegadeesh and Titman (1993) and Sloan (1996) include firms listed on NYSE/AMEX. In order to maintain consistency, we exclude firms listed on NASDAQ. The sample starts from January 1965, consistent with Jegadeesh and Titman (1993). Selection criteria include: first, stocks must have at least six consecutive monthly return observations; second, we exclude all stocks priced less than $5 at the beginning of the holding period and all stocks with market capitalization that would place them in the smallest NYSE decile. As in Jegadeesh and Titman (2001), the purpose is to ensure that the results are not driven primarily by low priced and illiquid stocks. The results in this study are robust to the inclusion of stocks listed on NASDAQ, stocks priced below $5 and those that belong to the smallest NYSE decile.

[6] Collins and Hribar (2002) argue that accruals based on the balance sheet approach suffer from measurement errors

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep \qquad (2.1)$$

Where

ΔCA = change in current assets (Compustat item 4)

$\Delta Cash$ = change in cash (Compustat item 1)

ΔCL = change in current liabilities (Compustat item 5)

ΔSTD = change in debt included in current liabilities (Compustat item 34)

ΔTP = change in income taxes payable (Compustat item 71)

Dep = depreciation and amortization (Compustat item 14)

The measure of earnings is operating income after depreciation before interest expense, taxes and special item (Compustat data item 178). The measure of cash flows is calculated as the difference between earnings and accruals. All three variables-earnings, accruals and cash flows are standardized by firm size to facilitate the empirical analysis, where firm size is measured as the average of the beginning and end of year book value of total assets (Compustat data item 6), as follows:

$$\begin{aligned} &\text{Earnings} = \frac{\text{Operating income after depreciation}}{\text{Average total assets}} \\ &\text{Accrual component} = \frac{\text{Accruals}}{\text{Average total assets}} \qquad (2.2) \\ &\text{Cash flow component} = \frac{\text{Operating income after depreciation - Accruals}}{\text{Average total assets}} \end{aligned}$$

To make my strategies implementable, I calculate future stock returns that begin four months after the end of the fiscal year from which the financial statement data are gathered. The reason is, by this time, almost all firms' financial statements are publicly

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due to mergers and acquisitions and recommend to measure accruals using cash flow statement information. However, the cash flow statement data are available only after 1988. Accordingly, the sample will become much shorter if this alternative measure of accruals is used.

available according to Alford, Jones and Zmijewski (1994).[7] After I merge the CRSP with Compustat, the final sample includes 5,195 firms for the period of January 1965 to December 2008.

<Table 2.1>

Panel A of Table 2.1 provides descriptive statistics for the distribution of monthly raw returns of the full sample. For instance, the average monthly return is 1.18% and the median size of firms is $552.49 millions. Panel B of Table I shows monthly returns for the loser portfolio (P1), the winner portfolio (P10), and the momentum strategy of buying the winner and selling the loser portfolio (P10−P1), which is created as in Jegadeesh and Titman (1993). At the beginning of each month t, I rank all stocks based on their cumulative returns over the formation period (months t−6 to t-1) and assign them to one of ten portfolios based on their past six-month returns. Then, these portfolios are held for 6 months. In addition, I skip a month between the formation period and the holding period. Each portfolio return is calculated as the equally weighted average return of the stocks in the portfolio. The evidence in Panel B suggests significant momentum profitability in the full sample. In particular, the momentum profit (P10−P1) averages 1.03% (t-stat=5.90) per month, which is statically significant at the 1% level.[8]

<Table 2.2>

Panel A of Table 2.2 provides statistics on the characteristics of decile portfolios formed by ranking firms on the magnitude of accrual component of earnings. The firms

[7] For instance, if a firm's fiscal year ends in month 't', we match the accounting data with CRSP return data from month 't+4' to 't+15'. Furthermore, we consider a one month lag between the formation period and holding period.

[8] Consistent with Jegadeesh and Titman (1993), momentum profits are prominent in non-January months (1.23% per month with t-stat=7.11) and negative in January months (-1.29% per month with t-stat=-1.68).

are sorted and assigned in equal numbers to ten portfolios, A1 to A10, where A1 indicates the lowest accrual group and A10 the highest. The mean value of accrual component is -0.14 for the lowest accrual portfolio and 0.11 for the highest accrual portfolio. There is a strong negative relation between accruals and cash flows. The mean value of cash flows falls from 0.22 for the lowest accrual portfolio to 0.02 for the highest accrual portfolio. In contrast, earnings are positively related to accruals. The mean value of earnings is 0.08 for the lowest accrual portfolio and 0.13 for the highest accrual portfolio. The magnitude of the three measures and their relations are consistent with prior studies (Dechow, 1994 and Sloan, 1996).

Panel B of Table 2.2 shows monthly returns for the lowest accrual portfolio (A1), the highest accrual portfolio (A10), and the profit of buying the lowest accrual portfolio and selling the highest accrual portfolio (A1−A10). At the beginning of each month t, I rank all stocks based on their annual accruals and assign them to one of ten portfolios based on magnitude of their accruals. Then, these portfolios are held for 6 months. I skip a month between the formation period and the holding period. Each portfolio return is calculated in the same way as in Panel B of Table 2.1. Panel B suggests the significantly negative relation between accruals and future stock returns in the first six months in the holding period. In particular, the accrual strategy return to a zero-cost portfolio of taking a long position in the lowest-accrual portfolio and an equally valued short position in the highest-accrual portfolio is 0.49% per month (t-stat =4.06).

Overall, Tables 2.1 and 2.2 confirm that the full sample generates significantly positive price momentum profits (sorted based on past six-month stock returns) and accrual profits (sorted based on past fiscal year accruals) for the next six-month holding period. It indicates that future stock returns are positively related to past stock returns and negatively related to past accruals.

2.3. Empirical Results

2.3.1 Independent Sorting Based on Past Returns and Accruals

In this subsection, I propose a combined strategy based on both past returns and accruals. For each month t, all stocks are ranked into decile portfolios according to their cumulative past six-month returns. Simultaneously, stocks are also ranked into decile portfolios according to their past fiscal year accruals. Decile portfolios are formed monthly and their returns are computed by weighting equally all firms in that decile. The positions are held for the following six months (t+1 through t+6). There is a one month lag between the formation and the holding periods. This independent two-way sorting procedure yields 100 portfolios.

<Table 2.3>

To establish the link between momentum and accruals, I examine the average monthly raw returns of four extreme portfolios in Table 2.3. Portfolio (A1, P1) has the monthly raw return 1.39%, belonging to the lowest past six-month returns and the lowest accrual group simultaneously. Portfolios (A1, P10), (A10, P1) and (A10, P10) have the monthly raw returns 1.66%, -0.02% and 1.57%, respectively. I first note that only Portfolio (A10, P1) has a negative (but insignificant) monthly return and the other three extreme portfolios have significantly positive monthly returns. Next, I examine the trading strategies applying these four extreme portfolios.

I observe that the profit is significantly positive at the 1% level (t-stat = 6.8) in the highest accrual group with monthly raw return 1.59% using strategy1 (A10, P10)-(A10, P1). The momentum strategy in the highest accrual group outperforms the single price momentum strategy (1.03% per month from Table I) by 0.56% per month. On the other hand, the momentum profit is surprisingly insignificant in the lowest accrual group with monthly raw return 0.27% (t-stat = 0.93). See strategy2, (A1, P10) - (A1, P1). In addition, strategy3 (A1, P10) - (A10, P1) with a long position in the winners with the lowest accruals, and a short position in the losers with the highest accruals generates the highest profit. Comparing with the investment strategy constructed solely on past six-month returns (1.03% per month as shown in Table 2.1), the combined strategy produces a significantly positive return of 1.68 percent which is statistically significantly larger than that in the previous strategy by 0.65% per month. This result implies the importance of incorporating accruals to improve investors' ability in separating winners from losers.[9]

In summary, the empirical results suggest that the combined strategy (strategy1 in Table 2.3) improves the return to the price momentum by incorporating accruals. More importantly, I find that the momentum profitability is positively significant only in the highest accrual group, while it is insignificant in the lowest accrual group. The findings convince us that accruals might affect price momentum profits. As my conclusions are drawn from four extreme portfolios out of one hundred portfolios in the full sample, one may wonder whether this independent two-way sorting may cause a small sample bias in

[9] The difference between strategy3 profit and price momentum profit is 0.65% per month with a t-stat 3.23.The average monthly return of strategy (A1, P1) - (A10, P1) is 1.41 percent for the loser stocks. The monthly profit of accrual anomaly in the loser stocks is even greater than the profit of the one-way accrual sorting strategy (0.49% in Table II panel B). In contrast, accrual anomaly does not exist in the winner stocks. Strategy (A1, P10) - (A10, P10) generates only 0.09% return per month which is statistically insignificant. We leave this effect of momentum on accrual anomaly for future research, as this paper concentrates on explaining the effect of accruals on momentum.

each extreme portfolio. To address this issue, I examine the effect of accruals on momentum under a sequential sorting procedure in the next subsection.

2.3.2 Results from Sequential Sorting

From the previous subsection, I find that momentum profit is affected by accruals. There is a significant discrepancy in momentum payoff across different accrual groups. In this subsection, portfolios are formed on a sequential basis, sorting first on accruals and then on past six-month returns. For each month t, all stocks are ranked into three equal groups based on their past fiscal year accruals (A1 for the lowest accruals and A3 for the highest accruals).[10] The stocks in each accrual group are then divided into deciles based on their past six-month returns (P1 for the past loser stocks and P10 for the past winner stocks). The two-step sequential sorting procedure generates 30 accruals - momentum portfolios.

<Table 2.4>

Panel A of Table 2.4 shows that the payoffs to momentum strategies strongly depend on accruals. For the low- and medium-accrual groups, the average equally-/value-weighted payoffs of P10−P1 strategy are 0.26%/0.45% (t-stat=1.12/1.61) and 0.36%/0.54% (t-stat=1.76/1.71) per month, respectively. None of them is statistically significant at the 5% level. The payoff is much larger as well as statistically significant at 1.37%/1.29% (t-stat=7.26/5.06) for the high-accrual group. This result is consistent with the finding in

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[10] Using this sorting procedure, each accrual group contains more than 800 firms on average across time. This provides a sufficiently large number of firms to rebalance the portfolio at each point in time. Conrad, Cooper, and Kaul (2003) indicate that the procedures that simultaneously condition on two (or more) characteristics may bring potential bias. Our results are robust to the independent two-way sorting procedure.

Table 2.3: momentum effect is significantly positive only in the highest accrual group, while it is insignificant in the lowest accrual group. Moreover, the monthly equally-/value-weighted raw return of loser stocks with high accruals is only 0.13%/-0.03%, which is quite different from the returns of loser stocks with low and medium accruals (1.29%/0.83% and 1.11%/0.72%). However, the monthly raw returns of winner stocks are comparable for all three accrual groups (1.55%/1.27%, 1.47%/1.26% and 1.50%/1.26%) for low-, medium- and high-accrual groups). The discrepancy in payoff of the loser-stock portfolio (P1) among three accrual groups implies that accrual-based momentum profit is largely driven by the downward effect of loser stocks with high accruals.

Panel A of Table 2.3 also provides the percentage of market capitalization represented by each accrual group. The payoffs to momentum strategies are insignificant in the low- and medium-accrual groups, which account for 76.9% of total market capitalization of the full sample. In other words, the momentum profits are derived from firms that accounts for about one quarter of the total market capitalization of the full sample.

Thus far, I have examined raw returns to momentum strategies. A normal check is to adjust returns for risk to ensure that the profitability of momentum strategies among high-accrual firms is not just a compensation for exposures to common sources of risk. Panel B of Table 2.3 presents results from regressing momentum profits for the three accrual groups under alternative asset pricing models: the CAPM, the conditional CAPM, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model.

In Panel B, I find that the monthly equally-/value-weighted market risk adjusted return (alpha) is 0.31%/0.50% (t-stat=1.28/1.78), 0.39%/0.55% (t-stat=1.87/1.79%) and 1.38%/1.33% (t-stat=7.25/5.19) in the low-, medium- and high-accrual groups, respectively. For the conditional CAPM, I directly estimate the conditional alphas and betas using short-window regressions following Lewellen and Nagel (2006). The monthly alpha is 0.45%/0.49% (t-stat=1.90/1.77), 0.61%/0.56% (t-stat=3.08/2.28) and 1.55%/1.34% (t-stat=7.97/5.20) in the low-, medium- and high-accrual groups, respectively. It indicates that time-variation in betas and the equity premium cannot explain accrual-based momentum profit. Under the Fama and French (1993) three-factor model, the three-factor risk adjusted return (alpha) increases with accruals. The monthly alpha is 0.42%/0.48% (t-stat=1.76/1.40), 0.51%/0.63% (t-stat=2.41/2.52) and 1.53%/1.46% (t-stat=7.96/5.60) in the low-, medium- and high-accrual groups, respectively. Furthermore, adding the momentum factor from Carhart (1997) four-factor model, the monthly risk adjusted return is still significant with monthly return 0.81%/0.50% (t-stat=5.64/2.42) for high-accrual firms. The significant profit implies the robust effect of accruals and sheds light on the additional contribution of accruals to momentum profitability. The evidence strongly suggests that momentum profitability in high-accrual firms does not represent compensation for systematic risk based on the market factor, the time-varying beta, the Fama-French three risk factors or the Carhart four risk factors.

2.3.3 Controlling for Alternative Firm Characteristics

Although there is no general consensus in academic research regarding the cause of momentum profits, a number of studies demonstrate the significance of momentum for stocks with certain firm characteristics. For instance, recent work argues that momentum is stronger in stocks that have high information uncertainty (defined as the degree of ambiguity about firm fundamentals). Specifically, Jiang, Lee and Zhang (2005) and Zhang (2006) argue that the price drift is larger in stocks with greater information uncertainty, which is proxied by firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility and cash flow volatility. The prior literature also documents that stocks with a low trading volume generate higher future returns than those with a high trading volume. Lee and Swaminathan (2000) find that low-volume stocks outperform high- volume ones after controlling for price momentum and momentum is stronger among high-volume stocks. Avramov, et al. (2007) show that momentum profitability is statistically significant and economically large among low-grade firms, but it is nonexistent among high-grade firms.

An essential question that arises is whether the effect of accruals on momentum profits is subsumed by other firm financial characteristics. To address this question, I conduct the robustness check of momentum profitability across the accrual dimensions based on 3×3 portfolios sorted independently on accruals and other firm financial characteristics, including firm size, trading volume and credit ratings.[11]

<Table 2.5>

Table 2.5 presents results for sorting by accruals and firm size (proxied by market capitalization of equity). Following Fama and French (2008), the size breakpoints are defined as the NYSE 20th and 50th percentiles of market cap for NYSE stocks. Momentum returns increase with accruals across size groups. In Panel A, for the micro-

[11] In this three-way sorting, each portfolio (out of 9 portfolios in the full sample) contains over 200 firms on average across time.

cap /small-cap/large-cap firms, momentum raw returns increase monotonically from 0.35%/0.08%/0.57% to 1.43%/1.51%/1.23% per month moving from low-accrual to high-accrual firms. The difference in momentum profits between low- and high-accrual groups is significant (t-stat=4.09/4.67/2.45 for the micro-cap /small-cap/large-cap firms) within all size groups. I also observe that for the big-cap stocks, momentum profit is statistically significant at the 5% level for the low- and medium-accrual groups, although the magnitudes are substantially smaller. Overall, the result that momentum effect is significantly positive in high-accrual group is robust after controlling for firm size, the market factor, Fama-French factors and even momentum factor, as can be seen from Panel B.

<Table 2.6>

Following Lee and Swaminathan (2000), I define trading volume for a given stock as the average monthly turnover within the six-month portfolio formation period. The monthly turnover is calculated as the number of shares traded divided by the number of shares outstanding at the end of the month. In Panel A of Table 2.6, for the low /medium /high turnover firms, momentum raw returns increase monotonically from 0.04% /0.18%/0.17% to 0.83% /0.90%/1.71% per month moving from low-accrual to high-accrual firms. The results indicate that even though stocks with high turnover tend to display higher momentum than stocks with low turnover, the high-accrual stocks generate larger momentum profits than low-accrual stocks for each turnover group. The difference in profit between low and high turnover groups is significant for all accrual groups. Panel B presents the risk adjusted accrual-based momentum profit by applying the CAPM, the

Fama-French three-factor model and the Carhart four-factor model. Overall, the result that momentum profit is significantly positive only in high-accrual group is robust after controlling for trading volume.

<Table 2.7>

In order to separate the effect of accruals from credit rating effect, I consider credit rating as a control variable. Credit ratings are measured by S&P Domestic Long Term Issuer Credit Rating which is available from June 1985 to December 2008. I convert a rating letter to a numeric number (AAA=1, AA+=2, …, D=22) for sorting purpose. Table 2.7 presents results for sorting by accruals and credit ratings. Momentum profits increase with accruals for all rated groups. In Panel A, for the low/medium/high rated firms, the raw momentum returns increase monotonically from 0.06% /0.04%/0.02% to 1.77%/1.24%/0.39% per month moving from low-accrual to high-accrual firms. There is also a clear impact of credit rating on momentum return among the low/medium/high-accrual firms, largely consistent with Avramov, et al. (2007). Momentum profit is higher in low rated firms, especially among high-accrual group from 1.77% in low rated firms to 0.39% in high rated firm. The result that momentum effect is significantly positive only in high-accrual group is robust after controlling for the credit ratings factor. The evidence implies that accruals and credit ratings have separate effects on momentum profitability. One cannot be subsumed by the other.[12]

The portfolio sorting methodology in the previous section indicates that the effect

[12] While firms with medium credit ratings and high accruals also have significant momentum returns of 1.24% per month (t-stat=3.25), this finding is unobserved in Avramov, et al. (2007). They document that momentum profitability is large and significant only among low-grade firms. Our result indicates that accruals might have a stronger effect on momentum profitability than credit ratings.

of accruals on momentum is not subsumed by several control variables. However, even though I use the full sample of NYSE/AMEX, the number of stocks might not be sufficiently large to evaluate in certain portfolios, through a two or three-way portfolio sorting. To avoid this problem, I estimate the incremental effect of accruals on momentum, considering other characteristics. Specifically, I run the following cross-sectional regression for each sample period:

$$Accurals_{i,t} = \gamma_0 + \gamma_1 MV_{i,t} + \gamma_2 BM_{i,t} + \gamma_3 Turnover_{i,t} + \gamma_4 Credit_{i,t} + \varepsilon_{i,t} \quad (2.3)$$

I orthogonalize accruals with respect to other stock characteristics and sort firms on past returns and "residual accruals" (i.e., $\varepsilon_{i,t}$). I document that the orthogonal test supports my previous finding that accruals have the significant and distinct effect on price momentum.

The time matching follows my previous procedures. *Accruals* are previous fiscal year measures, obtained from equation (2.1). *MV* is the log market value of equity and *BM* is book-to-market equity based on accounting data from the fiscal year ending in calendar year t. *Turnover* is the lagged six-month turnovers used in my earlier portfolio sorting process, measured from month t-1 to t-6. *Credit* is measured by S&P Domestic Long Term Issuer Credit Rating. I winsorize all variables except *Credit* and *MV* at the 1st and 99th percentile of their cross-sectional distributions to reduce the effects of outliers.

<Table 2.8>

I examine the average correlations between the explanatory variables along the cross-section to avoid the potential multicollinearity problem. Panel A of Table 2.8 reports Pearson and Spearman correlations among the relevant firm-specific characteristics. All the correlations are statistically significant at the 1% level. The largest Pearson/Spearman correlation is found between *MV* and *Credit* (average -0.525/-0.508). The correlations between accruals and other firm financial characteristics are significant, but low in magnitude, confirming that accruals do not capture too much overlapped information as other previously documented characteristics. This provides another cross validation that the effect of accruals on momentum profits is not subsumed by other firm financial characteristics.

Panel B reports incremental effect of accruals on momentum, considering other characteristics. For each month t, all qualified stocks with return for months t−6 through t-1 (formation period) are equally divided into three groups based on residual accruals ($\varepsilon_{i,t}$) from equation 2.3. For each group, I compute the return of the loser portfolio P1 as the equally-weighted average return over the holding period of the worst-performing 10% and the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period. There is a one month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for six months. Since the momentum strategy is implemented each month, the monthly returns represent the equally-/value-weighted average return from this month's momentum strategy and all strategies from up to five months ago. Panel B shows the similar pattern to Table 2.4: the momentum profit is mostly concentrated in the firm with high residual accruals.

In sum, sorting on accruals provides different payoffs of momentum strategies across three accrual groups, and the same trend holds when sorting on size, trading volume and credit ratings factors. These proxies for size, volume and credit ratings seem to provide different momentum payoffs only in high-accrual stocks. The evidence strongly suggests that accruals have a unique and pervasive effect not captured by previously documented variables.

2.3.4 Evidence under Different Market States

The previous subsections study the firm-level accruals as a determinant variable of momentum profits in the cross-section of U.S. stocks. I now turn my attention to the time series of momentum profits and investigate the effect of accruals on momentum profits in different market states.

<Table 2.9>

Chordia and Shivakumar (2002) report a business-cycle pattern of momentum profits: momentum profits are significantly positive during expansion periods and negative (though insignificant) during recession periods. I show that the effect of accruals on momentum profits exists during both expansion and recession periods. Panel A of Table 2.9 concentrates on momentum profits during different business cycle periods.[13] I find that momentum profits are significantly positive in high-accrual group during both expansion and recession periods. Indeed, the magnitude is somewhat larger during the recession periods, although t-statistics are lower. Monthly raw return and the Fama-French three-factor risk-adjusted return in high-accrual group are 1.49% (t-stat=2.98)/

[13] We divide the full sample into expansion and recession months based on NBER's classifications, available on its website.

1.46% (t-stat=6.64) and 1.84% (t-stat=3.71)/1.59% (t-stat=7.22) during recession/expansion periods, respectively. Interestingly, I find that momentum returns for firms with medium accruals are also significant in the expansion state.

Cooper, Gutierrez, and Hameed (2004) report that momentum profits are significant when the lagged one- to three-year stock market returns are positive and insignificant when lagged stock market returns are negative. Panel B of Table 2.9 provides the momentum profits for the accrual groups in up- and down-markets. I use 12-month cumulative returns on the CRSP value-weighted market index as a proxy for market returns. If the 12-month lagged return on the index is positive (negative), I define a holding-period month as an UP (DOWN) month. I show that the effect of accruals on momentum profits exists during both up-and down-markets. Monthly raw return and risk adjusted return in high-accrual group are 1.37% (t-stat=7.22)/1.34% (t-stat=6.37) and 1.52% (t-stat=7.93)/1.50% (t-stat=7.11) during down/up market, respectively. I also notice that momentum return is significant at the 5% level for the medium-accrual group in the up-market state, albeit its magnitude is much smaller.

Antoniou, Doukas, and Subrahmanyam (2011) argue that market-wide investor sentiment should be connected to aggregate momentum profits. Applying different proxies for sentiment, they find that momentum profits are significant and positive when sentiment is optimistic and insignificant when sentiment is pessimistic.[14] Following Antoniou, Doukas, and Subrahmanyam (2011), a formation period is classified as optimistic (pessimistic) if the average sentiment belongs to the top (bottom) 30% of the

[14] We use the monthly sentiment index constructed by Baker and Wurgler (2006, 2007) to classify the sample months into pessimistic and optimistic periods. The sentiment index is available from Jeffrey Wurgler's homepage.

three-month rolling average sentiment time series. I show that the effect of accruals on momentum profits holds in both pessimistic and optimistic market states. In Panel C of Table 2.9**,** monthly raw momentum return and risk adjusted return in high-accrual group are 1.29% (t-stat=5.98)/1.40% (t-stat=6.30) and 1.40% (t-stat=6.28)/1.53% (t-stat=6.74) during periods of pessimistic and optimistic states, respectively. Momentum profits in medium-accrual group are also positively significant during optimistic state.

Overall, the evidence on the significant relation between momentum profitability and accruals is robust to the various checks I have implemented, including adjusting for size, trading volume, credit ratings, and under alternative asset pricing models. The effect of accruals on momentum profits is not subsumed by previously documented cross-sectional characteristics, and it holds in various time-series market states. Given the robustness of my results, the remainder of this paper provides possible explanations for the profitability of momentum in high-accrual stocks.

2.4 Possible Explanations for the Sources of Momentum Profitability

The preceding section reports that momentum profitability is economically large and statistically significant among high-accrual firms, but is insignificant among low- and medium-accrual firms. Especially, the discrepancy in payoff of the loser portfolio (P1) among three accrual groups implies that accrual-based momentum profit is largely driven by the downward payoff of loser stocks with high accruals.

In this section, I analyze the predictive power of accruals for stock returns based on two hypotheses — earnings manipulation and earnings overestimation. I focus on firms with high accruals because of the asymmetric effects of high and low accruals.

Investors, analysts and the media usually pay more attention to firms' short-term earnings performance. For example, earnings overestimation possibly occurs to firms with high current earnings associated with high accruals. Even under the view that accruals represent managerial manipulation, given the attention paid by investors and analysts, there are strong incentives and pressures to blow up a firm's earnings prospects (Chan, Karceski, and Lakonishok, 2007). In comparison, there are weaker motives to lower current earnings and defer them.[15] Accordingly, traces of manipulation are more likely to be found when accruals are high than when accruals are low. Kothari, Loutskina, and Nikolaev (2008) also report the information asymmetry between firms with low and high accruals. They indicate that managers of overvalued firms are likely to manage their firms' accruals upwards to prolong the overvaluation.

As managers inflate earnings above cash flows, accruals rise. From the operating sheet and balance sheet, I can rewrite equation (2.1) as:

$$\begin{aligned} Accruals = {} & (\Delta\ accounts\ receivable + \Delta\ inventories + \Delta\ other\ current\ assets) \\ & - (\Delta\ accounts\ payable + \Delta\ other\ current\ liabilities) - Dep \end{aligned} \tag{2.4}$$

Chen, et al. (2006) indicate that Δ *accounts receivable,* Δ *inventories* and Δ *accounts payable* are three items that contribute most to differentiating accruals across firms. For instance, high accruals may reflect increases in accounts receivable when managers record sales prematurely, or decreases in current liabilities when managers understate accounts payable. Since investors fixate on reported fundamental accounting income, they are temporarily misled. Teoh, Welch and Wong (1998a, 1998b) and Gong, Louis and Sun (2008) provide evidence supporting the existence of managerial

[15] Under the "big bath" phenomenon, if a company will miss their earnings target anyway, it is more beneficial to recognize all losses at once so that there will only be a one-time market reaction to bad news.

manipulation through accruals.[16] In order to capture managerial manipulation, I decompose the accruals into nondiscretionary accruals and discretionary accruals. Since discretionary accruals cannot be observed directly from financial statements, I estimate them following Jones (1991):[17]

$$TA_{it} / A_{it-1} = a(1/A_{it-1}) + b(\Delta REV_{it} / A_{it-1}) + c(PPE_{it} / A_{it-1}) + \varepsilon_{it} \qquad (2.5)$$

where:

TA_{it} = total accruals in year t for firm i; (calculated from equation (1))

ΔREV_{it} = change in revenues in year t for firm i; (Compustat item 12)

PPE_{it} = gross property, plant, and equipment in year t for firm i; (Compustat item 7).

A_{it-1} = total assets in year t -1 for firm i;

ε_{it} = error term in year t for firm i;

I estimate equation (2.5) in cross-section for each two-digit SIC code and year combination. I denote the predicted values of the Jones model as nondiscretionary accruals and the residuals as discretionary accruals. The nondiscretionary component captures the impact of business conditions while the discretionary portion reflects managerial choices. The manipulation hypothesis suggests that the discretionary component of accruals should have most predictive power for future returns, and thus serves as a better and more accurate measure of earnings manipulation (see, e.g., Kasznik,

[16] Teoh, Welch, and Wong (1998a. 1998b) show that before an initial public offering (IPO) or a seasoned equity offering (SEO), management will want to inflate earnings to make the offering more attractive to investors. Gong, Louis, and Sun (2008) provide evidence on managers' choices of accounting accruals during stocks repurchase.

[17] The decomposition method we use in this study is based on Jones (1991), which is different from Chan, et al. (2006). The nondiscretionary component captures the impact of business conditions while the discretionary portion reflects managerial choices. Dechow, Sloan, and Sweeney (1995) suggest the Jones' model as the most appropriate procedure to capture the effect of earnings management after they evaluate different decomposition procedures.

1999; Xie, 2001; and Kothari, Leone and Wasley, 2004).

I propose another hypothesis that the effect of accruals may arise from the similar ways of investor behavior as other widely-documented explanations in stock returns, such as price and earnings momentum (see, e.g., Hirshleifer, 2001; and Barberis and Thaler, 2002). I use broad categories of business activities—current operating activities, noncurrent operating activities and financing activities. I refer to the corresponding accruals categories as the change in non-cash working capital (ΔWC) and depreciation, respectively:

$$\begin{aligned} Accruals &= (\Delta\ accounts\ receivable + \Delta\ inventories - \Delta\ accounts\ payable) \\ &+ (\Delta\ other\ current\ assets - \Delta\ other\ current\ liabilities) - Dep = \Delta WC - Dep \quad (2.6) \end{aligned}$$

From equation (2.6), accruals are mainly driven by changes in working capital, which in turn tend to rise with sales. Managers of growing firms with high accruals may extrapolate this past fast growing trend into the future. Since they overestimate the persistence in sales growth, they build up inventories and other working capital items under overstated expectations. Similarly, analysts and investors tend to rely too heavily on past growth in their forecasts and valuations (see, e.g., De Bondt and Thaler, 1990; La Porta, et al., 1997; and Chan, Karceski and Lakonishok, 2003). Richardson, et al. (2005) report that less reliable categories of accruals have lower earnings persistence and the investors do not fully anticipate the lower earnings persistence. Consequently, if the market pricing of high-accrual firms is built on an overoptimistic estimate of future growth rates, future returns are more likely to be disappointing.

2.4.1 Operating Performance of the Winner and Loser Stocks

To understand the persistence of winners and losers across the three accrual groups, I analyze the sales growth reflecting operating performance. The ratio is an industry-adjusted and time-series average of the cross-sectional median values. The industry adjustment involves subtracting the industry median from each firm's accounting ratio. I focus on the winner (P10) and loser (P1) portfolios for each of the three accrual groups. The results are presented in Table 2.10 starting from the portfolio sorting periods and going through the holding periods from month t−6 through month t+12. My goal is to relate the return persistence of winner and loser stocks with high accruals to their underlying operating performance.

<Table 2.10>

I examine the operating performance (proxied by industry-adjusted sales growth) of the winner and loser stocks that are sorted across low-, medium- and high-accrual groups. Table 2.10 shows substantial differences in operating performance between winners and losers, and among low-, medium- and high-accrual stocks. Focusing on the high-accrual group, the industry-adjusted sales growth of loser stocks maintain the relative high sales growth rate over the formation period from an average of 6.61% in month t−6 to 8.22% in month t = 0. The sales growth starts deteriorating over the holding period, reaching a low of 3.08% in month t+6 and 0.00% in month t+12. Such deterioration in sales growth is observed over the holding period for the low- and medium-accrual losers as well; however, the magnitude of deterioration is relatively small in those cases.

Sales growth for the winner stocks with high accruals is large and positive over the formation period and the holding period. The industry-adjusted sales growth increases from 3.88% in month t= −6 to 6.63% in month t=0 and the sales growth continues to improve over the holding period, reaching a high of 7.39% in month t+6. As for the low- and medium-accrual winners, the industry-adjusted sales growth also improves over the holding period. In sum, the industry-adjusted sales growth of high-accrual losers have decreased dramatically over the holding period, while the high-accrual winners have positive industry-adjusted sales growth that improves and remains high over the first six months of the holding period and into 12 months.

Given the dramatic decline in stock prices and the rise in industry-adjusted sales growth over the formation period (t-6 through t-1) for the loser stocks in high-accrual group, it can be argued that, as of the formation date, the market has already anticipated the improvement in operating performance of the firms. If the future performance is fully anticipated, then I should not observe the payoffs to momentum strategies. However, Table X shows that the winner and loser stocks in high-accrual group display the opposite industry-adjusted sales growth behavior for the holding period. This operating performance check could also explain the different holding returns across three accrual groups. While loser stocks of all three accrual groups experience sales growth deterioration, losers with high accruals experience the more serious sales growth deterioration than those with low and medium accruals. Considering their corresponding sales growth level over the formation period, investors are most likely to overestimate the sales growth of the loser stocks with high accruals. In particular, these firms have enjoyed high sales growth in the past and investors extrapolate past growth to form exaggerated expectations about future growth. Over the holding period, the release of sales growth deterioration information will indicate a bad signal to the market and definitely have a negative effect on stock price.

This explanation is consistent with the discrepancy in payoff of loser stocks and non-discrepancy in payoff of winner stocks across three accrual groups (returns of P1 and P10 in Table 2.4). The evidence supports the hypothesis: the market pricing of firms with high accruals may be built on earnings overestimation. In addition, I cannot reject the existence of managers that manipulate earnings through accruals, because this misvaluation might be induced by managerial efforts to manipulate earnings and stock prices.[18] Another possible explanation for high level sales growth of loser stocks with high accruals during formation period is that such high level sales growth does not reflect the real performance of these firms. The loser firms with high accruals may just mimic the performance of winner firms with high accruals and disguise the fact. However, the market may gradually (or immediately) realize this point. That is why the returns of loser firms with high accruals could not match their performance from financial statements during the formation period, so these loser firms with high accruals still fall into the lowest past returns.[19] The time series behavior of accruals and operating performance for firms with high accruals gives strong evidence that managers have strong incentives to manipulate earnings through accruals. This temporary sales growth inflation may mislead

[18] For instance, when sales growth starts to slow down, managers may face increasing pressures to inflate earnings in order to meet analyst forecasts, thus leading to an increase in accruals. These pressures may be much stronger if investors and analysts also maintain overstated expectations about future profitability growth. At the same time, inventory may start to accumulate as sales growth declines, and accounts receivable may increase as competitive pressures force firms to extend better credit terms, so accruals increase (Thomas and Zhang, 2002).

[19] Dechow, Sloan, and Sweeney (1996) find that after investors discover accounting manipulations, these firms experience significant increases in their cost of capital. Similarly, Karpoff, Lee, and Martin (2008) document that firms on average lose 41 percent of their market value when financial misrepresentations are publicly disclosed.

investors. It implies that accrual-based momentum profit is affected by both earnings manipulation and earnings overestimation.

2.4.2 The Behavior of Special Items

Another popular interpretation of high accruals could be that high accruals reflect managers' deliberate attempts to manipulate accounting numbers in order to avoid disappointing analysts and investors. While this results in higher earnings, the cash flow situation does not improve because accruals are raised due to the increase in inventory. Inflating earnings in one period has consequences for reported earnings in the future. In the case of overstating inventory, one potential impact is an increase in writedowns of inventory in subsequent years. Such writedowns will show up at least in part as a reversal of future accruals: after the original overstatement of inventory which increases accruals, accruals become lower in future years. Part of the previous high accruals may also be reported as a special item on the income statement. Many studies report evidence supporting the existence of managerial manipulation of earnings (see, e.g., Subramanyam, 1996; Teoh, Welch, and Wong, 1998a, 1998b; and Kothari, Loutskina, and Nikolaev, 2008). I extract special items from Compustat annual data (item 17), which reflect unusual charges to a firm's income, and include writedowns of inventory or receivables, as well as restructuring or reorganization costs. I check the behavior of accruals and special items in the years following portfolio formation in order to track the traces of earnings manipulation in the previous years, especially in high-accrual group.

<Table 2.11>

Table 2.11 reports the level of special items as a percentage of average total assets for firms sorted by accruals. I track special items over each of the six months up to the portfolio formation date and the subsequent year. The level of special items is usually negative because analysts and investors generally focus on earnings from continuing operations. When earnings are below expectation, managers may conceal or remedy such information and try to put the best face on the situation. They may interpret the earnings disappointment as a one-time event, and count it as a special item in order to shield net income from continuing operations. What is especially striking is the difference in how special items behave over the years before and after portfolio formation.

For the loser stocks with high accruals, special items experience the largest decline over the 12 months following portfolio formation, comparing with the prior years. Their special items are on average -3.59 basis points (bp) of total assets before portfolio formation, and jump to -9.8bp on average in the post-formation period. The corresponding average special items for the loser stocks in low- and medium- accrual group change from -14.93bp and -6.18bp (pre-formation) to -13.06bp and -9.24bp (post-formation). The largest amount of decline from the loser stocks with high accruals in income-decreasing special items in the subsequent year may reflect the effects of managerial manipulation of earnings in prior years. Such effect of earnings manipulation is reversed over time or is eliminated in terms of special items in the subsequent years. The evidence shows that the loser stocks in high-accrual group may experience the most serious earnings manipulation. At the same time, the market may gradually realize this point implying the low payoff of loser stocks with high accruals during the holding period. While earnings manipulation may also exist in the portfolios including winner and loser stocks in low- and medium-accrual groups, their effect could be offset from each other. Since earnings manipulation effect could not be offset in high-accrual group, this causes the discrepancy in payoff of momentum profits across three accrual groups.

2.4.3 The Role of Nondiscretionary and Discretionary Accruals

To differentiate the earnings overestimation and earnings manipulation, I decompose accruals into nondiscretionary and discretionary components and examine the information in each component for returns. The nondiscretionary component captures the impact of business conditions while the discretionary portion reflects managerial choices. The overestimation hypothesis posits that firms with high accruals represent instances of overvaluation because of investors' extrapolated biases. In particular, these firms have enjoyed high sales growth in the past and investors extrapolate past growth to form exaggerated expectations about future growth. The manipulation hypothesis suggests that the discretionary component of accruals that is unrelated to sales growth should predict future returns.

<Table 2.12>

Stocks are sorted into three groups by nondiscretionary accruals in Panel A, and by discretionary accruals in Panel B of Table 2.12. In Panel A, the magnitude of momentum profits does not change much across three groups. I observe a 0.42% monthly return for low, 0.39% for medium and 0.51% for high nondiscretionary accrual group, respectively. The decomposition procedure assumes that nondiscretionary accruals grow proportionally with sales. However, Panel A indicates that there is no significant discrepancy in momentum payoff across nondiscretionary accrual group and future returns. Accordingly, this evidence is not consistent with the earnings overestimation hypothesis.

In terms of the monthly return profits between the loser and winner portfolios, the sort by discretionary accruals comes close to matching the performance of the sort by total accruals. In Panel B, the average monthly profit for high discretionary accrual group over the first six months is 1.00% which is significant at the 1% level (t-stat=5.02). The monthly profit corresponding to the classification by total accruals is 1.37% (see Table 2.4). The average monthly profits for low and medium discretionary accrual group are lower and less significant (0.39% for low and 0.49% for medium group).

Panel C shows the percentage of discretionary accruals divided by total accruals across three accrual groups. This percentage could be considered as a proxy of earnings management since discretionary accruals capture the effect of managerial discretion. I find that the loser stocks have a higher percentage of discretionary accruals than winner stocks in the high accrual group, implying that loser stocks with high accruals suffer more earnings management. Instead, I do not find much difference in earnings management between loser and winner stocks among low and medium accrual groups. These results are consistent with the earnings manipulation hypothesis.[20]

In summary, most momentum profitability is attributable to high discretionary accrual group. In each nondiscretionary accrual group, the magnitude of momentum profitability is almost at the same level as that from total accruals. Since discretionary

[20] As pointed out in Xie (2001), discretionary accruals are negatively related to future stock returns. One more question arises: why winners in high discretionary accruals group continue to earn high returns? One possible explanation is due to the different portfolio holding periods. Xie (2001) holds his portfolios for at least 12 months after portfolio formation, while we hold the portfolios for only 6 months after formation. If we hold the portfolios for 12 months after the portfolio formation in Panel B of Table XII, the momentum profits will be much less significant because of the large drop in payoff of winner stocks with high discretionary accruals. It implies the less persistent effect of discretionary accruals on stock returns.

accruals are more likely to capture accruals arising from managerial discretion, the above findings indicate that the market overprices the portion of discretionary accruals stemming from earnings management. If managers are manipulating earnings, they are more likely to inflate earnings than to decrease or smooth earnings. As a result, the potential impact of manipulation on returns may be more apparent in the portfolio with high accruals. In particular, the effect is largely driven by the poor performance of the loser stocks with high accruals, where the incentive to manipulate earnings might be the strongest among the three accrual groups.

2.5 Conclusion

Price momentum is an anomaly not explained by the Fama and French (1996) three-factor model and other risk based models. In this paper, I provide evidence on both rational and behavioral arguments by examining the relationship between price momentum and accruals.

To answer the three empirical questions raised at the beginning of this paper, I employ data on 5,195 NYSE and AMEX firms with sufficient accounting information over the January 1965-December 2008 period. My analysis indicates that momentum profitability is statistically significant and economically large among high-accrual firms, but it is nonexistent among low- and medium-accrual firms. The results are robust and cannot be explained by the market factor, the time-varying beta, the Fama-French three factors, trading volume, credit ratings and even the momentum factor.

I propose two hypotheses-earnings manipulation and earnings overestimation and analyze the predictive power of accruals for stock returns based on three tests. Over the portfolio holding period, the industry-adjusted sales growth of loser stocks with high accruals deteriorates significantly while that of the winner stocks with high accruals improves. I track special items to check the existence of earnings manipulation. Over the portfolio formation period and the holding period, the largest amount of income-decreasing special items for the loser firms with high accruals indicates that the effect of earnings manipulation in prior years is eventually reversed. I find no significant discrepancy in momentum profit across nondiscretionary component of accruals which provides weak support for the earnings overestimation hypothesis. The discretionary accruals contribute the most to the discrepancy in momentum profits, strongly supporting the earnings manipulation hypothesis. My findings indicate that accrual-based momentum profit is largely driven by downward payoff of loser stocks with high accruals, implying that earnings manipulation plays a major role on the effect of accruals on momentum profits.

My paper also highlights the predictive power of accruals for equity valuation. Conceivably, accruals may deserve much more attention from investors and analysts in future research. As suggested by Campbell, Polk and Vuolteenaho (2010), accounting variables are not sufficiently emphasized in contemporary academic research.[21] The robust effect of accruals on momentum documented in this paper sheds light on the contribution of accruals to momentum profitability.

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[21] This paper is not to assess the costs and benefits of accrual basis accounting. Actually, accrual basis accounting has gained universal acceptance recently. For instance, worldwide, public sectors have started adopting accrual accounting instead of traditional cash-basis accounting. Bradshaw, Richardson, and Sloan (2001) show that analysts do not incorporate into their forecasts the earnings reversal that is associated with high accruals. They also find that although firms with high accruals exhibit higher incidence of SEC enforcement actions, their auditors are not more likely to issue qualified opinions.

Table 2.1 Summary Statistics of Monthly Raw Return and Price Momentum Profit

Panel A presents descriptive statistics of monthly returns for all stocks listed on CRSP after merging with Compustat. I exclude stocks where at time t the price is below $5 and the market capitalization is in the lowest NYSE size decile. Returns are computed as the time-series mean of the cross-sectional average return for each month (in percent per month). Standard deviation, skewness, and kurtosis are computed for each stock and then averaged across all stocks. Size is computed as the time-series mean (median) of the cross-sectional mean of all market capitalizations in each month (in $millions).

In Panel B, for each month t, all NYSE and AMEX stocks on the monthly CRSP tape with returns for month t–6 through t-1 are ranked into decile portfolios according to their cumulative returns during that period. Decile portfolios are formed monthly and their returns are computed by weighting equally all firms in that decile ranking. The momentum strategy involves buying the winner portfolio P10 and selling the loser portfolio P1. The positions are held for the following six-months (t+1 through t+6). There is a one month lag between the formation and the holding periods. Monthly returns represent the equally-weighted average return from this month's momentum strategy and all strategies from up to five months ago. The table shows the monthly average raw return during the holding period of the winner P10, the loser P1, and the momentum portfolio. T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Panel A: Return and Size Characteristics of Sample Firms

No. of firms	5,195
Mean return (%)	1.18
Median return (%)	0.77
Standard deviation of return (%)	10.65
Skewness of return	0.63
Kurtosis of return	6.38
Mean size ($millions)	3,319.08
Median size ($millions)	552.49

Panel B: Price Momentum Profit (in percent per month)

Portfolio		Return	t-stat
Overall	P10-P1	1.03**	(5.90)
	P1	0.59	(2.09)
	P10	1.62	(5.76)
January	P10-P1	-1.29	(-1.68)
	P1	4.55	(3.81)
	P10	3.26	(3.27)
Non-January	P10-P1	1.23**	(7.11)
	P1	0.24	(0.83)
	P10	1.47	(5.03)

Table 2.2 Components in Accounting Earnings and Accrual Anomaly

Panel A presents the mean value of the accrual, earnings and cash flow component. Ten portfolios of firms are formed annually by assigning firms to deciles based on the value of accruals. Following Sloan (1996), accruals are defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable) and depreciation expense, all divided by average total assets. Earnings are defined as operating income after depreciation divided by average total assets. Cash flows are defined as the difference between earnings and accruals.

In Panel B, for each month t, qualified stocks are ranked into decile portfolios according to their fiscal year accruals (A1 for the lowest accrual group and A10 for the highest). Decile portfolios are formed monthly and their returns are computed by weighting equally all firms in that decile ranking. The strategy involves buying the lowest accrual portfolio A1 and selling the highest accrual portfolio A10. The positions are held for the following six-months (t+1 through t+6). There is a one month lag between the formation and the holding periods. Monthly returns represent the equally-weighted average return from this month's strategy and all strategies from up to five months ago. The table shows the monthly average raw return during the holding period of the lowest accruals A1, the highest accruals A10 and accruals strategy portfolios. T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Panel A: Mean Value of Accruals, Earnings and Cash Flow Components

	Sorted by accruals									
	Lowest	2	3	4	5	6	7	8	9	Highest
Accruals	-0.14	-0.08	-0.06	-0.05	-0.03	-0.02	-0.01	0.00	0.03	0.11
Earnings	0.08	0.10	0.11	0.10	0.10	0.11	0.11	0.12	0.13	0.13
Cash flows	0.22	0.18	0.17	0.15	0.13	0.13	0.12	0.12	0.10	0.02

Panel B: Accrual Anomaly

	Return (in percent per month)
A1-A10 (accruals profit)	0.49 ** (4.06)
A1 (lowest)	1.46 (5.45)
A10 (highest)	0.97 (3.23)

Table 2.3: Combined Momentum and Accruals Effects (Independent Two-way Sorting)

For each month t, all NYSE and AMEX stocks on the monthly CRSP tape with returns for month t−6 through t-1 are ranked into decile portfolios according to their cumulative returns (P1 for the loser portfolio, P10 for the winner portfolio) and ranked into decile portfolios according to their fiscal year accruals (A1 for the lowest and A10 for the highest accruals) simultaneously. Four extreme portfolios are shown in the table below. (A1, P1) stands for the portfolio of loser stocks with the lowest accruals. (A10, P1) stands for the portfolio of loser stocks with the highest accruals. (A1, P10) stands for the portfolio of winner stocks with the lowest accruals. (A10, P10) stands for the portfolio of winner stocks with the highest accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. Decile portfolios are formed monthly and their returns are computed by weighting equally all firms in that decile ranking. The positions are held for the following six-months (t+1 through t+6). There is a one month lag between the formation and the holding periods. Monthly raw returns represent the equally-weighted average return from this month's combined strategy and all strategies from up to five months ago. T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Portfolio	(A1, P1)	(A10, P1)
Raw return (in percent per month)	1.39 (4.08)	-0.02 (-0.07)
Portfolio	(A1, P10)	(A10, P10)
Raw return (in percent per month)	1.66 (4.99)	1.57 (4.50)
Strategy 1	Diff_1 = (A10, P10) - (A10, P1)	
Raw return (in percent per month)	1.59** (6.80)	
Strategy 2	Diff_2 = (A1, P10) - (A1, P1)	
Raw return (in percent per month)	0.27 (0.93)	
Strategy 3	Diff_3 = (A1, P10) - (A10, P1)	
Raw return (in percent per month)	1.68** (6.59)	

Table 2.4 Momentum Profits across Accruals

For each month t, all qualified stocks with return for months t−6 through t-1 (formation period) are equally divided into three groups based on accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each accrual group, I compute the return of the loser portfolio P1 as the equally-weighted average return over the holding period of the worst-performing 10% and the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period. There is a one month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for six months. Since the momentum strategy is implemented each month, the monthly returns represent the equally-/value-weighted average return from this month's momentum strategy and all strategies from up to five months ago. The table shows, for accrual group, the average returns of the momentum strategy, as well as the average return of the loser and winner portfolios.

Panel A shows monthly raw equally-/value-weighted return of momentum profits sorted by three accruals. Panel B shows the risk adjusted equally-/value-weighted return (alpha) applying alternative asset pricing model (CAPM, Conditional CAPM, FF three-factor model and Carhart four-factor model). T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Panel A: Momentum Profits (Raw Return) by Accrual Group

	Low Accruals (A1)				Medium Accruals (A2)				High Accruals (A3)			
	EW-return	t-stat	VW-return	t-stat	EW-return	t-stat	VW-return	t-stat	EW-return	t-stat	VW-return	t-stat
P10-P1 (in percent)	0.26	(1.12)	0.45	(1.61)	0.36	(1.76)	0.54	(1.71)	**1.37****	**(7.26)**	**1.29****	**(5.06)**
P1	1.29	(4.04)	0.83	(2.58)	1.11	(3.77)	0.72	(2.48)	0.13	(0.42)	-0.03	(-0.11)
P2	1.22	(4.08)	0.96	(3.70)	1.14	(4.77)	0.85	(3.65)	0.64	(2.36)	0.33	(1.21)
P3	1.25	(5.01)	0.92	(4.04)	1.04	(4.70)	0.87	(4.13)	0.93	(3.90)	0.73	(2.87)
P4	1.26	(5.48)	0.99	(4.62)	1.15	(5.62)	0.96	(4.81)	0.98	(3.92)	0.71	(2.93)
P5	1.23	(5.54)	0.92	(4.63)	1.18	(5.67)	0.92	(4.73)	1.04	(4.18)	0.76	(3.24)
P6	1.21	(5.41)	0.92	(4.69)	1.11	(5.50)	0.94	(4.88)	1.03	(4.23)	0.77	(3.33)
P7	1.25	(5.53)	1.01	(4.99)	1.18	(5.81)	0.95	(4.86)	1.11	(4.57)	0.80	(3.35)
P8	1.28	(5.44)	0.96	(4.41)	1.09	(5.05)	0.90	(4.39)	1.05	(4.37)	0.81	(3.47)
P9	1.53	(6.01)	1.23	(5.12)	1.23	(5.41)	1.14	(5.29)	1.24	(4.81)	0.94	(3.90)
P10	1.55	(5.40)	1.27	(4.57)	1.47	(5.65)	1.26	(4.95)	1.50	(5.08)	1.26	(4.32)
Percent of market cap	41.5%				35.4%				23.1%			

Panel B: Risk Adjusted Monthly (Equally-/Value-weighted) Return of Momentum Profits by Accrual Group

	Intercept (alpha)		Market factor		SMB		HML		Momentum factor	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
					Adjusted by CAPM					
Low (A1)	0.31	0.50	-0.11*	-0.14*						
	(1.28)	(1.78)	(-2.07)	(-2.12)						
Medium (A2)	0.39	0.55	-0.07	-0.06						
	(1.87)	(1.79)	(-1.54)	(-1.15)						
High (A3)	**1.38****	**1.33***	-0.01	-0.09						
	(7.25)	**(5.19)**	(-0.17)	(-1.74)						
					Adjusted by conditional CAPM					
Low (A1)	0.45	0.49	-0.08	-0.19						
	(1.90)	(1.77)	(-0.79)	(-1.72)						
Medium (A2)	0.61**	0.56*	0.09	-0.01						
	(3.08)	(2.28)	(1.03)	(-0.12)						
High (A3)	**1.55****	**1.34****	0.08	-0.01						
	(7.97)	**(5.20)**	(0.91)	(-0.13)						
					Adjusted by the Fama-French three-factor model					
Low (A1)	0.42	0.48	-0.15**	-0.26**	-0.06	0.09	-0.23*	-0.10**		
	(1.76)	(1.40)	(-2.76)	(-3.86)	(-0.74)	(1.11)	(-2.50)	(-3.67)		
Medium (A2)	0.51*	0.63*	-0.09	-0.11	-0.12	0.04	-0.20**	-0.16*		
	(2.41)	(2.52)	(-1.87)	(-1.84)	(-1.85)	(0.39)	(-2.63)	(-2.03)		
High (A3)	**1.53****	**1.46****	-0.05	-0.15*	-0.10	-0.04	-0.26**	-0.24*		
	(7.96)	**(5.60)**	(-1.12)	(-2.41)	(-1.68)	(-0.51)	(-3.73)	(-2.55)		
					Adjusted by the Carhart four-factor model					
Low (A1)	-0.47**	-0.31	-0.02	-0.11*	-0.05	0.11	0.03	-0.10	0.90**	0.99**
	(-2.62)	(-1.42)	(-0.39)	(-2.11)	(-0.89)	(1.57)	(0.47)	(-1.22)	(21.4)	(19.05)
Medium (A2)	-0.32*	-0.35	0.03	0.04	-0.11*	0.06	0.03	0.11	0.83**	0.98**
	(-2.18)	(-1.94)	(0.91)	(0.90)	(-2.54)	(0.85)	(0.63)	(1.84)	(23.84)	(23.27)
High (A3)	**0.81****	**0.50***	0.06	0.01	-0.10*	-0.03	-0.06	0.04	0.72**	0.10**
	(5.64)	**(2.42)**	(1.72)	(0.20)	(-2.18)	(-0.57)	(-1.12)	(0.58)	(21.42)	(22.28)

Table 2.5 Independent Sorts by Accruals and Size

For each month t, all stocks with available return data for months t−6 through t-1 (formation period) are divided into 9 groups based on their size equally and accruals equally. The table shows, for each group, the average returns of the momentum strategy, which involves buying the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period and selling the loser portfolio P1 and holding the position for six months (t +1 through t+6). The size breakpoints are defined as the NYSE 20th and 50th percentiles of market cap for NYSE stocks.
Panel A shows monthly raw return of momentum profits of 9 groups. Panel B apply alternative asset pricing model (CAPM, FF three-factor model and Carhart four-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Panel A: Independent Sort by Accruals and Size (Raw Return)

	Low accruals	Medium accruals	High accruals
Micro-cap	0.35	0.38	1.43**
	(0.92)	(0.99)	(5.28)
Small-cap	0.08	0.30	1.51**
	(0.26)	(1.11)	(6.00)
Big-cap	0.57*	0.50*	1.23**
	(2.23)	(1.99)	(4.98)

Panel B: Independent Sort by Accruals and Size (Risk Adjusted Return)

	Low accruals	Medium accruals	High accruals
	Micro-cap		
CAPM	0.42	0.41	1.43**
	(1.08)	(1.08)	(5.27)
FF three-factor	0.56	0.65	1.49**
	(1.42)	(1.68)	(5.41)
Carhart four-factor	-0.14	0.04	1.02**
	(-0.36)	(0.10)	(3.77)
	Small-cap		
CAPM	0.15	0.34	1.49**
	(0.45)	(1.27)	(5.88)
FF three-factor	0.12	0.54	1.66**
	(0.35)	(1.94)	(6.48)
Carhart four-factor	-0.73*	-0.20	1.03**
	(-2.43)	(-0.96)	(4.38)
	Big-cap		
CAPM	0.61*	0.52*	1.24**
	(2.38)	(2.06)	(5.02)
FF three-factor	0.78**	0.57*	1.39**
	(2.99)	(2.24)	(5.54)
Carhart four-factor	-0.14	-0.29	0.51*
	(-0.72)	(-1.38)	(2.57)

Table 2.6 Independent Sorts by Accruals and Volume

For each month t, all stocks with available return data for months t−6 through t-1 (formation period) are divided into 9 groups based on volume equally and accruals equally. The table shows, for each group, the average returns of the momentum strategy, which involves buying the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period and selling the loser portfolio P1 and holding the position for six months (t +1 through t+6). Volume is measured by average past six monthly turnovers. Panel A shows monthly raw return of momentum profits of 9 groups. Panel B apply alternative asset pricing model (CAPM, FF three-factor model and Carhart four-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant. The sample period is January 1965 to December 2008.

Panel A: Independent Sort by Accruals and Volume (Raw Return)

	Low accruals	Medium accruals	High accruals
Low volume	0.04	-0.06	0.83**
	(0.18)	(-0.38)	(4.39)
Medium volume	0.18	0.38	0.90**
	(0.71)	(1.56)	(3.81)
High volume	0.17	0.41	1.71**
	(1.51)	(1.17)	(6.57)

Panel B: Independent Sort by Accruals and Volume (Risk Adjusted Return)

	Low accruals	Medium accruals	High accruals
		Low volume	
CAPM	0.07	-0.05	0.83**
	(0.33)	(-0.23)	(4.52)
FF three-factor	0.19	0.08	0.94**
	(0.80)	(0.39)	(5.02)
Carhart four-factor	-0.48*	-0.43*	0.52**
	(-2.23)	(-2.09)	(2.94)
		Medium volume	
CAPM	0.25	0.40	0.89**
	(0.94)	(1.66)	(3.75)
FF three-factor	0.42	0.08	1.03**
	(1.60)	(0.39)	(4.31)
Carhart four-factor	-0.32	-0.43*	0.45*
	(-1.35)	(-2.09)	(2.05)
		High volume	
CAPM	0.23	0.47	1.71**
	(0.71)	(1.33)	(6.53)
FF three-factor	0.34	0.61	1.86**
	(1.03)	(1.70)	(7.04)
Carhart four-factor	-0.62*	-0.48	1.10**
	(-2.14)	(-1.57)	(4.74)

Table 2.7 Independent Sorts by Accruals and Credit Ratings

For each month t, all stocks with available return data for months t−6 through t-1 (formation period) are divided into 9 groups based on their credit ratings equally and accruals equally. The table shows, for each group, the average returns of the momentum strategy, which involves buying the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period and selling the loser portfolio P1 and holding the position for six months (t+1 through t+6). Credit ratings are measured by S&P Domestic Long Term Issuer Credit Rating. Panel A shows monthly raw return of momentum profits of 9 groups. Panel B apply alternative asset pricing model (CAPM, FF three-factor model and Carhart four-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is June 1985 to December 2008.

Panel A: Independent Sort by Accruals and Credit Ratings (Raw return)

	Low accruals	Medium accruals	High accruals
Low ratings	0.06	-0.04	1.77**
	(0.13)	(-0.07)	(4.65)
Medium ratings	0.04	0.19	1.24**
	(0.08)	(0.47)	(3.25)
High ratings	0.02	0.10	0.39
	(0.06)	(0.35)	(1.24)

Panel B: Independent Sort by Accruals and Credit Ratings (Risk Adjusted Return)

	Low accruals	Medium accruals	High accruals
		Low ratings	
CAPM	0.15	0.02	1.80**
	(0.32)	(0.04)	(4.73)
FF three-factor	0.21	0.12	1.89**
	(0.42)	(0.22)	(4.87)
Carhart four-factor	-0.79	-1.03*	1.17**
	(-1.88)	(-2.16)	(3.40)
		Medium ratings	
CAPM	0.12	0.25	1.25**
	(0.27)	(0.63)	(3.24)
FF three-factor	0.16	0.34	1.51**
	(0.34)	(0.85)	(3.96)
Carhart four-factor	-0.80*	-0.48	0.70*
	(-2.06)	(-1.40)	(2.18)
		High ratings	
CAPM	0.01	0.10	0.38
	(0.04)	(0.33)	(1.18)
FF three-factor	0.10	0.14	0.42
	(0.28)	(0.48)	(1.29)
Carhart four-factor	-0.52	-0.61**	-0.26
	(-1.68)	(-2.76)	(-0.96)

Table 2.8 The Incremental Effect of Accruals on Momentum

I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. *Accruals* are previous fiscal year measures, obtained from equation (2.1). *MV* is the log market value of equity and *BM* is book-to-market equity based on accounting data from the fiscal year ending in calendar year t. *Credit* is measured by S&P Domestic Long Term Issuer Credit Rating.

Panel A reports Pearson (Spearman) correlations between the relevant firm-specific variables in the upper (lower) diagonal. All the correlations are statistically significant at the 1% level. The sample period is June 1985 to December 2008.

In Panel B, for each month t, all qualified stocks with return for months t−6 through t-1 (formation period) are equally divided into three groups based on residual accruals ($\varepsilon_{i,t}$) in the following equation

$$Accruals_{i,t} = \gamma_0 + \gamma_1 MV_{i,t} + \gamma_2 BM_{i,t} + \gamma_3 Turnover_{i,t} + \gamma_4 Credit_{i,t} + \varepsilon_{i,t}$$

For each group, I compute the return of the loser portfolio P1 as the equally-weighted average return over the holding period of the worst-performing 10% and the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period. There is a one month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for six months. Since the momentum strategy is implemented each month, the monthly returns represent the equally-/value-weighted average return from this month's momentum strategy and all strategies from up to five months ago. The table shows, for residual accrual group, the average returns of the momentum strategy, as well as the average return of the loser and winner portfolios.

Panel A: Pearson (Spearman) Correlations between Firm-specific Variables

Variable	Accruals	MV	BM	Turnover	Credit
Accruals		-0.046	-0.006	0.008	0.026
MV	-0.035		-0.459	0.152	-0.525
BM	-0.008	-0.474		-0.101	0.170
Turnover	0.007	0.218	-0.119		0.240
Credit	0.017	-0.508	0.158	0.219	

Panel B: Momentum Profits (Equally-/Value-weighted Raw Return) by Residual Accruals ($\varepsilon_{i,t}$)

	Low ($\varepsilon_{i,t}$)				Medium ($\varepsilon_{i,t}$)				High ($\varepsilon_{i,t}$)			
	EW-return	t-stat	VW-return	t-stat	EW-return	t-stat	VW-return	t-stat	EW-return	t-stat	VW-return	t-stat
P10-P1 (in percent)	0.29	(0.98)	0.36	(1.16)	0.31	(1.07)	0.34	(1.21)	**0.90****	**(3.25)**	**0.88****	**(3.06)**
P1	1.02	(2.65)	0.95	(2.48)	0.91	(2.23)	0.78	(2.13)	0.44	(1.07)	0.43	(1.04)
P2	1.16	(3.42)	1.12	(3.32)	1.11	(3.74)	1.02	(3.62)	0.68	(2.48)	0.63	(2.35)
P3	1.00	(3.22)	0.96	(3.16)	1.10	(3.82)	0.99	(3.80)	0.85	(2.63)	0.82	(2.57)
P4	1.04	(3.54)	1.03	(3.54)	1.07	(3.86)	0.94	(3.81)	0.89	(3.00)	0.87	(2.97)
P5	1.08	(3.87)	1.06	(3.78)	1.10	(3.92)	1.00	(3.93)	0.88	(3.01)	0.85	(2.97)
P6	0.97	(3.06)	0.95	(3.00)	1.06	(2.94)	0.94	(2.89)	0.92	(2.69)	0.91	(2.68)
P7	1.08	(3.84)	1.04	(3.78)	1.08	(3.92)	0.97	(3.88)	0.91	(3.19)	0.88	(3.11)
P8	1.07	(3.65)	1.05	(3.63)	1.07	(3.76)	0.96	(3.75)	0.92	(3.07)	0.86	(2.99)
P9	1.20	(3.63)	1.18	(3.62)	1.13	(3.74)	1.07	(3.72)	1.23	(3.30)	1.08	(3.25)
P10	1.31	(4.47)	1.31	(3.49)	1.22	(4.32)	1.12	(3.34)	1.34	(3.70)	1.31	(3.65)

Table 2.9 Momentum Profits Conditioning on Various Market States

For each month t, all qualified stocks with return for months t−6 through t-1 (formation period) are equally divided into three groups based on accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each accrual group, I compute the return of the loser portfolio P1 as the equally-weighted average return over the holding period of the worst-performing 10% and the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period. There is a one month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for six months. Since the momentum strategy is implemented each month, the monthly returns represent the equally-weighted average return from this month's momentum strategy and all strategies from up to five months ago. Each panel shows monthly raw return and risk adjusted return (applying FF three-factor model) of momentum profits sorted by three accruals to check the significance of abnormal return (alpha).

Panel A examines momentum profits during different business cycle periods. The expansion and recession months are based on the classifications made by the NBER.

Panel B reports momentum profits in up and down markets. The 12-month cumulative returns on the CRSP value-weighted market index are used as a proxy for market returns. If the 12-month lagged return on the index has been positive (negative) (skipping one month before the holding period), a holding-period month is classified as an up (down) month.

Panel C of reports results on the accruals/momentum interaction in pessimistic and optimistic market states using the monthly sentiment index constructed by Baker and Wurgler (2006, 2007) is used to classify my sample months in pessimistic and optimistic periods. Following Antoniou, Doukas and Subrahmanyam (2011), a formation period is classified as optimistic (pessimistic) if the average sentiment belongs in the top (bottom) 30% of the three-month rolling average sentiment time series. T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. The sample period is January 1965 to December 2008.

Panel A: Momentum Profits under NBER Business Cycle

	Recession			Expansion		
	Low (A1)	Medium (A2)	High (A3)	Low (A1)	Medium (A2)	High (A3)
P1(in percent)	1.78	1.32	0.13	0.99	0.87	-0.02
	(2.02)	(1.57)	(0.16)	(2.16)	(2.08)	(-0.08)
P10	1.45	1.39	1.62	1.49	1.41	1.44
	(1.97)	(2.22)	(1.29)	(4.04)	(4.24)	(3.71)
P10-P1(raw return)	-0.33	0.07	1.49**	0.50	0.53*	1.46**
	(-0.52)	(0.14)	(2.98)	(1.76)	(2.02)	(6.64)
Risk adjusted return	0.16	0.43	1.84**	0.61	0.60*	1.59**
	(0.77)	(1.29)	(3.71)	(1.95)	(2.38)	(7.22)

Panel B: Momentum Profits under Up and Down Market

	Down			Up		
	Low (A1)	Medium (A2)	High (A3)	Low (A1)	Medium (A2)	High (A3)
P1 (in percent)	1.17 (4.01)	1.01 (3.72)	0.12 (0.41)	1.34 (4.16)	1.04 (3.62)	0.17 (0.55)
P10	1.45 (5.30)	1.38 (5.66)	1.49 (5.06)	1.44 (4.84)	1.58 (5.79)	1.51 (5.01)
P10-P1 (raw return)	0.28 (1.10)	0.37 (1.86)	1.37** (7.22)	0.10 (0.40)	0.54* (2.49)	1.34** (6.37)
Risk adjusted return	0.43 (1.79)	0.52 (1.50)	1.52** (7.93)	0.19 (0.75)	0.62** (2.78)	1.50** (7.11)

Panel C: Momentum Profits under Investor Sentiment

	Pessimistic			Optimistic		
	Low (A1)	Medium (A2)	High (A3)	Low (A1)	Medium (A2)	High (A3)
P1 (in percent)	1.26 (3.76)	1.15 (4.01)	0.36 (1.16)	1.19 (3.74)	1.11 (3.93)	0.19 (0.64)
P10	1.66 (5.66)	1.39 (5.38)	1.65 (5.46)	1.56 (5.46)	1.68 (4.24)	1.59 (5.34)
P10-P1 (raw return)	0.40 (1.52)	0.24 (1.09)	1.29** (5.98)	0.36 (1.45)	0.57* (2.39)	1.40** (6.30)
Risk adjusted return	0.63 (1.77)	0.34 (1.55)	1.40** (6.28)	0.54* (2.13)	0.76** (3.18)	1.53** (6.74)

Table 2.10: Operating Performance of the Winner and Loser:
Median of Industry-adjusted Sales Growth (in percent)

For each month t, all stocks with available return data for months t−6 through t-1 (formation period) are divided into 3 groups based on accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each of the 12 months in the holding period (months t+1 through t+12), I compute the cross-sectional median over each firm-level characteristic for stocks in the loser portfolio P1 and the winner portfolio P10 constructed based on the stocks' return over the formation period. The table shows the time-series average of these cross-sectional medians of each characteristic for each month of the holding period. The industry adjustment consists of subtracting from each stock characteristic the median characteristic for the industry to which the stock belongs. The median industry characteristics are recomputed each month based on the available stocks for the month. The sample period is January 1965 to December 2008.

Adjusted sales growth	Low accruals		Medium accruals		High accruals	
Month	P1	P10	P1	P10	P1	P10
-6	-0.59	-0.62	0.32	0.05	6.61	3.88
-3	-1.03	-1.12	0.44	0.11	7.75	4.76
0 (formation time t)	-1.47	-1.67	0.21	0.32	8.22	6.63
3	-1.46	-0.29	0.00	0.61	5.34	7.03
6	-1.93	0.82	-0.54	1.63	3.08	7.39
9	-2.03	2.26	-1.28	2.30	1.20	8.15
12	-1.94	3.67	-1.99	2.81	0.00	8.69

Table 2.11 Special Items in Pre- and Post- Formation Years for Portfolios Sorted by Accruals
Mean of Industry-adjusted Special Item/Total Asset *10,000

For each month t, all stocks with available return data for months t−6 through t-1 (formation period) are divided into 3 groups based on accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each month of the 12 months in the holding period (months t+1 through t+12), I compute the cross-sectional median over each firm-level characteristic for stocks in the loser portfolio P1 and the winner portfolio P10 constructed based on the stocks' return over the formation period. The table shows the time-series average of these cross-sectional means of each characteristic for each month of the holding period. Special item represents unusual or nonrecurring items presented above taxes by the company. The industry adjustment consists of subtracting from each stock characteristic the median characteristic for the industry to which the stock belongs. The median industry characteristics are recomputed each month based on the available stocks for this month. The sample period is January 1965 to December 2008.

	Low accruals		Medium accruals		High accruals	
Month	P1	P10	P1	P10	P1	P10
-6	-12.56	-14.50	-5.41	-4.80	-3.85	2.56
-3	-13.17	-11.57	-4.79	-5.03	-3.86	9.12
0 (formation time t)	-14.93	-11.56	-6.18	-4.85	-3.59	10.70
3	-13.76	-11.07	-5.85	-3.84	-4.93	10.10
6	-13.53	-8.58	-7.44	-3.47	-6.50	10.50
9	-12.52	-5.16	-8.27	-2.98	-8.07	7.69
12	-13.06	-3.60	-9.24	-2.96	-9.80	6.05

Table 2.12 Momentum Profits Sorted by Nondiscretionary and Discretionary Components of Accruals

For each month t, all qualified stocks with available return data for months t−6 through t-1 (formation period) are equally divided into three groups based on nondiscretionary (discretionary) accruals in. Based on equation (7), the prediction error is the measure of discretionary accruals and predicted value is the measure of nondiscretionary accruals. I exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each group, I compute the return of the loser portfolio P1 as the equally-weighted average return over the holding period of the worst-performing 10% and the winner portfolio P10 of the best-performing 10% of the stocks based on their returns over the formation period. There is a one month lag between the formation and the holding periods. The momentum strategy involves buying the winner portfolio and selling the loser portfolio and holding the position for six months. Since the momentum strategy is implemented each month, the monthly returns represent the equally-weighted average return from this month's momentum strategy and all strategies from up to five months ago. Panel A and Panel B show, for nondiscretionary (discretionary) accrual group, the average returns of the momentum strategy, as well as the average return of the loser and winner portfolios. T-statistics are in parentheses. '*' and '**' indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels, respectively. Panel C shows the percentage of discretionary accruals divided by total accruals across three accrual groups. The sample period is January 1965 to December 2008.

Panel A: Nondiscretionary Accruals

	Low	Medium	High	High-Low	High-Medium
P10-P1	0.42	0.39*	0.51*	0.09	0.12
(in percent per month)	(1.78)	(2.03)	(2.31)	(0.40)	(0.52)
P1	1.16	1.05	0.83	-0.33	-0.22
	(3.67)	(3.63)	(2.50)	(-1.56)	(-0.87)
P10	1.58	1.44	1.34	-0.24	-0.10
	(5.39)	(5.32)	(4.43)	(-1.07)	(-0.76)

Panel B: Discretionary Accruals

	Low	Medium	High	High-Low	High-Medium
P10-P1	0.39	0.49*	1.00**	0.61**	0.51*
(in percent per month)	(1.83)	(2.33)	(5.02)	(2.86)	(2.12)
P1	1.14	0.96	0.44	-0.70	-0.52
	(3.69)	(3.31)	(1.45)	(-2.25)	(-1.96)
P10	1.53	1.45	1.44	-0.09	-0.01
	(5.27)	(5.41)	(4.92)	(-0.37)	(-0.17)

Panel C: Percentage of Discretionary Accruals/Accruals

Sorted by accruals	Low	Medium	High
P1	35.7%	37.4%	50.1%
P10	36.8%	37.4%	41.7%

Chapter 3

Distress Risk in Accrual Anomaly: One Anomaly or Two?

3.1 Introduction

Accruals are defined as the difference between accounting earnings and cash flows. Since Sloan (1996) first documents the existence of accrual anomaly, it raises much research attention Sloan shows that a hedge strategy of buying firms with low accruals and selling firms with high accruals can generate around 10% abnormal returns in 12 months following the portfolio formation. He suggests that investors fail to correctly price the accrual component of earnings. In particular, the accrual component of earnings has lower persistence than the cash component but the market overestimates the accrual component while simultaneously underestimating the cash component. Fama and French (2008) highlight the pervasive effect of accrual anomaly. They demonstrate that the returns associated with accruals are strong and robust in all size groups, cross-sectional regressions, and tests based on different portfolio sorting methods. There is no consensus yet on why abnormal returns to the accrual trading strategy exist.[1] This paper finds that firms with extreme low and high accruals are mostly distressed firms. I investigate whether the continued existence of the accrual anomaly can be accounted by distress risk.

Recent studies show that financial distress predicts low future stock returns. Researchers explore different characteristics and explanations for the low returns of

[1] Researchers argue that accrual anomaly could be: (i) explained by misspecified models (e.g., Khan, 2008; Wu et al., 2010); (ii) caused by management manipulation (e.g., Xie, 2001; Chan et al., 2006; and Kothari et al., 2007); (iii) explained by high transaction costs(Lev and Nissim, 2006; Mashruwala, et al. , 2006).

distressed firm.[2] This finding challenges the basic concept in finance that high non-diversifiable risk is compensated by high returns, and is termed "distress anomaly". Campbell, et al. (2008) recommend an explanation of distress anomaly related to the preferences of institutional investors for low distress risk stocks, with the demand driving up the subsequent returns for low distress risk stocks and the lack of demand driving down the subsequent returns for high distress risk stocks.

Dechow (1994) states that the primary role of accruals is to overcome problems with measuring firm performance when firms are in continuous operation. I investigate the accrual anomaly from the perspective that accruals convey information not only about the future cash flows, but also about the distress risk of the firm. The motivation for investigating the interaction between accruals and distress risk is from two pieces of academic and practical evidence. These studies suggest that distress risk may increase in both the extreme low- and high-accrual portfolios. For instance, Sloan (1996) documents a negative association between accruals and cash flow from operations. From a fundamental analysis viewpoint, a combination of a low level of accruals and a high level of cash flow from operations is likely to be a signal that the firm is in trouble because the firm is apparently not replenishing its accruals-related assets with its cash assets (Ng, 2005).[3] Kraft, et al. (2006) report that most of the low-accrual firms record large write downs and/or disposed of significant assets. Dechow and Ge (2006) document that firms with low accruals have a higher percentage of delistings and distress risk as measured by

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[2] For example, Dichev (1998); Griffin and Lemmon (2002); Avramov, et al., (2007); Campbell, et al. (2008); Chava and Purnanandam (2010); George and Hwang (2010); and Garlappi and Yan (2011).

[3] For example, DeAngelo, et al. (2002) document that L.A. Gear's equity fell from $1 billion in 1989 to zero in 1998. As revenues declined sharply, management tried a series of radical strategy shifts while subsidizing the firm's large losses through working capital liquidations that reduced accruals and increased cash flow from liquidating operations. The cash flow from operations added to its cash balance that was used to pay its debts and finance (unsuccessful) investments.

the Shumway (2001) score. Khan (2008) provides a theoretical justification that the returns behavior of the low-accrual portfolio is similar to the returns behavior of a high bankruptcy risk portfolio. The first group of study implies that firms with low accruals may have high distress risk.

Simultaneously, Chen, et al. (2006) indicate that changes in accounts receivable, changes in inventories and changes in accounts payable are three items that contribute most to differentiating accruals across firms. For instance, high accruals may reflect increases in accounts receivable when managers record sales prematurely, or decreases in current liabilities when managers understate accounts payable. Managers can use accruals to signal their private information or to opportunistically manipulate earnings. Because investors fixate on reported earnings, they might be temporarily misled and induced to misvalue stock prices.[4] Teoh, et al. (1998a, 1998b), Rangan (1998), Shivakumar (2000), and Gong, et al. (2008) provide evidence supporting the existence of managerial manipulation through accruals. Before an initial public offering (IPO), a seasoned equity offering (SEO), and stocks repurchase, managers want to inflate earnings to make the offering more attractive to investors. Kothari et al. (2007) use an agency model and propose that managers face incentives to overstate earnings using accruals when their firm's equity is overpriced, so that high accruals indicate overvaluation and therefore negative future firm abnormal returns. This camp of studies suggests that earnings manipulation is more likely to be found in firms with high accruals, and such manipulation implies possible bad performance of firms in the past and/or results in

[4] For instance, the second largest accounting fraud in US history – the WorldCom scandal, is a case of earnings manipulation through adjusting accruals. WorldCom's improper accounting includes two principal types: reduced reported line costs and exaggerated reported revenues. From the second quarter of 1999 through the first quarter of 2002, WorldCom improperly reduced its reported line costs (and increased pretax income) by over $7 billion. (http://www.worldcomnews.com).

potential default in the future.[5] If so, one should expect to find that firms with high accruals may also have high distress risk.

In view of the above, I argue that firms with extreme accruals (both extremely low and extremely high accruals) have high distress risk. If this "*U-shape*" pattern of distress risk does exist across accruals, the return to accrual strategies after controlling for distress can be stated alternatively that the profitability of accrual anomaly is concentrated in the most distressed firms. In this study, I employ data on 6,601 NYSE, AMEX, and NASDAQ firms from the period January 1965 to December 2008 and confirm the "*U-shape*" pattern of distress risk in the extremely low- and high-accrual firms. More specifically, I use the 12-month-ahead probability of financial failure distress measure by Campbell, Hilscher, and Szilagyi (2008, henceforth *CHS*). The distress measure *CHS* in the lowest- and highest-accrual deciles is much higher than the median accrual deciles, implying that firms in extreme accrual deciles might be more likely to default in the following 12 months. Using trading strategies that sequentially sort on distress-*CHS* and accruals, I find that the returns of accrual anomaly are largely driven by implementing the accrual trading strategy within the high distress risk quintile. In particular, there appears to be an increasing trend of payoffs to the accrual strategy across the increasing distress risk quintiles, with the highest distress risk quintile having the highest equally/value-weighted excess returns of 1.03%/1.20% (t-stat=5.67/5.18). The t-statistics of the excess returns across the increasing distress risk quintiles show that the returns are mostly significant in the highest distress risk quintile. The above evidence

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[5] Dechow, et al. (1996) find that after investors discover accounting manipulations, these firms experience significant increases in their cost of capital. Similarly, Karpoff, et al. (2008) document that firms on average lose 41 percent of their market value when financial misrepresentations are publicly disclosed.

shows that accrual anomaly is mostly concentrated in firms with high distress and suggests that the abnormal returns to the accrual trading strategy may involve exposure to high distress risk. The effect of distress risk on accrual anomaly is robust after I control for the CAPM, the Fama-French three-factor model, and Carhart's (1997) four-factor model. The previously documented cross-sectional characteristics related to accrual anomaly such as size, volume, M/B, and idiosyncratic risk do not subsume the interaction between accruals and distress. In addition, the effect of distress risk on accrual anomaly survives in up or down markets or during recessions or expansions.

This paper provides a direct link between distress risk and abnormal returns to the accrual trading strategy. My work contributes to both the accrual anomaly and distress risk literature in three ways. First, I examine the characteristics of firms with different levels of accruals and find that firms with extreme low and high accruals are more likely to be distressed firms. My study provides the evidence that the abnormal returns to the accrual trading strategy could be attributed to high distress risk exposure. To the extent that the accrual anomaly exits, it should be labeled "distressed accrual anomaly". This study suggests that distress risk could provide a risk-based explanation of accrual anomaly. Second, this study provides a link between distress risk and idiosyncratic volatility. Mashruwala, et al. (2006) show that the accrual anomaly is concentrated in firms with high idiosyncratic volatility. This is consistent with the pattern I observe: the abnormal returns to the accrual trading strategy are economically large and statistically significant only among firms with high distress risk. While distress risk is not necessarily equivalent to idiosyncratic risk, they may have different effect on accrual anomaly. Even after I control for the idiosyncratic volatility, the effect of distress risk on accrual anomaly still survives. The significant accrual profits in the high distress quintile imply the robust effect of distress risk and shed light on the additional contribution of distress risk to accrual profitability. Third, my study highlights the importance of controlling for distress risk in the investigation of anomalies, especially when the anomaly requires the implementation of a trading strategy that could possibly result from exposure to high distress risk, consistent with recent studies by Avramov, et al. (2011), and Garlappi and Yan (2011).

The remainder of this paper is organized as follows. Section 3.2 provides a brief review of the accrual and distress anomaly literature. Section 3.3 details the data and summary statistics. Section 3.4 presents the empirical results of testing the abnormal returns to the accrual trading strategy in combination with distress risk and accruals. Section 3.5 summarizes the results and concludes.

3.2 Literature Review

3.2.1 Accrual Anomaly

Sloan (1996) first documents the existence of accrual anomaly - firms with high accruals underperform firms with low accruals. On average, for the period 1962–1991, a hedge strategy of buying firms with low accruals and selling firms with high accruals can generate around 10% abnormal returns in 12 months following portfolio formation. This accrual anomaly also exists in international markets (Pincus, et al., 2007). The interpretations of the evidence in the accrual anomaly literature are controversial. Sloan suggests that investors are overly optimistic about the future prospect of firms with high accruals and overly pessimistic about the future prospect of firms with low accruals. Other researchers argue that the accrual strategy's profitability is a manifestation of systematic pricing errors resulting from the lower earnings persistence of accrual information.

Several studies follow Sloan (1996) to further investigate different aspects of the accrual anomaly. In the first category, researchers examine various components of accruals that may contribute to the accrual anomaly (e.g., Xie, 2001; Thomas and Zhang, 2002; Fairfield, et al., 2003; Richardson, et al., 2005). The second set of papers examine the behavior of third parties such as analysts, auditors, insiders, institutions, short-sellers and bond-market investors (e.g., Bradshaw, et al., 2001; Beneish and Vargus, 2002; Collins, et al., 2003; Barth and Hutton, 2004; and Bhojraj and Swaminathan, 2009). The third group studies whether the accrual anomaly is related to managerial manipulation (e.g., Teoh, et al., 1998a, b; Shivakumar, 2000; Xie, 2001; Chan, et al., 2006; and Gong, et al, 2008); The fourth group investigates whether the accrual anomaly is distinct from the post-earnings announcement drift (Collins and Hribar, 2000) and the value-glamour anomaly (Desai, et al., 2004). The fifth category of studies explores some cross-sectional characteristics in the accrual strategy's return. For example, Ali, et al. (2001) find fewer returns to the accruals trading strategy for smaller firms, firms that are covered by fewer analysts, and firms that are mostly not held by institutions. Mashruwala, et al. (2006) show that the accrual anomaly is concentrated in firms with high idiosyncratic volatility. My study belongs to the last two categories.

3.2.2 Distress Anomaly

There is no consensus on whether distress is priced in expected stock returns. Most studies find that higher distress risk is associated with lower future returns and this negative relationship between distress risk and subsequent realized returns is termed as "distress anomaly". For instance, Dichev (1998) documents this negative relationship using two accounting based distress measures: Altman's (1968) Z-score and Ohlson's (1980) O-score measures. He finds that lower returns are concentrated in growth distressed firms. Griffin and Lemmon (2002) use the O-score to proxy the financial distress, and find that firms with high O-scores earn lower stock returns than their counterparts. Vassalou and Xing (2004) use the Merton (1974) type, distance-to-default measure and find that the equally-weighted portfolios with higher default probability earn greater returns.[6] More recently, Campbell, et al. (2008) construct a measure of financial distress by estimating the probability of failure in a logistic model and find similar results to those of Griffin and Lemmon (2002). They argue that distress anomaly is related to the preferences of institutional investors for low distress risk stocks, with the demand driving up the subsequent returns for low distress risk stocks and the lack of demand driving down the subsequent returns for high distress risk stocks.

As discussed above, previous researchers use various types of distress measures to estimate a firm's default risk. The advantages and disadvantages of these measures have been discussed. [7] In this study, I employ the probability of failure measure by

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[6] This significantly positive relation will disappear if I calculate the value-weighted returns instead of equally weighted portfolios.

[7] For example, Vassalou and Xing (2004) mention that the accounting-based measures use information which is inherently backward looking, since the financial statements report on a firm's past performance. However, option-pricing-based measures of distress risk require certain assumptions such as the validity of the option-pricing model in evaluating distress risk and presence of market efficiency. When a study uses bond downgrades and upgrades as a measure of default risk, it usually assumes that all assets within a rating category share the same default risk. However, a firm experiences a substantial change in its default risk prior to its rating change..

Campbell, et al. (2008) because their measure applies a reduced form model that uses both market adjusted and accounting based variables, rather than only accounting variables. They include most of the other inputs that other accounting variable based distress measures or distance-to-default measures use. Recent papers focus on the explanatory power of the failure models and document the low returns of distressed firms. Different from these studies, this paper provides a new perspective by linking the accrual anomaly to distress risk.[8]

3.3 Data and Empirical Design

The data universe includes monthly stock returns from the Center for Research in Security Prices (CRSP) as well as quarterly and annual Compustat industrial data over the period January 1965 to December 2008. This study includes all the common stocks listed on the NYSE, AMEX, and NASDAQ with CRSP codes 10 or 11, excluding firms from the financial and utility sectors. The monthly data of the Fama-French factors, momentum factor, and the risk-free rate are from Kenneth French's website.

The accrual component of earnings is computed using information from the balance sheet and income statement, consistent with the existing literature on earnings management (see, e.g., Dechow, et al., 1995; and Sloan, 1996):

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep \qquad (3.1)$$

where ΔCA = change in current assets (Compustat item 4), $\Delta Cash$ = change in

[8] Chava and Purnanandam (2010); Griffin and Lemmon (2002); Avramov, et al.(2007); George and Hwang (2010); and Garlappi and Yan (2011) explore different characteristics and explanations for the low returns of distressed firm.

cash (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), Dep = depreciation and amortization (Compustat item 14). The measure of earnings is operating income after depreciation before interest expense, taxes and special item (Compustat data item 178). *Cash flows* is calculated as the difference between earnings and accruals. All three variables-earnings, accruals and cash flows are standardized by firm size to facilitate the empirical analysis, where firm size is measured as the average of the beginning and end of year book value of total assets (Compustat data item 6), as follows:

$$\begin{aligned}
&\text{Earnings} = \frac{\text{Operating income after depreciation}}{\text{Average total assets}} \\
&\text{Accrual component} = \frac{\text{Accruals}}{\text{Average total assets}} \\
&\text{Cash flow component} = \frac{\text{Operating income after depreciation - Accruals}}{\text{Average total assets}}
\end{aligned} \tag{3.2}$$

The distress measure used in this paper is from Campbell, Hilscher, and Szilagyi (2008).The measure is the 12-month-ahead probability of financial failure estimated by a logit model. Failure is defined as delisting for performance-related reasons, receiving a D rating from a rating agency, or filing for Chapter 7 or Chapter 11 bankruptcy.

The distress measure is:

$$\begin{aligned}
CHS = &-20.26*NIMTAAVG + 1.42*TLMTA - 7.13*EXRETAVG + 1.41*SIGMA \\
&-0.045*RSIZE - 2.13*CASHMTA + 0.075*MB - 0.058*PRICE - 9.1
\end{aligned} \tag{3.3}$$

where *NIMTAAVG* is a profitability measure, *TLMTA* is a leverage measure, *EXRETAVG* is the average past excess stock returns, *SIGMA* is the volatility of the stock return, *RSIZE* is the size of the firm relative to the size of the market, *CASHMTA* is a cash and short-term investment measure, *MB* is the market-to-book ratio, and PRICE is the price of stock winsorized above $15. Definitions and detailed derivations of each variable can be found in Appendix. This paper uses this particular monthly-basis distress measure for some reasons. First, the distress measure provides a clear negative correlation between degree of distress and equity returns. In addition, the explanatory variables in *CHS* include most variables used in other distress measures.

Since *CHS* is the estimation from a logit regression, the failure probability is the logistic distribution transformation that predicts a 12-month-ahead probability interpretation for the measure.

$$Failure\, P_{i,t} = \frac{1}{1+\exp(-CHS_{i,t})} \tag{3.4}$$

<Table 3.1>

I calculate *SIZE* as the logarithm of market value of equity, by taking the logarithm of the product of the price at the end of the fiscal year (Compustat item 199) and the number of shares outstanding (Compustat item 199). *BM* is the ratio of the fiscal year-end book value of equity (Compustat item 60) to the market value of equity. *VOLUME* is measured by cumulative past 12 month turnovers. I winsorize *Accruals*, *Cash flows*, *Earnings*, *BM*, and *VOLUME* at the 1st and 99th percentile in each fiscal year to reduce the effects of outliers. *SIZE* and *CHS* are not winsorized. To make my strategies implementable, I calculate future stock returns that begin four months after the end of the fiscal year from which the financial statement data are gathered. The reason is, by this time, almost all firms' financial statements are publicly available according to Alford, et al. (1994).[9] After eliminating firms without adequate data to compute any of the financial statement variables, returns, the final sample includes 6,601 firms for the period of January 1965 to December 2008.

Table 3.1 Panel A reports the means, standard deviations, medians, 1st percentiles, and 99th percentiles of the above variables for the 6,601 firms in my sample. The average *Accruals*, *Cash flows*, *Earnings* are -3%, 12%, and 9% respectively. The positive *Cash flows* indicate that on average, firms are generating positive cash flow from their operating activities. *Accruals* are negative mainly because accruals include depreciation and amortization. Panel B reports the Pearson and Spearman correlations among the variables. The two key variables in this study, *CHS* and *Accruals*, have a statistically significant negative Pearson (Spearman) correlation of -0.11 (-0.06). There is also a negative Pearson (Spearman) correlation between *CHS* and *Earnings* of -0.53 (-0.50) and between *CHS* and *Cash flows* of -0.43 (-0.40), implying that high distress risk firms have low income and low cash flow from operations. Similar to Sloan (1996), I observe a statistically significant negative Pearson (Spearman) correlation between *Accruals* and *Cash flows* of -0.37 (-0.45).

3.4 Empirical Results

3.4.1 Characteristics of Accrual Portfolios

<Table 3.2>

Panel A of Table 3.2 provides statistics on the characteristics of decile portfolios

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[9] For instance, if a firm's fiscal year ends in month 't', we match the accounting data with CRSP return data from month 't+4' to 't+15'. Furthermore, we consider a one month lag between the formation period and holding period.

formed by ranking firms on the magnitude of accruals. The firms are sorted and assigned in equal numbers to ten portfolios, A1 to A10, where A1 indicates the lowest accrual group and A10 the highest. The mean value of accrual component is -0.15 for the lowest accrual portfolio and 0.11 for the highest accrual portfolio. There is a strong negative relation between accruals and cash flows. The mean value of cash flows falls from 0.19 for the lowest accrual portfolio to 0.01 for the highest accrual portfolio. In contrast, earnings are positively related to accruals. The mean value of earnings is 0.04 for the lowest accrual portfolio and 0.12 for the highest accrual portfolio. The magnitude of three measures and their relations are consistent with prior studies (Dechow, 1994 and Sloan, 1996).

More importantly, the descriptive statistics in panel A of Table 3.2 show that the distress measure *CHS* for the extreme accrual deciles is much higher than median accrual decile (-6.69 for A1, -7.27 for A10, and -7.91 for A5, which is equivalent to 0.12% default rate in the following 12 months for A1, 0.07% default rate for A10, and 0.035% default rate for A5), implying that firms in extreme accrual deciles might be more likely to default in the following 12 months. An empirical implication of the above discussion is that returns to the accrual trading strategy would be concentrated in stocks with higher *CHS*. I argue that if this "*U-shape*" pattern of distress risk does exist across accruals, the return to accrual strategies after controlling for distress is stated alternatively that the profitability of accrual anomaly is concentrated in the most distressed firm. To assess whether that is indeed the case, I further use a two-way sequential sorting procedure to sort stocks on *CHS* and accruals in 5*5 portfolios in the next subsection. I also find that firms in extreme accrual deciles have relatively smaller *size*, lower *B/M ratio*, and higher turnover ratio.

Panel B of Table 3.2 shows monthly returns for the lowest accrual portfolio (A1), the highest accrual portfolio (A10), and the profit of buying the lowest accrual portfolio and selling the highest accrual portfolio (A1−A10). At the beginning of each month t, I rank all stocks based on their fiscal year end accruals and assign them to one of ten portfolios based on magnitude of their accruals. Then, these portfolios are held for 12 months. In addition, I skip a month between the formation period and the holding period. Each portfolio return is calculated as the equally/value weighted average excess (*Ret-Rf*) return of the stocks in the portfolio. Panel B suggests the significantly negative relation between accruals and future stock returns in the first 12 months of holding periods, consistent with Sloan (1996). In particular, the monthly equally/value weighted excess return is 0.96%/0.74% for the lowest accrual portfolio, and 0.27%/0.12% for the highest accrual portfolio. The monthly equally/value-weighted payoff of the accrual strategy of taking a long position in the lowest-accrual portfolio and a short position in the highest-accrual portfolio is 0.69% /0.62%(t-stat =4.99/t-stat =3.19), which statistically significant at 1% for the period of January 1965 to December 2008. In addition, I find that the monthly equally/value-weighted risk adjusted profit (alpha) is 0.81%/0.67% (t-stat= 5.20/ t-stat=3.39), and 0.70%/0.66% (t-stat=4.57/ t-stat=3.31), and 0.58%/0.59% (t-stat=4.01/ t-stat=2.86) after applying CAPM, Fama-French three-factor model, and Carhart four-factor model to the accrual strategy. The evidence strongly suggests that accrual profitability does not represent a compensation for systematic risk based on the market factor, Fama-French three risk factors, and Carhart four factors.

3.4.2 Characteristics of Distress portfolios

<Table 3.3>

Panel A of Table 3.3 provides statistics on the characteristics of decile portfolios formed by ranking firms on the distress measure *CHS*. The firms are sorted and assigned in equal numbers to ten portfolios, D1 to D10, where D1 indicates the lowest distressed group and D10 the highest. We can see that firms with higher distress risk have lower earnings and lower cash flow from operations. This pattern is consistent with the correlations in Table 3.1 Panel B. *Morank* refers to the rank from 1 to 10 , where all qualified stocks are assigned one of ten portfolios based on their cumulative past twelve-month returns. I find that *Morank* decreases across the increasing distress risk portfolios, suggesting that firms with higher distress risk are more likely to be loser stocks in the past 12 months. The patterns for size, book-to-market, and volume appear to be non-linear across the distress risk portfolios. One possible explanation for this could be that size and book-to-market are noisy proxies for distress risk, at least in their linear forms. In general, distressed firms have relatively small size, high book-to-market, and high turnover, consistent with Dichev (1998).

Panel B of Table 3.3 shows monthly returns for the least distressed portfolio (D1), the most distressed portfolio (D10), and the profit of buying the least distressed portfolio and selling the most distressed portfolio (D1−D10). I replicate Campbell, et al. (2008) over the extended period of 1965 to 2008 and my results are comparable to theirs. The portfolio sorting and formation procedure is similar to Panel B of Table 3.2. The distress sorted equally-/value-weighted excess returns are presented in this table. The monthly equally/value-weighted payoff of the distress strategy of taking a long position in the least distressed portfolio and a short position in the most distressed portfolio is 0.89% /0.95% (t-stat =4.20/ t-stat =3.89), which statistically significant at 1% for the period of January 1965 to December 2008. The monthly equally/value-weighted risk adjusted profit (alpha) is statistically significant at 1%, suggesting that CAPM and Fama-French three-factor model, and Carhart four-factor model cannot explain the distress anomaly.

3.4.3 Accrual Strategy after Controlling for Distress Risk

From the previous subsection, I find that return to the accrual trading strategy would be compensated in stocks with higher distress. To assess whether that is indeed the case, I thus classify portfolios on a sequential basis. For each month t, all stocks are ranked into quintiles based on their distress risk *CHS* (D1 for the lowest distressed and D5 for the highest distressed). The stocks in distress accrual group are then divided into quintiles based on their past fiscal year accruals (A1 for the lowest accruals and A5 for the highest accruals. The two-step sequential sorting procedure generates 25 distress-accruals - portfolios.[10]

<Table 3.4>

Panel A of Table 3.4 indicates the monthly abnormal returns of implementing the accruals trading strategy within each distress risk quintile. The pattern of the abnormal returns suggest that the abnormal returns to the accruals trading strategy are economically and statistically significant only within the segment of the market that contains the firms with the highest distress risk. There appears to be an increasing trend of payoffs across the increasing distress risk quintiles, with the highest distress risk quintile having the

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[10] Using this sorting procedure, each accrual group contains more than 1,000 firms on average across time. This provides a sufficiently large number of firms to rebalance the portfolio at each point in time. Conrad, Cooper, and Kaul (2003) indicate that the procedures that simultaneously condition on two (or more) characteristics may bring potential bias. Our results are robust to the independent two-way sorting procedure.

highest equally/value-weighted excess returns of 1.03%/1.20% (t-stat=5.67/5.18). The t-statistics of the abnormal returns across the increasing distress risk quintiles suggest that the abnormal returns are statistically significant at 1% only for the higher distress risk quintiles. This result is implied by the *U-shape* of distress risk across accrual portfolios: both the lowest and highest accrual portfolios have higher distress risk. Moreover, I find that distress anomaly is not affected by accruals much. The profits of distressed strategy are significantly positive in most accrual quintiles. The equally-weighted average excess return is significantly positive in all accrual quintiles except A2 and the value-weighted average excess return is significantly positive in A3, A4, and A5 quintiles.

Thus far, we have examined raw excess returns to accrual strategies. A normal check is to adjust returns for risk to ensure that the profitability of accrual strategies among high-distress firms is not just a compensation for exposures to common sources of risk. Panel B, C, and D of Table IV presents results from regressing accrual profits under alternative asset pricing models: the CAPM, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. There still appears to be an increasing trend of abnormal returns across the increasing distress risk quintiles, with the highest distress risk quintile having the highest abnormal returns. In Panel B, we find that the monthly equally/value-weighted risk adjusted profit (alpha) is 1.03%/1.09% (t-stat= 6.47/5.34) in the highest distress risk quintile, which is most statistically significant. Under the Fama and French (1993) three-factor model in Panel C, the risk adjusted return (alpha) increases with distress risk quintiles. The monthly alpha is increasing from 0.30%/0.35% (t-stat=1.33/1.78) in the lowest distress risk quintile to 0.97%/1.16% (t-stat=5.92/5.08)in the highest distress risk quintile. Furthermore, adding the momentum factor from Carhart (1997) four-factor model in Panel D, the monthly risk adjusted return is still significant with monthly return 0.98%/0.96% (t-stat=5.65/t-stat=4.23) in the highest distress risk quintile. The significant profit implies the robust effect of distress risk and sheds light on the additional contribution of distress risk to accrual profitability. The evidence strongly suggests that accrual profitability in high distressed firms does not represent compensation for systematic risk based on the market factor, the Fama-French three risk factors, and the Carhart four factors.

3.4.4 Robustness Check

Although there is no general consensus in academic research regarding the cause of accrual anomaly, a number of studies demonstrate the significance of accrual anomaly for stocks with certain firm characteristics. For instance, Ali, et al. (2001) find that fewer returns to the accruals trading strategy for smaller firms, firms that are covered by fewer analysts, and firms that are mostly not held by institutions. Some studies propose that high transaction costs may prevent investors from fully competing way the hedge returns to the accrual strategy. Evidence from Lev and Nissim(2006) , Mashruwala et al.(2006), and Green, et al.(2011) indicates that the accrual anomaly is concentrated in firms(such as firms with low liquidity or firms with high idiosyncratic volatility) likely to have high transaction cost. While Bushee and Raedy (2005) show that the accrual strategy is profitable even after imposing constraints related to the impact of price pressure, restrictions against short sales, and incentives to ownership.

An essential question that arises is whether the effect of distress risk on accrual anomaly is subsumed by other firm financial characteristics. To address this question, I conduct the robustness check of accrual profitability across the distress dimensions based on 5 × 2 portfolios sorted independently on distress risk and other firm financial characteristics, including firm size, trading volume , M/B ratio, credit ratings, and idiosyncratic risk.

<Table 3.5>

Table 3.5 presents results for sorting by distress and firm size (proxied by market capitalization of equity). Following Fama and French (2008), the size breakpoints are defined as the 50th percentiles of market cap for NYSE stocks. The accrual anomaly is mostly concentrated in firms with high distress. In Panel A, for the small-cap/large-cap firms, the value weighted average returns to the accrual strategy are 0.83%/1.19% (t-stat=3.90/4.71) per month in the most distressed decile (D5), which are statistically significant at 1%. The return to accrual strategies in the distress D4 is also significant with payoff of 0.35%/0.58% (t-stat=2.14/2.59). I find that a clear pattern that the return to the accrual strategy is increasing across the distress quintiles. In Panel B, the distress effect on accrual anomaly still holds after controlling for Fama-French three factors. I also find that the size effect- smaller returns to the accruals trading strategy for smaller firms- exists when I compare the returns to the accrual trading strategy after controlling for distress risk between small-cap and large-cap firms.

<Table 3.6>

Table 3.6 presents results for sorting by distress and trading volume. I define trading volume for a given stock as the cumulative past 12-month turnover before portfolio formation. The monthly turnover is calculated as the number of shares traded divided by the number of shares outstanding at the end of the month. The volume breakpoints are defined as the median of cumulative past 12-month turnover in the full sample. In Panel A, for the low-volume/high-volume firms, the value weighted average returns to the accrual strategy are 1.02%/0.89% (t-stat=4.61/3.65) per month in the most distressed decile (D5), which are statistically significant at 1%. The results indicate that even though stocks with low turnover tend to display higher accrual profits than stocks with high turnover, the high-distress stocks generate larger accrual profits than low-distress stocks for each turnover group. Panel B presents the risk adjusted accrual profits by applying the Fama-French three-factor model. Overall, the result that accrual profit is mostly significantly positive in high distress stocks is robust after controlling for trading volume.

<Table 3.7>

Table 3.7 presents results for sorting by distress and B/M ratio. *B/M* is the ratio of the fiscal year-end book value of equity (Compustat item 60) to the market value of equity (Compustat item 25* Compustat item 199). The B/M breakpoints are defined as the median of B/M ratios in the full sample. The effect of distress risk on accrual anomaly is robust in Panel A and B. The monthly raw returns/risk adjusted returns to the accrual strategy are 0.86%/0.95% (t-stat=2.93/3.46) in the distress quintile D5 for low B/M sample, and 1.00% / 1.26% (t-stat=3.75 /4.29) in the distress quintile D5 for high B/M sample. All of four returns are significantly positive at 1%.

<Table 3.8>

Table 3.8 presents results for sorting by distress and credit ratings. Credit ratings are measured by S&P Domestic Long Term Issuer Credit Rating which is available from June 1985 to December 2008. I convert a rating letter to a numeric number (AAA=1, AA+=2 , …, D=22) for sorting purpose. Numeric ratings of 10 or below (BBB- or better) are considered as investment-grade, and ratings of 11 or higher (BB+ or worse) are labeled as non-investment grade. The monthly raw returns/risk adjusted returns to the accrual strategy are 1.11%/1.08% (t-stat=3.74/3.48) in the distress quintile D5 for non-investment grade stocks, and 0.71% / 0.74% (t-stat=2.43 /2.56) in the distress quintile D5 for investment grade stocks. All of four returns are significantly positive at 5%. The result that accrual profit is mostly concentrated in the firms with high distress risk is robust after controlling for the credit ratings factor. Different from this study, Avramov, et al. (2011) consider a credit rating downgrade as the proxy of distress risk and find that accrual anomaly is robust among high and low credit risk firms regardless of periods of deteriorating, stable, and improving credit conditions. The evidence implies that the distress measure *CHS* I use in this study may contain different information from credit ratings.

<Table 3.9>

Table 3.9 presents results for sorting by distress and idiosyncratic risk. I calculate the idiosyncratic risk as the residual variance from a regression of firm-specific returns on the returns of the CRSP equally weighed market index over the previous month. The monthly raw returns/risk adjusted returns to the accrual strategy are 0.68%/0.77% (t-stat=3.21/3.50) in the distress quintile D5 for low idiosyncratic risk sample, and 1.16%/1.14% (t-stat=4.08/3.37) in the distress quintile D5 for high idiosyncratic risk sample. The returns to accrual strategies in firms with low idiosyncratic risk are much lower than those in firms with high idiosyncratic risk. This pattern is consistent with Mashruwala, et al. (2006) that accrual anomaly is concentrated in firms with high idiosyncratic volatility. In addition, the significant accrual profits in firms with low idiosyncratic risk still exist indicating that the effect of distress risk on accrual anomaly could not be offset by the idiosyncratic risk.

<Table 3.10>

I now turn my attention to the time series of accrual profits and investigate the effect of distress risk on accrual profits in different markets states. Panel A of Table 3.10 shows that the effect of distress risk on accrual profits exists during both expansion and recession periods. The expansion and recession months are based on NBER's classifications. Monthly Fama-French three-factor risk-adjusted returns in the high-distress quintile are 0.91% (t-stat=2.83)/ 1.09% (t-stat=4.69) during recession /expansion periods, respectively. Panel B of Table 3.10 provides the accrual profits for the distress quintile in up- and down-markets. I use 12-month cumulative returns on the CRSP value-weighted market index as a proxy for market returns. If the 12-month lagged return on the index is positive (negative), I define a holding-period month as an UP (DOWN) month. I find that the effect of distress risk on accrual profits exists during both up-and down-markets. Monthly risk adjusted return in the high-distress quintile are 0.94% (t-stat=4.34)/ 1.01% (t-stat=3.88) during down/up market, respectively.

In sum, sorting on distress provides different payoffs of accrual strategies across distress quintiles, and the same trend holds when sorting on firm size, trading volume, M/B ratio, credit ratings, and idiosyncratic risk factors. These proxies seem to provide the highest and mostly significant accrual payoffs in the high distress quintile. The evidence strongly suggests that distress risk have a unique and pervasive effect on accrual anomaly, which is not subsumed by previously documented cross-sectional characteristics, and holds in various time-series market states. The U-shape distress risk pattern (extreme low and high accrual stocks have high distress risk) suggests that the abnormal returns of accrual anomaly studies could be driven by the implementation of the accruals trading strategy with high distress risk firms. To the extent that extreme accruals imply distress risk, it is possible that at least some of the abnormal returns within the high distress risk quintile portfolios could be normal returns due to extreme low accruals amplifying the distress risk and the extreme high accruals failing to mitigate the distress risk of the firm.

3.4.5 Further Discussion

There are different types of distress measures, such as Moody's KMV used by Garlappi and Yan (2011), and credit rating downgrade used by Avramov, et al. (2011). The distress measure I used in this study is the probability of failure measure *CHS*, derived from Campbell, et al. (2008), who employ a reduced-form econometric model to predict corporate bankruptcies and failures at both short and long horizon. They argue that their model has greater explanatory power than the existing models estimated by Shumway (2001) and Chava and Jarrow (2004), and includes additional variables with sensible economic motivation. They indicate that the probability of failure measure has more information advantage than Altman's Z-score and Ohlson's O-score. Their model doubles the explanatory power relative to "distance to default" measure based on the structural default model of Merton (1974).

<Table 3.11>

I further examine the industry-adjusted financial ratios and confirm the predictive power of probability of failure that firms are experiencing financial distress after the distress portfolio formation. Specifically, I check the profit margin, interest coverage, and asset turnover before and after the portfolio formation. Profit margin is defined as net income over sales; interest coverage is defined as EBIT over interest expense; and asset turnover is defined as sales over total assets. Table 3.11 shows the median industry-adjusted ratio from eight quarters before to eight quarters after the portfolio formation sorting on CHS. It is clear that, after the distress portfolios are formed, stocks in the high-distress quintile experience substantial deterioration in their underlying business relative to their industry as measured by the profit margin, interest coverage, and asset turnover.

One argument is that accrual profits disappear or attenuate in the recent years because the activities of practitioners who implement and take advantage of such strategies can cause the anomalies to disappear(e.g., Green, et al., 2011). In this study, the effect of distress risk on accrual anomaly profit is not only significant in the full sample, but also significant in several time sub-samples (results upon request). A potential question is raised: why these anomalous profits are not arbitraged away? Several studies provide possible explanations. For example, Mashruwala, et al. (2006) find that accrual anomaly is concentrated in firms with high idiosyncratic stock return volatility making it risky to for risk-averse arbitrageurs to exploit; transaction costs such as low-price and low-volume stocks impose further barriers to exploiting accrual mispricing. Avramov, et al. (2011) show that short selling costs and poor liquidity could establish non-trivial hurdles for exploiting market anomalies. The robustness check in the previous subsection shows the robust effect of distress risk on accrual anomaly and sheds light on the additional contribution of distress risk to accrual profitability.

3.5 Conclusion

This paper draws a direct link between distress risk and accrual anomaly. I consider the effect of distress risk on accruals and how the compensation for distress risk could possibly account for the abnormal future returns related to the accrual trading strategy. I investigate whether the continued existence of the accrual anomaly is due to the failure to account for the compensation for distress risk. Using data on 6,601 NYSE, AMEX, and NASDAQ firms with sufficient accounting information over the January 1965-December 2008 period, I find a U-shape pattern of distress risks across accrual portfolios. The accrual profit is mostly concentrated in firms with high distress, suggesting that the abnormal returns to the accrual trading strategy may result from the high distress-risk exposures. The previously documented cross-sectional characteristics related to accrual anomaly such as size, volume, M/B, credit ratings, and idiosyncratic risk do not subsume the interaction between accruals and distress, and such interaction survives in up or down markets or during recessions or expansions.

I argue that financial distress is the source of the abnormal returns to accrual strategies. As suggested by Avramov, et al. (2011), financial distress causes the anomalies' conditioning variables to go to extremes, which in turn puts these stocks into the trading strategy. Subsequently these distressed stocks realize extremely low returns causing the anomalous profits from the short side of the trading strategies. It is important to mention that idiosyncratic stock return volatility, illiquidity, and short-sale constraints only pose the limits to arbitrage and prevent prices of distressed stocks from an immediate adjustment. In other words, such market frictions do not generate the anomalies, but they prevent prices from adjusting once financial distress triggers the abnormal returns to accrual strategies.

Appendix: Constructing CHS Measure

This section discusses the construction of the Campbell, Hilscher, and Szilagyi (2008) distress measure. I use the quarterly Compustat data to calculate the probability of failure.

$$\begin{aligned} CHS = &-20.26NIMTAAVG + 1.42TLMTA - 7.13EXRETAVG + 1.41SIGMA \\ &-0.045RSIZE - 2.13CASHMTA + 0.075MB - 0.058PRICE - 9.1 \end{aligned} \quad \text{(A3.1)}$$

The explanatory variables included in the measure are constructed as follows: *NIMTAAVG* is the moving average of the net income

$$NIMTVAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + ... + \phi^9 NIMTA_{t-10,t-12}) \quad \text{(A3.2)}$$

, and *EXRETAVG* is the moving average of the relative excess returns

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + ... + \phi^{11} EXRET_{t-12}) \quad \text{(A3.3)}$$

where $\phi = 2^{-1/3}$ indicates that the weight is halved each quarter. *NIMTA* is net income (COMPUSTAT quarterly item 69) divided by the sum of market equity and total liabilities (item 54); $EXRET = \log(1+R_{it}) - \log(1+R_{s\&p500,t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index; *TLMTA* is the ratio of total liabilities divided by the sum of market equity and total liabilities; *SIGMA* is the volatility of daily stock return over the past three months; *RSIZE* is the relative size measured as the log ratio of its market equity to that of the S&P 500 index; *CASHMTA* is the ratio of cash and short-term investments divided by the sum of market equity and total liabilities; *MB* is the market-to-book equity; *PRICE* is the log price per share.

When the variables are missing, past *NIMTA* and *EXRET* are also replaced with the cross- sectional means when the variables are missing in calculating the average measures *NIMTAAVG* and *EXRETAVG*. All explanatory variables are cross-sectionally winsorized above and below at the 1% level, except for *PRICE* (where the value is winsorized above \$15).

Table 3.1: Descriptive Statistics

Following Sloan (1996), *accruals* are defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable) and depreciation expense, all divided by average total assets. *Earnings* are defined as operating income after depreciation divided by average total assets. *Cash flows* are defined as the difference between earnings and accruals. *CHS* refers to the distress measure from Campbell, Hilscher, and Szilagyi (2008).The failure probability is the logistic distribution transformation (Failure P=1/[1+exp(1-CHS)]) of the distress measure that predicts 12-month probability of failure using a logistic regression. *Size* is the log market value of equity and *BM* is Book-to-market equity based on accounting data from the fiscal year ending in each calendar year. *Volume* is measured by cumulative past 12 month turnovers (monthly turnover equals to the CRSP monthly volume divided by total shares outstanding). At the beginning of each month, Morank refer to the momentum rank where all qualified stocks are assigned one of ten portfolios (Morank=1…10) based on their cumulative past twelve-month returns. The sample period is January 1965 to December 2008.

Panel A presents the statistics of selected characteristics. Panel B reports Pearson (Spearman) correlations between the relevant firm-specific variables in the upper (lower) diagonal. All the correlations are statistically significant at the 1% level.

Panel A: Descriptive statistics (means, standard deviations, medians, 1st percentiles, and 99th percentiles)

Variable	Mean	Standard deviation	Median	1st Percentile	99th Percentile
Accruals	-0.03	0.07	-0.03	-0.37	0.24
Cash flows	0.12	0.13	0.12	-0.76	0.47
Earnings	0.09	0.12	0.09	-0.79	0.38
CHS	-7.67	1.17	-7.81	-10.08	3.37
SIZE	6.17	1.57	5.99	1.65	10.26
BM	0.58	0.41	0.48	0.02	4.08
VOLUME	1.27	1.70	0.92	0.12	10.26

Panel B: Correlation table

Variable	Accruals	Cash flows	Earnings	CHS	SIZE	BM	VOLUME
Accruals		-0.37	0.22	-0.11	-0.07	-0.09	0.04
Cash flows	-0.45		0.81	-0.43	0.21	-0.04	-0.12
Earnings	0.20	0.69		-0.53	0.17	-0.10	-0.10
CHS	-0.06	-0.40	-0.50		-0.13	0.04	0.18
SIZE	-0.07	0.21	0.16	-0.15		-0.33	0.13
BM	-0.09	-0.15	-0.28	-0.03	-0.32		-0.25
VOLUME	0.04	-0.14	-0.10	0.20	0.18	-0.36	

Table 3.2: Characteristics of Accrual Decile Portfolios

Following Sloan (1996), *Accruals* are defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable) and depreciation expense, all divided by average total assets. *Earnings* are defined as operating income after depreciation divided by average total assets. *Cash flows* are defined as the difference between earnings and accruals. *CHS* refers to the distress measure from Campbell, Hilscher, and Szilagyi (2008).The failure probability is the logistic distribution transformation (Failure P=1/[1+exp(1-CHS)]) of the distress measure that predicts 12-month probability of failure using a logistic regression. *Size* is the log market value of equity and *BM* is Book-to-market equity based on accounting data from the fiscal year ending in each calendar year. *Volume* is measured by cumulative past 12 month turnovers (monthly turnover equals to the CRSP monthly volume divided by total shares outstanding). At the beginning of each month, Morank refer to the momentum rank where all qualified stocks are assigned one of ten portfolios (Morank=1…10) based on their cumulative past twelve-month returns. The sample period is January 1965 to December 2008.

Panel A presents the mean value of selected characteristics. For each month t, qualified stocks are ranked into decile portfolios according to their fiscal year accruals (A1 for the lowest accrual group and A10 for the highest).
In panel B, for each month t, qualified stocks are ranked into decile portfolios according to their fiscal year accruals (A1 for the lowest accrual group and A10 for the highest). The strategy involves buying the lowest accrual portfolio A1 and selling the highest accrual portfolio A10. The positions are held for the following twelve months (t+1 through t+12). There is a one month lag between the formation and the holding periods. Monthly returns represent the equally/ value -weighted average excess return (*Rt-Rf*) in percent. The table shows the monthly average raw and risk adjusted returns across accrual deciles during the holding period. T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively.

Panel A: Mean values of selected characteristics for ten portfolios of firms based on the magnitude of accruals

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Accruals	-0.15	-0.09	-0.07	-0.05	-0.04	-0.02	-0.01	0.01	0.04	0.11
Cash flows	0.19	0.17	0.16	0.15	0.14	0.12	0.11	0.10	0.08	0.01
Earnings	0.04	0.08	0.09	0.10	0.10	0.10	0.10	0.11	0.12	0.12
CHS	-6.69	-7.29	-7.70	-7.82	-7.91	-7.90	-7.93	-7.80	-7.65	-7.27
SIZE	5.58	5.99	6.20	6.25	6.35	6.22	6.10	5.92	5.73	5.45
BM	0.67	0.71	0.70	0.70	0.69	0.70	0.66	0.60	0.58	0.51
VOLUME	1.42	1.18	1.15	1.08	1.02	1.10	1.14	1.31	1.40	1.76

Panel B: Replication of accrual strategy

	Sorted by Accruals										
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A1-A10
	Monthly Equally-Weighed Average Excess Return										
Ret-Rf	0.96	0.97	0.93	0.90	0.94	0.81	0.84	0.70	0.68	0.27	**0.69****
	(2.86)	(3.49)	(3.59)	(3.59)	(3.75)	(3.43)	(3.24)	(2.55)	(2.31)	(0.80)	**(4.99)**
CAPM α	0.29	0.32	0.30	0.31	0.27	0.27	0.17	0.05	-0.05	-0.52	**0.81****
	(2.10)	(2.68)	(2.73)	(3.00)	(2.68)	(2.70)	(1.53)	(0.40)	(-0.39)	(-3.20)	**(5.20)**
3-factor α	0.03	0.07	0.01	0.03	0.01	0.03	-0.02	-0.12	-0.22	-0.67	**0.70****
	(0.15)	(0.81)	(0.17)	(0.46)	(0.07)	(0.41)	(-0.15)	(-1.15)	(-2.24)	(-5.61)	**(4.57)**
Carhart	0.13	0.20	0.12	0.14	0.13	0.13	0.12	0.03	-0.06	-0.45	**0.58****
4-factor α	(0.86)	(2.25)	(1.58)	(1.84)	(1.69)	(1.81)	(1.59)	(0.27)	(-0.70)	(-4.11)	**(4.01)**
	Monthly Value-Weighted Average Excess Return										
Ret-Rf	0.74	0.73	0.51	0.56	0.68	0.47	0.51	0.49	0.39	0.12	**0.62****
	(2.19)	(2.95)	(2.31)	(4.66)	(2.20)	(1.66)	(1.76)	(1.64)	(1.24)	(0.46)	**(3.19)**
CAPM α	0.07	0.17	-0.07	0.02	-0.01	-0.03	-0.11	-0.10	-0.26	-0.60	**0.67****
	(0.62)	(0.89)	(-0.38)	(0.17)	(-0.09)	(-0.08)	(-1.05)	(-0.85)	(-2.07)	(-3.70)	**(3.39)**
3-factor α	0.11	0.16	-0.03	-0.04	-0.02	-0.04	-0.07	-0.09	-0.16	-0.55	**0.66****
	(0.77)	(0.45)	(-0.31)	(-0.16)	(-0.33)	(-0.39)	(-0.60)	(-0.93)	(-1.32)	(-3.40)	**(3.31)**
Carhart	0.15	0.11	-0.05	-0.04	-0.01	0.01	-0.05	-0.04	-0.12	-0.44	**0.59****
4-factor α	(0.89)	(0.98)	(-0.30)	(-0.32)	(-0.09)	(0.06)	(-0.34)	(-0.56)	(-1.68)	(-3.43)	**(2.86)**

Table 3.3: Characteristics of Distress Decile Portfolios

Following Sloan (1996), *accruals* are defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable) and depreciation expense, all divided by average total assets. *Earnings* are defined as operating income after depreciation divided by average total assets. *Cash flows* are defined as the difference between earnings and accruals. *CHS* refers to the distress measure from Campbell, Hilscher, and Szilagyi (2008).The failure probability is the logistic distribution transformation (Failure P=1/[1+exp(1-CHS)]) of the distress measure that predicts 12-month probability of failure using a logistic regression. *Size* is the log market value of equity and *BM* is Book-to-market equity based on accounting data from the fiscal year ending in each calendar year. *Volume* is measured by cumulative past 12 month turnovers (monthly turnover equals to the CRSP monthly volume divided by total shares outstanding). At the beginning of each month, Morank refer to the momentum rank where all qualified stocks are assigned one of ten portfolios (Morank=1…10) based on their cumulative past twelve-month returns. The sample period is January 1965 to December 2008.

Panel A presents the mean value of selected characteristics. For each month t, qualified stocks are ranked into decile portfolios according to their CHS-distress measures accruals (D1 refers to the least distressed decile portfolio and D10 refers to the most distressed decile portfolio.).
In panel B, for each month t, qualified stocks are ranked into decile portfolios according to *CHS* (A1 for the lowest accrual group and A10 for the highest). The strategy involves buying the least distressed decile portfolio D1 and selling the most distressed decile portfolio D10. The positions are held for the following twelve months (t+1 through t+12). There is a one month lag between the formation and the holding periods. Monthly returns represent the equally/ value -weighted average excess return (Rt-Rf) in percent. The table shows the monthly average raw and risk adjusted returns across accrual deciles during the holding period. T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively.

Panel A: Mean values of selected characteristics for ten portfolios of firms formed based on the magnitude of distress

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
CHS	-9.06	-8.64	-8.43	-8.26	-8.09	-7.90	-7.69	-7.39	-6.93	-5.53
Accruals	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.04
Cash flows	0.18	0.18	0.16	0.15	0.14	0.13	0.11	0.10	0.06	0.01
Earnings	0.15	0.15	0.14	0.13	0.12	0.11	0.09	0.07	0.03	-0.03
SIZE	6.08	6.41	6.45	6.34	6.22	6.10	5.91	5.67	5.42	5.19
BM	0.61	0.55	0.55	0.60	0.62	0.65	0.69	0.71	0.75	0.79
VOLUME	1.21	1.11	1.10	1.12	1.15	1.17	1.24	1.32	1.45	1.70
Morank	6.99	6.77	6.48	6.19	5.95	5.58	5.13	4.68	4.08	3.13

Panel B: Replication of distress strategy

Sorted by *CHS*											
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Monthly Equally-Weighed Average Excess Return											
Ret-Rf	1.14	0.86	0.81	0.93	0.86	0.87	0.79	0.68	0.48	0.25	0.89**
	(4.46)	(3.93)	(3.27)	(3.66)	(3.42)	(3.27)	(2.91)	(2.27)	(1.48)	(0.66)	(4.20)
CAPM α	0.53	0.40	0.23	0.25	0.24	0.13	0.11	-0.02	-0.21	-0.57	1.10**
	(3.60)	(2.97)	(1.40)	(1.57)	(1.38)	(1.28)	(1.01)	(-0.16)	(-1.25)	(-2.48)	(5.56)
3-factor α	0.34	0.24	0.07	0.06	0.03	-0.08	-0.12	-0.30	-0.49	-0.88	1.22**
	(3.71)	(2.81)	(0.88)	(0.70)	(0.32)	(-0.15)	(-1.31)	(-2.75)	(-3.84)	(-4.86)	(6.47)
Carhart	0.34	0.25	0.11	0.11	0.10	0.05	0.09	-0.03	-0.20	-0.53	0.87**
4-factor α	(3.61)	(2.81)	(1.27)	(1.37)	(1.25)	(0.71)	(1.25)	(-0.35)	(-1.78)	(-3.25)	(5.04)
Monthly Value-Weighed Average Excess Return											
Ret-Rf	0.80	0.62	0.46	0.64	0.53	0.58	0.43	0.25	0.24	-0.15	0.95**
	(3.46)	(2.24)	(2.48)	(2.98)	(2.63)	(2.51)	(1.85)	(0.81)	(1.20)	(-1.01)	(3.89)
CAPM α	0.25	0.13	-0.04	0.01	-0.03	-0.11	-0.18	0.10	-0.39	-0.92	1.17**
	(1.12)	(0.73)	(-0.29)	(0.06)	(-0.38)	(-0.78)	(-1.15)	(0.45)	(-1.82)	(-5.21)	(5.00)
3-factor α	0.32	0.18	0.02	0.03	-0.04	-0.15	-0.26	-0.54	-0.55	-1.04	1.36**
	(1.34)	(0.92)	(0.09)	(0.18)	(-0.29)	(-1.45)	(-1.79)	(-2.41)	(-3.43)	(-4.88)	(5.82)
Carhart	0.16	0.07	-0.03	0.02	-0.03	-0.06	-0.09	-0.81	-0.87	-0.84	1.00**
4-factor α	(0.77)	(0.35)	(-0.44)	(0.08)	(-0.28)	(-0.75)	(-0.42)	(-2.98)	(-4.05)	(-4.85)	(4.52)

Table 3.4: Accrual Anomaly Profits across Distress Quintiles

For each month t, all qualified stocks are equally divided into quintiles based on CHS. We exclude stocks which at the end of month t are priced below $5 or are smaller than the smallest NYSE size decile. For each distress quintile, we buy the lowest accrual portfolio A5 and selling the highest accrual portfolio A5. The positions are held for the following twelve months (t+1 through t+12). There is a one month lag between the formation and the holding periods. Monthly returns represent the equally/ value -weighted average excess return (Rt-Rf) in percent. The table shows the monthly average raw and risk adjusted returns across accrual deciles during the holding period. T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A shows monthly raw equally/value-weighted excess return of accrual profits across distress quintiles. Panel B, C, and D shows the risk adjusted equally/value-weighted return (alpha) applying alternative asset pricing models (CAPM, Conditional CAPM, FF three-factor model and Carhart four-factor model).

Panel A: Raw return to the accrual trading strategy after controlling for distress

	Equally-weighted excess return							Value-weighted excess return					
	D1	D2	D3	D4	D5	D1-D5		D1	D2	D3	D4	D5	D1-D5
A1	1.26	1.05	0.99	0.84	0.83	0.43*	A1	0.86	0.72	0.73	0.55	0.48	0.38
	(4.74)	(3.94)	(3.59)	(2.71)	(1.93)	(2.07)		(4.37)	(3.74)	(3.75)	(2.68)	(1.83)	(1.75)
A2	1.10	0.97	0.89	0.86	0.59	0.51	A2	0.66	0.55	0.50	0.55	0.29	0.37
	(4.59)	(4.19)	(3.66)	(3.10)	(1.64)	(1.95)		(3.18)	(2.73)	(2.04)	(2.39)	(1.58)	(1.52)
A3	1.00	0.80	0.96	0.87	0.50	0.50*	A3	0.68	0.64	0.52	0.22	0.04	0.64*
	(4.18)	(3.57)	(4.08)	(3.37)	(1.47)	(2.30)		(3.24)	(2.69)	(2.70)	(1.73)	(0.18)	(2.48)
A4	0.97	0.94	0.87	0.64	0.36	0.61**	A4	0.67	0.43	0.40	0.29	-0.19	0.86**
	(3.93)	(3.67)	(3.46)	(2.26)	(1.05)	(3.15)		(2.92)	(1.91)	(1.93)	(1.59)	(-0.94)	(3.57)
A5	1.03	0.61	0.57	0.55	-0.20	1.23**	A5	0.62	0.31	0.38	0.12	-0.72	1.34**
	(3.47)	(1.96)	(1.75)	(1.65)	(-0.84)	(5.69)		(3.28)	(1.54)	(1.69)	(0.85)	(-3.72)	(5.05)
A1-A5	0.23	0.44	0.42	0.29	**1.03****		A1-A5	0.24	0.41	0.35	**0.43***	**1.20****	
	(1.09)	(1.90)	(1.70)	(1.56)	**(5.67)**			(1.25)	(1.70)	(1.52)	**(2.36)**	**(5.18)**	

Panel B: CAPM risk adjusted return after controlling for distress

	Equally-weighted excess return							Value-weighted excess return					
	D1	D2	D3	D4	D5	D1-D5		D1	D2	D3	D4	D5	D1-D5
A1	0.63	0.41	0.33	0.11	-0.01	0.64*	A1	0.30	0.13	0.12	-0.11	-0.34	0.64*
	(2.58)	(1.88)	(1.41)	(0.74)	(-0.34)	(2.45)		(1.61)	(0.83)	(1.29)	(-1.67)	(-1.88)	(2.47)
A2	0.57	0.42	0.31	0.11	-0.08	0.65*	A2	0.20	0.01	-0.09	-0.13	-0.39	0.59*
	(2.77)	(2.02)	(1.43)	(0.78)	(-0.40)	(2.01)		(1.06)	(0.10)	(-0.85)	(1.17)	(2.65)	(2.20)
A3	0.43	0.29	0.35	0.15	-0.24	0.67**	A3	0.16	-0.01	-0.05	-0.40	-0.57	0.73**
	(2.06)	(1.48)	(1.72)	(1.01)	(-1.23)	(2.98)		(0.98)	(-0.14)	(-0.60)	(-2.78)	(-2.43)	(2.97)
A4	0.44	0.26	0.26	-0.04	-0.43	0.87**	A4	0.17	-0.02	-0.15	-0.36	-0.96	1.13**
	(1.94)	(1.25)	(1.18)	(-0.32)	(-2.17)	(3.88)		(1.21)	(-0.12)	(-1.07)	(-2.67)	(-4.67)	(4.43)

A5	0.35	-0.12	-0.18	-0.26	-1.04	1.39**	A5	0.02	-0.33	-0.28	-0.63	-1.43	1.45**
	(1.38)	(-0.81)	(-1.20)	(-1.55)	(-5.30)	(6.34)		(0.25)	(-2.32)	(-2.05)	(-3.89)	(-6.81)	(6.05)
A1-A5	0.28	**0.53***	**0.51***	0.36	**1.03****		A1-A5	0.28	**0.46***	**0.40***	**0.52****	**1.09****	
	(1.35)	**(2.40)**	**(2.12)**	(1.54)	**(6.47)**			(1.47)	**(2.41)**	**(2.35)**	**(3.10)**	**(5.34)**	

Panel C: FF 3-factor risk adjusted return after controlling for distress

	Equally weighted excess return							Value-weighted excess return					
	D1	D2	D3	D4	D5	D1-D5		D1	D2	D3	D4	D5	D1-D5
A1	0.49	0.23	0.11	-0.15	-0.35	0.84**	A1	0.41	0.14	0.02	-0.26	-0.46	0.87**
	(2.40)	(1.14)	(0.64)	(-1.28)	(-2.13)	(3.73)		(2.22)	(0.95)	(0.07)	(-1.71)	(-1.93)	(3.50)
A2	0.36	0.17	0.02	-0.22	-0.45	0.81**	A2	0.17	-0.03	-0.12	-0.25	-0.52	0.69*
	(1.93)	(0.90)	(0.25)	(-1.98)	(-2.82)	(3.35)		(1.72)	(-0.30)	(-1.47)	(-1.84)	(-2.12)	(2.13)
A3	0.21	0.07	0.07	-0.12	-0.54	0.75**	A3	0.16	0.07	0.16	-0.44	-0.53	0.69*
	(1.14)	(0.77)	(0.88)	(-1.19)	(-3.49)	(3.90)		(1.29)	(0.83)	(-1.10)	(-2.53)	(-2.45)	(2.45)
A4	0.28	0.11	0.10	-0.26	-0.71	0.99**	A4	0.18	-0.02	0.16	-0.55	-1.12	1.30**
	(1.51)	(1.12)	(0.53)	(-2.49)	(-4.76)	(4.35)		(1.48)	(-0.27)	(-1.20)	(-2.40)	(-5.64)	(5.43)
A5	0.19	-0.20	-0.32	-0.47	-1.32	1.51**	A5	0.06	-0.19	-0.23	-0.74	-1.62	1.68**
	(0.85)	(-1.84)	(-1.75)	(-2.79)	(-7.62)	(6.06)		(0.22)	(-1.42)	(-1.01)	(-3.10)	(-7.11)	(7.02)
A1-A5	0.30	**0.43***	0.43	0.32	**0.97****		A1-A5	0.35	0.33	0.25	**0.48****	**1.16****	
	(1.33)	**(2.01)**	(1.84)	(1.31)	**(5.92)**			(1.78)	(1.73)	(1.49)	**(2.87)**	**(5.08)**	

Panel D: Carhart 4-factor risk adjusted return after controlling for distress

	Equally-weighted excess return							Value-weighted excess return					
	D1	D2	D3	D4	D5	D1-D5		D1	D2	D3	D4	D5	D1-D5
A1	0.47	0.24	0.21	0.05	-0.03	0.50*	A1	0.24	0.05	0.13	-0.10	-0.47	0.71**
	(2.20)	(1.15)	(1.13)	(0.49)	(-0.70)	(2.27)		(1.17)	(0.36)	(1.22)	(-0.76)	(-2.20)	(2.92)
A2	0.33	0.19	0.12	0.01	-0.14	0.47	A2	0.03	-0.04	-0.07	-0.07	-0.52	0.55*
	(1.75)	(1.04)	(1.37)	(0.03)	(-1.02)	(1.90)		(0.18)	(-0.53)	(-0.26)	(-0.89)	(-2.65)	(2.12)
A3	0.22	0.09	0.13	0.12	-0.19	0.41*	A3	0.05	0.05	-0.10	-0.22	-0.58	0.63*
	(1.18)	(1.01)	(1.57)	(1.21)	(-1.43)	(2.40)		(0.27)	(0.36)	(-0.68)	(-2.36)	(-2.54)	(2.57)
A4	0.32	0.17	0.22	-0.01	-0.38	0.70**	A4	0.13	-0.08	-0.11	-0.39	-0.82	0.95**
	(1.65)	(1.88)	(1.39)	(-0.14)	(-2.94)	(3.66)		(0.98)	(-0.79)	(-1.09)	(-2.89)	(-4.01)	(5.12)
A5	0.22	-0.08	-0.17	-0.21	-1.01	1.23**	A5	0.01	-0.18	-0.13	-0.54	-1.43	1.44**
	(0.96)	(-0.72)	(-0.38)	(-1.93)	(-7.38)	(5.39)		(0.08)	(-0.80)	(-0.73)	(-2.34)	(-5.91)	(7.65)
A1-A5	0.25	0.32	0.38	0.26	**0.98****		A1-A5	0.23	0.23	0.26	**0.44***	**0.96****	
	(1.54)	(1.49)	(1.61)	(1.15)	**(5.65)**			(1.16)	(1.18)	(1.48)	**(2.55)**	**(4.23)**	

Table 3.5 Independent Sorts by Distress and Size

For each month t, all stocks with available return data are divided into 10 groups based on their size and distress equally. The table shows, for each size group, the average returns to the accrual strategy, which involves buying the lowest accrual portfolio A5 and selling the highest accrual portfolio A5 and holding the position for twelve months (t + 1 through t + 12). The size breakpoints are defined as the 50th percentiles of market cap for NYSE stocks. Panel A shows monthly raw return of accrual profits. Panel B apply alternative asset pricing model (FF three-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A: Independent sort by accruals and size (value-weighted excess return)

	Small-cap						Large-cap				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	1.60	1.43	0.98	0.74	0.66	A1	0.76	0.68	0.70	0.51	0.41
	(4.26)	(4.93)	(4.25)	(3.54)	(3.53)		(2.99)	(3.61)	(2.54)	(2.59)	(2.69)
A2	1.41	1.33	0.99	0.63	0.38	A2	0.61	0.48	0.41	0.46	0.31
	(4.82)	(5.34)	(3.68)	(2.88)	(1.10)		(3.08)	(2.36)	(2.60)	(2.05)	(2.27)
A3	1.01	1.01	0.89	0.53	0.33	A3	0.65	0.48	0.38	0.21	0.07
	(4.78)	(5.27)	(3.57)	(2.63)	(1.55)		(2.91)	(2.83)	(2.26)	(1.63)	(0.56)
A4	1.13	1.08	0.79	0.42	0.27	A4	0.59	0.32	0.35	0.09	-0.48
	(4.21)	(4.28)	(3.43)	(2.25)	(1.29)		(2.56)	(1.86)	(1.64)	(0.75)	(-2.08)
A5	1.36	1.09	0.58	0.39	-0.17	A5	0.47	0.28	0.33	-0.07	-0.78
	(4.48)	(4.00)	(2.71)	(1.53)	(-1.06)		(2.72)	(1.81)	(1.82)	(-0.30)	(-3.75)
A1-A5	0.24	0.34	0.40	**0.35***	**0.83****	A1-A5	0.29	0.40	0.37	**0.58****	**1.19****
	(1.71)	(1.67)	(1.90)	**(2.14)**	**(3.90)**		(1.56)	(1.91)	(1.70)	**(2.59)**	**(4.71)**

Panel B: Independent sort by accruals and size (value-weighted FF 3-factor risk adjusted return)

	Small-cap						Large-cap				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.83	0.60	0.20	-0.11	-0.37	A1	0.34	0.14	0.03	-0.17	-0.40
	(3.65)	(2.55)	(1.24)	(-0.79)	(-1.84)		(1.79)	(1.34)	(0.21)	(-1.59)	(-2.40)
A2	0.66	0.54	0.17	-0.09	-0.62	A2	0.12	0.01	-0.19	-0.18	-0.42
	(3.15)	(2.69)	(1.12)	(-0.74)	(-2.97)		(1.07)	(0.08)	(-1.64)	(-1.87)	(-2.14)
A3	0.38	0.17	0.00	-0.14	-0.72	A3	0.11	0.00	-0.20	-0.42	-0.65
	(1.81)	(1.34)	(0.01)	(-0.76)	(-3.79)		(0.80)	(0.00)	(-1.74)	(-2.37)	(-3.10)
A4	0.44	0.23	-0.07	-0.35	-0.71	A4	0.09	-0.07	-0.15	-0.55	-1.03
	(2.58)	(1.87)	(-0.54)	(-2.34)	(-3.35)		(0.81)	(-0.28)	(-1.06)	(-2.40)	(4.59)
A5	0.54	0.33	-0.15	-0.59	-1.24	A5	-0.03	-0.18	-0.23	-0.78	-1.63
	(2.39)	(1.88)	(-1.26)	(-2.71)	(-5.03)		(-0.38)	(-1.18)	(-1.73)	(-3.52)	(-5.98)
A1-A5	0.29	0.27	0.35	**0.48***	**0.87****	A1-A5	0.37	0.32	0.26	**0.61***	**1.23****
	(1.50)	(1.11)	(1.69)	**(1.99)**	**(3.64)**		(1.87)	(1.54)	(1.36)	**(2.48)**	**(4.97)**

Table 3.6 Independent Sorts by Distress and Volume

For each month t, all stocks with available return data are divided into 10 groups based on their volume and distress equally. The table shows, for each volume group, the average returns to the accrual strategy, which involves buying the lowest accrual portfolio A5 and selling the highest accrual portfolio A5 and holding the position for twelve months (t + 1 through t + 12). The volume breakpoints are defined as the 50th percentiles of volume in the full sample. Panel A shows monthly raw return of accrual profits. Panel B apply alternative asset pricing model (FF three-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A: Independent sort by accruals and volume (value-weighted excess return)

	Low volume						High volume				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.81	0.66	0.56	0.47	0.43	A1	1.24	1.00	0.73	0.44	0.21
	(3.62)	(3.10)	(2.86)	(2.18)	(1.88)		(5.04)	(4.31)	(2.90)	(1.64)	(1.61)
A2	0.53	0.50	0.49	0.43	0.47	A2	1.08	0.89	0.57	0.47	0.04
	(2.60)	(2.57)	(2.83)	(2.38)	(2.10)		(4.95)	(4.29)	(2.36)	(2.41)	(0.36)
A3	0.52	0.45	0.42	0.36	0.12	A3	0.82	0.70	0.44	0.36	-0.11
	(2.55)	(1.99)	(2.19)	(1.97)	(1.07)		(3.98)	(3.89)	(1.82)	(1.89)	(-1.49)
A4	0.46	0.33	0.28	0.19	0.18	A4	0.89	0.73	0.47	0.15	-0.38
	(2.29)	(1.72)	(1.35)	(1.38)	(1.06)		(4.56)	(3.62)	(2.18)	(1.01)	(-1.82)
A5	0.42	0.26	0.24	0.00	-0.59	A5	0.77	0.60	0.27	-0.02	-0.68
	(2.39)	(1.47)	(1.27)	(0.01)	(-3.31)		(3.96)	(2.86)	(1.50)	(-0.20)	(-2.94)
A1-A5	0.39	0.40	0.32	**0.47***	**1.02****	A1-A5	0.47	0.40	0.46	**0.46***	**0.89****
	(1.61)	(1.79)	(1.53)	**(2.45)**	**(4.61)**		(1.85)	(1.23)	(1.46)	**(2.23)**	**(3.65)**

Panel B: Independent sort by accruals and volume (value-weighted FF 3-factor risk adjusted return)

	Low volume						High volume				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.20	-0.09	-0.08	-0.22	-0.33	A1	0.63	0.47	0.03	-0.30	-0.44
	(1.13)	(-0.55)	(-0.63)	(-1.17)	(-1.98)		(3.30)	(1.97)	(0.53)	(-1.52)	(-2.03)
A2	0.02	-0.13	0.18	-0.32	-0.51	A2	0.58	0.36	-0.02	-0.35	-0.71
	(0.28)	(-1.13)	(-1.49)	(-1.62)	(-3.07)		(3.45)	(1.70)	(-0.17)	(-1.69)	(-3.11)
A3	0.02	0.14	0.28	0.36	-0.53	A3	0.52	0.24	-0.09	-0.51	-1.02
	(0.27)	(-1.10)	(-2.01)	(-1.86)	(-3.21)		(2.39)	(1.50)	(-0.36)	(-2.05)	(-4.04)
A4	0.01	-0.16	-0.32	0.33	-0.63	A4	0.32	0.14	-0.23	-0.61	-1.25
	(0.09)	(-1.48)	(-1.25)	(-1.82)	(-3.76)		(1.68)	(1.09)	(-1.87)	(-3.54)	(-4.81)
A5	-0.12	-0.44	-0.40	-0.71	-1.45	A5	0.27	0.07	-0.39	-0.79	-1.48
	(-1.28)	(-2.37)	(-2.00)	(-3.07)	(-5.92)		(1.62)	(0.40)	(-1.78)	(-4.54)	(-5.36)
A1-A5	0.32	0.35	0.32	**0.49****	**1.12****	A1-A5	0.36	0.40	0.42	**0.49***	**1.04****
	(1.51)	(1.64)	(1.22)	**(2.62)**	**(4.66)**		(1.21)	(1.45)	(1.89)	**(2.49)**	**(3.37)**

Table 3.7 Independent Sorts by Distress and M/B

For each month t, all stocks with available return data are divided into 10 groups based on their M/B and distress equally. The table shows, for each M/B group, the average returns to the accrual strategy, which involves buying the lowest accrual portfolio A5 and selling the highest accrual portfolio A5 and holding the position for twelve months (t + 1 through t + 12). The volume breakpoints are defined as the 50th percentiles of M/B in the full sample. Panel A shows monthly raw return of accrual profits. Panel B apply alternative asset pricing model (FF three-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A: Independent sort by accruals and M/B ratio (value-weighted excess return)

	Low M/B						High M/B				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.69	0.52	0.54	0.49	-0.01	A1	1.09	0.87	0.85	0.80	0.43
	(3.52)	(2.32)	(2.08)	(1.90)	(-0.20)		(4.36)	(3.40)	(3.53)	(3.63)	(2.14)
A2	0.62	0.47	0.43	0.31	-0.22	A2	0.85	0.69	0.59	0.62	0.40
	(2.88)	(1.96)	(2.12)	(1.61)	(-1.49)		(4.25)	(2.41)	(2.10)	(2.66)	(2.06)
A3	0.60	0.40	0.31	0.19	-0.43	A3	0.90	0.68	0.54	0.59	0.45
	(2.32)	(2.01)	(1.73)	(1.21)	(-2.48)		(3.72)	(2.36)	(2.07)	(2.70)	(1.81)
A4	0.55	0.38	0.30	0.11	-0.62	A4	0.81	0.44	0.57	0.46	0.15
	(2.50)	(1.70)	(1.51)	(1.07)	(-3.33)		(3.98)	(2.30)	(2.91)	(1.91)	(0.81)
A5	0.54	0.22	0.29	0.07	-0.87	A5	0.79	0.38	0.37	0.34	-0.57
	(2.15)	(1.46)	(1.62)	(0.69)	(-4.16)		(3.23)	(1.95)	(1.91)	(1.60)	(-2.41)
A1-A5	0.15	0.30	0.35	0.42	**0.86****	A1-A5	0.30	0.39	**0.48***	**0.46***	**1.00****
	(0.72)	(1.44)	(1.73)	(1.89)	**(2.93)**		(1.24)	(1.93)	**(2.37)**	**(2.22)**	**(3.75)**

Panel B: Independent sort by accruals and M/B ratio (value-weighted FF 3-factor risk adjusted return)

	Low M/B						High M/B				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.36	0.23	0.05	-0.19	-0.73	A1	0.60	0.35	0.00	-0.23	0.18
	(1.72)	(1.78)	(0.45)	(-1.48)	(-3.13)		(2.27)	(1.42)	(0.01)	(-1.19)	(0.61)
A2	0.22	0.13	-0.07	-0.26	-0.75	A2	0.33	0.14	-0.22	-0.27	-0.54
	(1.18)	(1.11)	(-0.56)	(-1.39)	(-3.50)		(1.55)	(1.25)	(-1.59)	(-0.92)	(-2.26)
A3	0.09	0.12	-0.16	-0.41	-0.96	A3	0.29	0.05	-0.32	-0.28	-0.47
	(0.36)	(0.92)	(-1.25)	(-2.42)	(-3.57)		(1.67)	(0.75)	(-1.91)	(-1.60)	(-2.17)
A4	0.10	-0.02	-0.20	-0.53	-1.32	A4	0.33	-0.10	-0.31	-0.41	-0.70
	(0.54)	(-0.35)	(-1.21)	(-2.18)	(-5.13)		(1.45)	(-0.52)	(-2.31)	(2.71)	(-3.02)
A5	0.07	-0.14	-0.27	-0.72	-1.68	A5	0.27	0.10	-0.37	-0.67	-1.44
	(0.88)	(-1.45)	(-1.64)	(-3.75)	(-6.28)		(1.26)	(-0.41)	(-2.06)	(-3.44)	(-5.45)
A1-A5	0.29	0.37	0.32	**0.53***	**0.95****	A1-A5	0.33	0.45	0.37	**0.44***	**1.26****
	(1.20)	(1.81)	(1.54)	**(2.31)**	**(3.46)**		(1.57)	(1.85)	(1.79)	**(2.40)**	**(4.29)**

Table 3.8 Independent Sorts by Distress and Credit Ratings

For each month t, all stocks with available return data are divided into 10 groups based on their credit ratings and distress equally. The table shows, for each credit ratings group, the average returns to the accrual strategy, which involves buying the lowest accrual portfolio A5 and selling the highest accrual portfolio A5 and holding the position for twelve months (t + 1 through t + 12). Credit ratings are measured by S&P Domestic Long Term Issuer Credit Rating. S&P ratings BBB- or better are considered as investment-grade and ratings BB+ or worse are labeled as non-investment grade. Panel A shows monthly raw return of accrual profits. Panel B apply alternative asset pricing model (FF three-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is June 1985 to December 2008.

Panel A: Independent sort by accruals and credit ratings (value-weighted excess return)

	Non-investment grade					Investment grade					
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.58	0.51	0.44	0.45	0.12	A1	1.31	0.94	0.76	0.57	0.53
	(2.32)	(2.01)	(2.19)	(2.39)	(0.98)		(4.32)	(3.61)	(3.19)	(2.18)	(1.99)
A2	0.52	0.52	0.40	0.29	0.07	A2	1.23	0.90	0.74	0.51	0.46
	(2.56)	(1.78)	(1.86)	(1.75)	(0.67)		(5.03)	(3.55)	(3.69)	(2.65)	(1.85)
A3	0.55	0.49	0.41	0.29	-0.08	A3	1.28	0.72	0.73	0.46	0.41
	(2.58)	(2.00)	(1.66)	(1.70)	(-0.58)		(4.55)	(3.28)	(2.15)	(1.65)	(1.59)
A4	0.58	0.36	0.39	0.12	-0.06	A4	1.17	0.65	0.44	0.41	0.29
	(1.93)	(1.61)	(1.50)	(1.33)	(-0.33)		(4.01)	(2.10)	(1.36)	(1.31)	(1.19)
A5	0.31	0.26	0.01	-0.02	-0.99	A5	0.95	0.64	0.45	0.38	-0.18
	(1.19)	(1.38)	(0.09)	(-0.20)	(-4.16)		(3.44)	(2.59)	(1.91)	(1.09)	(-0.91)
A1-A5	0.27	0.25	**0.43***	**0.47***	**1.11****	A1-A5	0.36	0.30	0.31	0.19	**0.71***
	(1.36)	(1.68)	**(2.05)**	**(2.37)**	**(3.74)**		(1.15)	(0.85)	(1.07)	(0.72)	**(2.43)**

Panel B: Independent sort by accruals and credit ratings (value-weighted FF 3-factor risk adjusted return)

	Non-investment grade					Investment grade					
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	-0.05	-0.13	-0.17	-0.39	-0.59	A1	0.71	0.52	0.18	-0.29	-0.49
	(-0.52)	(-1.18)	(-1.64)	(-2.36)	(-2.33)		(2.85)	(2.46)	(1.22)	(1.80)	(-2.03)
A2	-0.08	-0.17	-0.21	-0.45	-0.60	A2	0.59	0.55	0.23	-0.32	-0.50
	(-0.71)	(-1.46)	(-1.18)	(-2.29)	(-2.27)		(2.13)	(2.51)	(1.64)	(-1.63)	(-2.01)
A3	-0.13	-0.18	-0.34	-0.46	-0.60	A3	0.53	0.46	0.13	-0.35	-0.58
	(-0.77)	(-1.27)	(-1.80)	(-2.22)	(-2.34)		(2.91)	(1.67)	(0.91)	(-2.06)	(-2.33)
A4	-0.11	-0.21	-0.48	-0.49	-0.80	A4	0.37	0.35	-0.01	-0.46	-0.75
	(-0.95)	(-1.57)	(-2.12)	(-2.05)	(-3.24)		(1.61)	(1.81)	(-0.08)	(-2.22)	(-3.06)
A5	-0.34	-0.40	-0.63	-0.89	-1.67	A5	0.41	0.31	-0.03	-0.59	-1.23
	(-1.97)	(-2.75)	(-2.64)	(-3.94)	(-5.85)		(2.05)	(1.02)	(-0.16)	(-2.94)	(-5.32)
A1-A5	0.29	0.27	**0.46***	**0.50****	**1.08****	A1-A5	0.30	0.21	0.21	0.30	**0.74***
	(1.66)	(1.84)	**(1.98)**	**(2.76)**	**(3.48)**		(1.27)	(0.57)	(0.91)	(1.16)	**(2.56)**

Table 3.9 Independent Sorts by Distress and Idiosyncratic Risk

For each month t, all stocks with available return data are divided into 10 groups based on their idiosyncratic risk and distress equally. The table shows, for each idiosyncratic risk group, the average returns to the accrual strategy, which involves buying the lowest accrual portfolio A5 and selling the highest accrual portfolio A5 and holding the position for six months (t + 1 through t + 12). Idiosyncratic risk is the residual variance from a regression of firm-specific returns on the returns of the CRSP equally weighed market index over the previous month. The idiosyncratic risk breakpoints are defined as the 50th percentiles of idiosyncratic risk in the full sample. Panel A shows monthly raw return of accrual profits. Panel B apply alternative asset pricing model (FF three-factor model) to check the significance of abnormal return (alpha). T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A: Independent sort by accruals and idiosyncratic risk (value-weighted excess return)

	Low idiosyncratic risk						High idiosyncratic risk				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	1.19	0.86	0.72	0.61	0.54	A1	0.70	0.68	0.55	0.36	0.26
	(5.34)	(3.71)	(2.91)	(2.09)	(2.48)		(2.93)	(2.84)	(2.23)	(1.71)	(1.42)
A2	0.96	0.79	0.60	0.46	0.28	A2	0.63	0.56	0.49	0.19	0.10
	(4.08)	(3.64)	(2.79)	(2.28)	(1.00)		(3.12)	(2.53)	(1.79)	(0.81)	(0.92)
A3	1.02	0.71	0.49	0.41	0.24	A3	0.56	0.51	0.34	0.21	0.09
	(4.63)	(2.65)	(1.61)	(1.83)	(1.17)		(1.72)	(2.06)	(1.72)	(1.09)	(0.70)
A4	0.95	0.59	0.36	0.36	-0.01	A4	0.54	0.40	0.17	-0.01	-0.31
	(4.46)	(1.99)	(1.85)	(1.78)	(-0.07)		(2.49)	(1.84)	(1.18)	(-0.09)	(-1.96)
A5	0.84	0.50	0.37	0.16	-0.14	A5	0.44	0.23	0.00	-0.27	-0.90
	(3.74)	(1.86)	(1.50)	(1.33)	(-1.20)		(1.85)	(1.81)	(0.00)	(-1.70)	(-4.69)
A1-A5	0.35	0.36	0.35	0.45	**0.68****	A1-A5	0.26	0.45	**0.55****	**0.63****	**1.16****
	(1.69)	(1.80)	(1.95)	(1.73)	**(3.21)**		(1.38)	(1.86)	**(2.63)**	**(2.86)**	**(4.08)**

Panel B: Independent sort by accruals and idiosyncratic risk (value-weighted FF 3-factor risk adjusted return)

	Low idiosyncratic risk						High idiosyncratic risk				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.55	0.45	0.08	-0.07	-0.38	A1	0.02	0.04	-0.05	-0.45	-0.65
	(2.26)	(1.85)	(0.64)	(-0.61)	(-1.73)		(0.17)	(0.33)	(-0.41)	(-2.42)	(-2.87)
A2	0.40	0.33	-0.07	-0.26	-0.53	A2	-0.09	-0.05	-0.17	-0.42	-0.77
	(1.91)	(1.92)	(-0.86)	(-1.21)	(-2.02)		(-0.93)	(-0.30)	(-1.18)	(-2.57)	(-3.55)
A3	0.40	0.19	-0.08	-0.28	-0.63	A3	-0.11	-0.16	-0.17	-0.51	-0.84
	(1.88)	(1.01)	(-1.02)	(-1.81)	(-3.00)		(-1.18)	(-0.71)	(-1.69)	(-3.03)	(-3.84)
A4	0.35	0.18	-0.20	-0.40	-0.88	A4	-0.12	0.15	-0.23	-0.68	-1.27
	(1.43)	(1.21)	(-1.47)	(-2.28)	(-4.21)		(-1.16)	(-1.07)	(-1.87)	(-3.49)	(-5.25)
A5	0.28	0.16	-0.20	-0.44	-1.15	A5	-0.30	-0.31	-0.54	-1.04	-1.79
	(1.61)	(1.37)	(-1.39)	(-2.40)	(-4.72)		(-1.62)	(-1.50)	(-3.38)	(-5.60)	(-6.04)
A1-A5	0.27	0.29	0.28	0.37	**0.77****	A1-A5	0.32	0.35	**0.49****	**0.59****	**1.14****
	(1.23)	(1.69)	(1.56)	(1.67)	**(3.50)**		(1.68)	(1.85)	**(2.80)**	**(2.85)**	**(3.37)**

Table 3.10 Accrual Profits Conditioning on Various Market States

For each month t, all qualified stocks are equally divided into quintiles based on CHS. For each distress quintile, we buy the lowest accrual portfolio A5 and selling the highest accrual portfolio A5. The positions are held for the following twelve months (t+1 through t+12). There is a one month lag between the formation and the holding periods. Monthly returns represent the monthly value-weighted average excess return (Rt-Rf) in percent after applying FF three-factor model. T-statistics are in parentheses. '*' and '**'indicate that the profits of trading strategies are statistically significant at the 5% and 1% levels respectively. The sample period is January 1965 to December 2008.

Panel A examines accrual profits during different business cycle periods. The expansion and recession months are based on the classifications made by the NBER.

Panel B reports accrual profits in up and down markets. The 12-month cumulative returns on the CRSP value-weighted market index are used as a proxy for market returns. If the 12-month lagged return on the index has been positive (negative) (skipping one month before the holding period), a holding-period month is classified as an up (down)-month.

Panel A: Accrual profits under NBER business cycle (value-weighted FF 3-factor risk adjusted return)

	Recession						Expansion				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.07	0.14	-0.04	-0.42	-0.82	A1	0.45	0.26	0.02	-0.19	-0.28
	(0.69)	(1.28)	(-0.58)	(-2.33)	(-3.71)		(1.46)	(1.76)	(0.31)	(-1.27)	(-1.95)
A2	0.01	0.03	-0.02	-0.50	-0.83	A2	0.28	0.17	-0.15	-0.27	-0.52
	(0.12)	(0.22)	(-0.28)	(-2.01)	(-3.96)		(1.37)	(1.18)	(-1.12)	(-1.50)	(-2.15)
A3	-0.05	-0.06	-0.10	-0.49	-0.91	A3	0.15	0.07	-0.15	-0.43	-0.53
	(-0.54)	(-0.72)	(-0.94)	(-2.18)	(-3.71)		(1.22)	(0.70)	(-1.01)	(-2.15)	(-2.32)
A4	-0.14	-0.13	-0.07	-0.59	-1.09	A4	0.15	-0.02	-0.18	-0.54	-1.05
	(-0.93)	(-1.03)	(-1.12)	(-3.57)	(-4.90)		(1.01)	(-0.29)	(-1.46)	(-2.32)	(-4.85)
A5	-0.17	-0.17	-0.13	-0.76	-1.73	A5	0.09	-0.08	-0.25	-0.64	-1.37
	(-1.75)	(-1.56)	(-1.30)	(-3.60)	(-5.81)		(0.79)	(-0.47)	(-1.91)	(-2.53)	(-5.82)
A1-A5	0.24	0.31	0.09	0.34	**0.91****	A1-A5	0.36	0.34	0.27	**0.45***	**1.09****
	(1.04)	(1.20)	(0.21)	(1.43)	**(2.83)**		(1.82)	(1.76)	(1.51)	**(2.56)**	**(4.69)**

Panel B: Accrual profits under up and down market (value-weighted FF 3-factor risk adjusted return)

	Down						Up				
	D1	D2	D3	D4	D5		D1	D2	D3	D4	D5
A1	0.19	0.08	-0.14	-0.30	-0.65	A1	0.55	0.27	-0.04	-0.15	-0.25
	(1.21)	(0.74)	(-1.19)	(-1.62)	(-3.51)		(2.11)	(1.33)	(-0.46)	(-1.29)	(-1.71)
A2	0.07	-0.03	-0.22	-0.35	-0.87	A2	0.30	0.04	-0.14	-0.36	-0.45
	(0.34)	(-0.47)	(-1.86)	(-1.71)	(-3.41)		(1.70)	(0.51)	(-1.38)	(-1.95)	(-2.55)
A3	-0.07	-0.14	-0.25	-0.53	-0.91	A3	0.16	-0.05	-0.22	-0.46	-0.61
	(-0.90)	(-1.83)	(-1.64)	(-2.41)	(-3.67)		(1.39)	(-0.33)	(-1.74)	(-2.14)	(-3.19)
A4	-0.11	-0.14	-0.28	-0.70	-1.24	A4	0.17	-0.06	-0.25	-0.60	-0.89
	(-1.12)	(-1.81)	(-2.24)	(-3.08)	(-4.02)		(0.96)	(-0.32)	(-1.38)	(-3.80)	(-3.66)

A5	-0.12 (-1.07)	-0.18 (-1.53)	-0.44 (-2.41)	-0.74 (-3.67)	-1.59 (-4.72)	A5	0.23 (1.69)	-0.08 (-0.80)	-0.26 (1.89)	-0.59 (-2.65)	-1.26 (-5.15)
A1-A5	0.31 (1.79)	0.26 (1.37)	0.30 (1.72)	**0.44*** **(2.29)**	**0.94**** **(4.34)**	A1-A5	0.32 (1.68)	0.35 (1.85)	0.22 (1.39)	**0.44*** **(2.34)**	**1.01**** **(3.88)**

Table 3.11 Industry-Adjusted Financial Ratios Before and After the Portfolio Formation

Financial ratios are industry-adjusted by subtracting from each firm ratio the median ratio for the industry to which the firm belongs, based on the first two digit of SIC codes. For each month t, all qualified stocks are equally divided into quintiles based on CHS. Each month, downgrades are assigned to a credit risk group based on the firm rating prior to the downgrade. I compute the median industry-adjusted financial ratio from 8 quarters before to 8 quarters after the portfolio formation. The table reports the time-series average of these median industry-adjusted ratios. Ratios are calculated from the Quarterly Compustat files. Profit margin is Net Income over Sales (NIQq/SALEQq) in %. Interest Coverage is EBIT over Interest Expense ((PIQq+XINTQq)/XINTQq. Total Asset Turnover is Sales over Total Assets (SALEQq/ATQq−1) in %.

	Profit margin			Interest coverage			Asset turnover		
Quarter	D1	D3	D5	D1	D3	D5	D1	D3	D5
-8	1.13	-0.07	-1.34	1.47	0.65	-1.63	1.02	0.26	-1.41
-7	1.26	-0.03	-1.46	1.62	0.56	-1.77	1.07	0.12	-1.68
-6	1.35	-0.02	-1.60	1.75	0.44	-1.97	1.18	0.22	-1.85
-5	1.44	-0.01	-1.81	1.92	0.39	-2.12	1.24	0.30	-1.82
-4	1.56	0.03	-1.99	2.10	0.53	-2.36	1.43	0.36	-1.94
-3	1.68	0.05	-2.20	2.40	0.60	-2.70	1.46	0.53	-2.16
-2	1.86	0.04	-2.60	2.66	0.57	-2.93	1.57	0.59	-2.28
-1	2.11	0.06	-3.17	3.00	0.45	-3.33	1.65	0.92	-2.66
0	2.37	0.08	-4.23	3.40	0.04	-3.74	1.87	0.99	-2.81
1	2.57	0.06	-4.92	3.66	0.03	-4.10	1.83	0.96	-2.47
2	2.70	0.04	-5.14	3.84	0.04	-4.11	1.73	0.62	-2.39
3	2.73	0.02	-4.89	3.82	0.02	-3.88	1.65	0.55	-1.97
4	2.61	-0.01	-4.13	3.74	0.02	-3.49	1.37	0.42	-1.44
5	2.39	-0.05	-3.27	3.58	-0.01	-3.17	1.20	0.20	-1.16
6	2.23	-0.08	-2.66	3.28	-0.06	-2.89	1.05	0.19	-0.96
7	2.03	-0.11	-2.22	2.99	-0.09	-2.57	1.02	0.12	-0.85
8	1.85	-0.12	-1.95	2.79	-0.08	-2.32	0.95	0.06	-0.60

Chapter 4

Conclusions

Price momentum and accrual anomaly are anomalies not explained by the Fama and French (1996) three-factor model and other risk based models. In this dissertation, I provide evidence on both rational and behavioral arguments by examining the relationship between price momentum and accruals, and the link between distress risk and accrual anomaly.

In the first essay, Chapter 2, I employ data on 5,195 NYSE and AMEX firms with sufficient accounting information over the January 1965-December 2008 period. My analysis indicates that momentum profitability is statistically significant and economically large among high-accrual firms, but it is nonexistent among low- and medium-accrual firms. The results are robust and cannot be explained by the market factor, the time-varying beta, the Fama-French three factors, trading volume, credit ratings and even the momentum factor. I propose two hypotheses-earnings manipulation and earnings overestimation and analyze the predictive power of accruals for stock returns based on three tests. Over the portfolio holding period, the industry-adjusted sales growth of loser stocks with high accruals deteriorates significantly while that of the winner stocks with high accruals improves. I track special items to check the existence of earnings manipulation. Over the portfolio formation period and the holding period, the largest amount of income-decreasing special items for the loser firms with high accruals indicates that the effect of earnings manipulation in prior years is eventually reversed. I find no significant discrepancy in momentum profit across nondiscretionary component of accruals which provides weak support for the earnings overestimation hypothesis. The discretionary accruals contribute the most to the discrepancy in momentum profits, strongly supporting the earnings manipulation hypothesis. My findings indicate that accrual-based momentum profit is largely driven by downward payoff of loser stocks with high accruals, implying that earnings manipulation plays a major role on the effect of accruals on momentum profits.

The second essay, Chapter 3, considers the effect of distress risk on accruals and how the compensation for distress risk could possibly account for the abnormal future returns related to the accrual trading strategy. I investigate whether the continued existence of the accrual anomaly is due to the failure to account for the compensation for distress risk. Using data on 6,601 NYSE, AMEX, and NASDAQ firms with sufficient accounting information over the January 1965-December 2008 period, I find a U-shape pattern of distress risks across accrual portfolios. The accrual profit is mostly concentrated in firms with high distress, suggesting that the abnormal returns to the accrual trading strategy may result from the high distress-risk exposures. The previously documented cross-sectional characteristics related to accrual anomaly such as size, volume, M/B, credit ratings, and idiosyncratic risk do not subsume the interaction between accruals and distress, and such interaction survives in up or down markets or during recessions or expansions.

One argument is that these anomalies disappear or attenuate in the recent years because the activities of practitioners who implement and take advantage of such strategies can cause the anomalies to disappear (e.g., Green, et al., 2011). A potential question is raised: why these anomalous profits are not arbitraged away? Several studies argue that price momentum anomaly is expensive for sophisticated investors to arbitrage. For example, high transition costs could offset the momentum profits (Lesmond, Schillb and Zhou, 2004, and Korajczyk and Sadka, 2004); Information disseminates more slowly when fewer analysts cover a stock (Hong, Lim, and Stein, 2000); short selling a stock is likely to be more difficult when there are few institutional investors ready to lend their shares (Nagel, 2005); As for accrual anomaly, Mashruwala, et al. (2006) find that accrual anomaly is concentrated in firms with high idiosyncratic stock return volatility making it risky to for risk-averse arbitrageurs to exploit; transaction costs such as low-price and low-volume stocks impose further barriers to exploiting accrual mispricing. Avramov, et al. (2011) show that short selling costs and poor liquidity could establish non-trivial hurdles for exploiting market anomalies. The robustness check in the previous chapters shows the robust effect of accruals on momentum, and the robust effect of distress risk on accrual anomaly. It is important to mention that market frictions such as idiosyncratic stock return volatility, illiquidity, and short-sale constraints do not generate the anomalies, but they prevent prices from adjusting once financial distress triggers the abnormal returns to related strategies.

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