THE EFFECT OF FIRM-SPECIFIC RETURNS VARIATION ON R^2: FROM THE PERSPECTIVE OF THE ACCRUAL ANOMALY

by

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Abstract

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R^2, calculated as CAPM of stock returns regressed on a market index, is constructed to explain stock price change by market-wide information. In my dissertation, I have analyzed the behavior of R^2 and its decomposed variations (firm-specific and market-wide variation) with regard to the accrual anomaly, domestically and internationally. My major results in the US are as follows. First, the effect of accrual anomaly significantly lowering future R^2 associated with higher firm-specific variations is robust and is not affected by (1) size, firm age, and other control variables; (2) industry risk and market risk; (3) other alternative explanations of accrual anomaly (value-glamour anomaly, bankruptcy risk, and arbitrage risk). Second, earning management is likely to be the reason why R^2 decreases the accrual anomaly. Third, the difference in R^2 between portfolios of good/poor accrual quality is subject to firm-specific variation. Fourth, the robustness of accrual anomaly significantly lowering future R^2 even applies to the industry level. Internationally, I find similar evidence for 9 countries (including the U.S.) out of 31 countries, and most of these 9 are developed countries. My study shows that an association between accrual anomaly and future R^2 is more likely in countries with certain characteristics: a common law tradition, a low level of government corruption, low accounting standards, and wide dispersion of stock ownership. Analysis of ADR supplements the international sample study in exploring the relation of institutional change to the impact of accruals on R^2. In chapter2, I also investigate the relation between stock return variation and extreme trading volume in the tail by demonstrating

the asymmetry of the return and volume in six emerging countries. For four out of six countries in the sample, the results from the bivariate threshold model indicate that during extreme price movements the asymmetry of the return and volume still holds.

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Chapter I

Could Accruals Predict R^2? Domestic and International Evidence

1. Introduction:

R^2, calculated for stock returns volatilities explained by market-wide variations, as shown in Roll (1988), is quite low in the US, especially when compared to emerging countries, in explaining stock price change with market-wide information. If I decompose individual stock returns into two explanatory groups in CAPM (Capital Asset Pricing Model): stock returns explained by firm-specific variations and stock returns explained by market-wide variations, a lower R^2 simply suggests that more and more firm-specific information is being captured in stock returns in US stock markets. Campbell et al. (2001) provide empirical evidence that average stock return volatilities have been increasing over time from 1962 to 1997 in the US, while the volatilities of the stock market returns remained basically unchanged. Therefore, R^2 of the market model for a typical stock has declined through time in the US.

The evidence is consistent with Roll (1988), who demonstrated that average adjusted R^2 is still low even with possible explanatory factors taken into account. Moreover, by considering the upward trend in firm-specific volatilities relative to market-wide volatilities, the firm-specific information plays more important role in the formation of R^2 than market-wide information. One might ask: Which factor might cause an upward trend of firm-specific variations? Is it possible that this factor can continuously increase firm-specific variations and, at the same time, without being captured by market-wide variations, decrease R^2?

Of course, the upward trend in average stock return volatilities might reverse its course once corporate earnings are improved and their uncertainty reduced, which implies that future return volatilities would tend to decrease and future R^2 might increase if there are no surprises or particularly no unexpected deterioration in future earnings below investors' expectations. In the

US, this is not the pattern for a typical stock, as shown by empirical evidence. The relationship between stock return and risk always plays an important role in CAPM. Fama and French (2003) also point out that there has been a sharp increase of new firms listed in the major US stock exchanges and a declining trend of profitability of newly listed firms after 1979. The declining profits trend of new firms and an increasing idiosyncratic risk pattern twist the positive risk-return relationship. They further suggest that the unexpected deterioration in earnings might be the main reason why R^2 continues to decrease through increasing firm-specific variations, with increasing idiosyncratic risks mainly attributable to newly listed firms. One might ask: Which factor would cause profits for these newly listed firms to decline? What can explain this low-return high-risk relationship?

To answer these questions, in this paper, I intend to apply capital market inefficiency to interpret the evidence in Campbell (2000) and Fama and French (2003) that given higher risk, particularly for new firms, investors' lower-than-expected returns are likely due to information uncertainty, measured by the absolute values of accruals.

Sloan (1996) proposed the accrual anomaly that is a direct challenge to capital market efficiency. Sloan studies the question whether stock prices fully reflect information in accruals and cash flows. He finds that stock prices are overpriced because of the persistence in accruals (that is, the Accrual Anomaly). So the stock price for high-accrual firms will be adjusted downward when full information is revealed. Therefore, the accruals measure uncertainty in firm fundamentals. The Mishkin (1983) test indicates that the accrual anomaly results from an inability of investors to fully recognize differences in reliability between accrual and cash flow components of current earnings with respect to their future earnings. That is, the investors implicitly assign a higher weight than market pricing accruals when forming their expectation of future earnings by not taking into account the fact that accruals are less persistent than cash. As a result, high (low) accruals firms earn negative (positive) abnormal returns in the future. These abnormal security returns still exist even though time has passed since Sloan discovered them (see table4b).

Morck et al (2000) find that R^2 is higher in emerging markets than in the U.S., and this finding is not due to market size and only slightly explained by differences in fundamentals. They do find that the degree of protection for property rights can explain the difference in R^2. They argue that the poor protection of property rights prevents firm-specific information from being incorporated into stock price. Consistent with Chan and Hameed (2002), they also use the R^2 of a market model as a measure of the synchronicity of stock price movements in emerging markets. They find that more analyst coverage produces market-wide information and leads to an increase in stock price synchronicity. Since those market-wide price fluctuations are uncorrelated with fundamentals, R^2 itself will be obviously less and less explained by firm fundamentals in emerging countries.

Therefore, lower (higher) R^2 for developed (developing) countries might simply suggest what dominates the unexpected price movement. If the deviation from expected stock price movement in the future were dominated by investors' expectations of fundamentals, then market inefficiency would increase future firm-level volatilities relative to future market volatilities. If the deviation from expected stock price movement in the future were dominated by investors' expectation regarding political or social factors, such as property rights or analyst coverage, this market inefficiency instead would increase market volatilities more than firm-level volatilities.

That is, I hypothesize that market inefficiency stemming from expectation on fundamentals partially explains the differences in behavior of R^2 between developed and developing countries. Therefore, in my paper, I would like to examine the relationship between $R^2_{(t+1)}$ and the accrual anomaly in a global setup, particularly the comparison between developed and developing countries.

A number of studies since Sloan have shown that the accrual anomaly exists and is robust across different samples of US firms. (e.g., Teoh et al. 1998;Collins and Hribar 2000; Bradshaw at al. 2001; Xie 2001; Zach 2003). Since the phenomenon of accruals overweighting is pervasive and known, it is evident that the investors still can't arbitrage away the future security returns.

Other explanations have been offered for the accrual anomaly: it is (1) a manifestation of the value-glamour anomaly (Desai, Rajgopal and Venkatachalam 2004); (2) due to earnings management (Teoh et al. 1998; Xie 2001); (3) not mispricing but rather reflects bankruptcy risk (Khan 2005); (4) due to barriers to arbitrage (Mashruwala, Rajgopal, and Shevlin 2006).

In this paper, I test whether the relation between R^2 (i.e., $R^2_{(t+1)}$) and accruals (the accrual anomaly) is influenced by one of the above reasons.

Since the accrual anomaly delivers a direct challenge to capital market efficiency with respect to accounting information, that is, fundamentals, so investors' misperception of accrual components of earnings (accrual overweighting) will lead to unexpected movement in security return, and this surprise will be likely to increase idiosyncratic security return volatility, and perhaps, lower R^2. If the relation between R^2 and accruals can be empirically connected, I could further provide alternative possible explanations between R^2 and accruals. First, the upward trend in return volatilities and downward trend in profitability of newly listed firms may be explained by accruals in the US, as firms with higher accruals are associated with the smaller, more risky stocks (Sloan 1996). Second, lower R^2 in the US might not be considered to be market efficient in terms of the accounting accruals. Third, whether market inefficiency depends on a relationship between the unexpected price movement and accruals or on investors' expectation regarding political or social factors determines whether R^2 will be lower (developed countries) or higher (developing countries).

Therefore, my paper examines the relation between R^2 and accruals, domestically and internationally.

My research is important for two reasons. First, it provides additional insights for capital asset pricing theory and market capital efficiency. Evidence of accrual anomaly implies a barrier to market efficiency, and this will result in unexpected stock price movement and R^2 of the Capital Asset Pricing Model would tend to decrease. This provides us another point of view to explain the behavior of R^2 from the perspective of market inefficiency, caused by accruals.

Second, it provides us international evidence regarding the relationship between future R^2 and accrual anomaly. By examining the occurrence of the relation between R^2 and accruals in the context of cross-country differences in institutional structures and accounting standards, it gives us insights into informational, corporate governance, and capital market factors associated with whether or why accounting accruals could affect stock return volatilities and R^2. Moreover, knowing the pattern or the relation between R^2 and accruals internationally will help us better understand why R^2 in emerging countries is significantly higher than R^2 in developed countries.

In this paper, I investigate (1) whether accruals affect R^2; (2) whether other alternative explanations of accrual anomaly that have been discussed in previous literature affect the relation between R^2 and accruals; (3) whether the relation between R^2 and accruals generalizes to other countries.

The first motivation for my research comes from Morck et al. (2000) explaining why emerging markets have higher R^2. They attribute their findings to inadequate protection for property rights, which will obviously have more effect on market-wide variation than on firm-specific variation through noise trading. But no researcher would deny the role of fundamental variables in determining stock prices. Hence the question often centers on whether the firm-specific variations in stock prices are fully explained by changes in the fundamental variables. Given Sloan's (96) work documenting the existence of the accrual anomaly brings us another perspective to discuss whether the increasing pattern of firm–specific variations in stock prices, or perhaps R^2, can be explained by accruals. The hedge-portfolio trading strategy also implies that future abnormal return, causing unexpected movement in future stock price, would tend to decrease R^2 attributable to firm-specific variations.

The second motivation is inspired by the work of Pincus et al. (2007) indicating whether the accrual anomaly exists in a global setup. They find that four of twenty countries in their sample, US, UK, Australia, and Canada, experience accrual overweighting. They also examine cross-country differences to explain the occurrence of the anomalies. Therefore it gives me the motive to investigate whether the relation between R^2 and accruals generalizes to other countries.

The third motivation is based on Roll (1988), who argues that there is little improvement in R^2 from eliminating all dates surrounding news reports in the financial press, implying that the changes in R^2 are hardly driven by firm-specific variations. One of the driving forces of stock price should be firm fundamentals. In my paper, I would like to investigate an alternative explanation of whether the changes in R^2 could be driven by the reliability of fundamentals like accruals, instead of current news. Roll also shows that diversification per se cannot be the explanation of the larger R^2s of individual large firms. He demonstrates that the diversified portfolios, size-matched to largest decile, display a positive relation between size and R^2. I would also like to examine the relation between R^2 and accruals within the size deciles, particularly for large firms.

I organize the remainder of the paper as follows. In the next section 2, I state my major research hypothesis regarding the relation between R^2 and accruals, domestically and internationally. Further, I examine several notions known to affect R^2 and/or accruals to see whether the relationship remains.

In Section 3, I discuss the sample formation and variable measurement in the US, and report the results. In Section 4, I discuss the sample formation and variable measurement in a global setup, which includes 31 countries in my final sample, including the US, and then report the results. In Section 5, I set up additional conjectures by examining what might cause the relationship between R^2 and accruals in the context of cross-country differences in institutional and governmental structures and accounting standards. In section 6, I perform a robustness check. Further, to test the effects of changes of governmental and institutional structures on the occurrence of this relationship, I perform an analysis of ADR (American Depository Receipts) traded in US capital markets. In Section 7, I summarize and conclude.

2. **Research Hypotheses**

In this section, I state my main hypothesis on the relationship between future R^2 and accrual anomaly.

As shown by Campbell et al (2001), it is apparent that the level of average stock return volatilities has been increasing over time from 1962 to 1997 in the US, while the volatilities of the stock market returns remained basically unchanged. Fama and French (2003) point out that there has been a sharp increase of new firms listing in the major US stock exchanges and a declining trend of profitability of newly listed firms after 1979. Wei and Zhang (2006) also point out that corporate earnings have deteriorated, particularly for newly listed stocks, and their volatility has increased through time. The pattern of increasing stock return volatility and the pattern of decreasing return corrode the risk-reward relationship. To explain this reverse risk-reward relationship, my focus is on market inefficiency stemming from accrual anomaly.

A growing literature on behavioral finance emphasizes investors' irrational behavior as an additional explanation for the variation in stock prices that is not explained by the fundamentals. Anecdotal evidence on fashions, fads and bubbles in the financial markets seems to support the point that stock prices are sometimes subject to errors. From the point of view of market inefficiency, these errors might not be random, but could be considered underreaction (or underprice) or overreaction (or overprice) to the fundamental variables. Sloan (1996) thus proposed the accrual anomaly that is a direct challenge to capital market efficiency. His point of view on accrual anomaly further supports my hypothesis that the increasing stock volatilities could be explained by accounting accruals. Since the volatilities of the stock market returns are quite stable, I have reason to believe that R^2 might decrease due to accounting accruals.

Hence, my goal is to determine whether R^2 of the capital asset pricing model is falling as the misperception of accruals (e.g. accrual overweight (US) or accrual underweight (other countries)) is increasing.

The main hypothesis is:

> H1: The R^2 of the market model falls as the misperception of accrual anomaly, measured by the absolute value of accruals, increases.

The R^2 represents stock return variations (firm-specific variations plus market-wide variations) explained by market-wide variations. I will take the absolute level of accrual components to measure the misperception of accrual anomaly and be a proxy for it. As Roll (1988) states, there is little relation between size and R^2 for individual firms within each size decile. He also suggests that higher R^2 for large firms cannot be explained by diversification. This conclusion raises the issue regarding whether large firms with higher R^2 and small firms with lower R^2 can be explained by accounting accruals.

So my first notion is:

> Notion1: Higher (lower) R^2 for large (small) firms can be explained by accruals.

I investigate a series of alternative explanations for the accrual anomaly suggested by prior research that might affect the relation between R^2 and accruals. The first explanation I examine is whether the accrual anomaly is an aspect of the value growth (a.k.a. value-glamour) anomaly that the finance literature has documented worldwide (Fama and French 1998). Desai et al. (2004) show that in the US, the accrual anomaly and the value-glamour anomaly (attributed to sales growth, book-to-market, and earnings-to-price) are captured by returns to a new variable, operating cash flow-to-stock price. Then my second notion is:

Notion2: The relation between R^2 and accruals can be influenced by value-glamour anomaly.

Next, I consider the possibility that the accrual anomaly is linked to earnings management. Xie (2001) demonstrates that the accrual anomaly in the U.S. is due mostly to the abnormal component of total accruals. Abnormal (or discretionary) accruals, referred to the portion of accruals related to firm abnormal operating activities under manager's discretion, have been linked to earnings management in numerous studies (e.g. Teoh et al., 1998a,b; Rangan, 1998; Shivakumar, 2000; Dechow and Schrand, 2004; Chan et al.,2006). I also consider earnings management, measured by abnormal accruals, in a global setting. Therefore, my third notion is:

Notion3: The relation between R^2 and accruals can be influenced by earnings management.

A third alternative explanation for the accrual anomaly is that low accruals is a proxy for firms with high risk of bankruptcy (Khan 2005). Khan argues that differences in returns between high and low accrual deciles reflect differences in bankruptcy risk, and the apparent abnormal returns associated with a zero-investment portfolio, long in low accrual firms and short in high accrual firms, actually reflect improper measurement of risk. Thus, the accrual anomaly is not mispricing, but rather is a return commensurate with greater bankruptcy risk. The next notion is:

Notion4: The relation between R^2 and accruals can be influenced by bankruptcy risk.

The last explanation I consider for the accrual anomaly is limits to arbitrage. Mashruwala et al. (2006) argue that an absence of close substitutes for mispriced stocks accounts for why the accrual anomaly is not fully arbitraged away in U.S. markets. Pontiff (1996); Wurgler and Zhuravskaya (2002); Mashruwala et al. (2006) use the idiosyncratic portion of a mispriced stock's volatility that cannot be avoided by holding offsetting positions in other stocks and indexes as a proxy for the absence of close substitutes. Idiosyncratic risk is relevant to arbitrageurs in these papers because they assume that arbitrageurs are risk averse and highly specialized and hence hold relatively few positions at a time. Hence, limits to arbitrage compose an important explanation of why accrual anomaly still exists. So my last notion is:

Notion5: The relation between R^2 and accruals can be influenced by limits to arbitrage.

In a global setup, Pincus et al. (2007) consider whether accrual anomaly generalized to other countries in 20 countries. Morck et al. (2000) and Chan and Hameed (2002) document that less respect for private property and more analyst coverage leads to an increase in stock price synchronicity, thus leading to higher R^2 in emerging countries. Given the perspective of the accrual anomaly, whether the accrual anomaly generalized to other countries might be a criterion to explain that lower R^2 (higher R^2) for developed (developing) countries by conducting cross-country analysis. So I hypothesize:

H2: lower R^2 (higher R^2) for developed (developing) countries is attributable to the accounting accruals.

3. Sample Formation and Variables Measurement in the US

3.1. Sample Formation

I start with firms listed on the NYSE and AMEX markets, for which financial and price information is available on the Compustat annual industrial database and CRSP monthly stock return database. I select my initial sample year starting from 1962 to 2006 because the Compustat data prior to 1962 suffer from a serious survivorship bias[1] (Fama and French, 1992). Since my analysis requires stock returns for 3 years after the sample year, plus insufficient information to calculate annual R^2 using daily observations prior to 1964 (at least 30 daily observations per firm per year), my final sample contains 45,536 firm-year observations for one 40-year period 1964-2003 on the NYSE and AMEX. In the US, all the tests in this paper are conducted on this final base sample. Within my sample period, I delete the following firm-year observations:

(1) Financial firms such as bank, insurance companies, with SIC code (6000-6999), because of peculiarity in the accruals for such firms.
(2) Missing average total assets or insufficient data to calculate accruals as defined as variable measurements.
(3) Missing monthly stock returns and missing market value of common equity.
(4) Fewer than six observations in any two-digit SIC code and year combination when calculating abnormal accruals by using the Jones model described below.
(5) Any variable in the Jones model (described in section 3.2.2) where there is a value that is more than three standard deviations away from its mean.

(6) R^2 of standard market model with less than 30 observations for both annual daily stock price and daily market index.

3.2. Variable Measurement

3.2.1 Accrual Anomaly

Hribar and Collins (2002) show that accruals derived from balance sheet data contain significant measurement error, especially for firms involved in mergers and divestitures. However, SFAS No.95, which went into effect in 1987, required the information necessary for computing the accruals to be identified in the operating section of the Statement of Cash Flow (S/CF) as part of the reconciliation of net income with operating cash flows. After 1988[2], when cash flow from operations (Compustat item #308) became available, one can directly calculate operating accruals using the difference between operating income and operating cash flows and eliminate measurement error. Prior to 1988, firms were required to produce a Statement of Changes in Financial Positions (Balance Sheet Approach), which focuses on working capital in stead of free cash flow, thus producing measurement error. Unfortunately, prior to 1988, the only way to calculate the accruals indirectly is by getting information from the balance sheet and income statement. So I use Sloan's (1996) definition of accruals prior to year 1988 as follows:

$$\text{Current Accruals (CAC)} = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep, \qquad (1)$$

where ΔCA = change in current assets (Compustat item #4),

$\Delta Cash$ = change in cash/cash equivalents (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 tax payable (Compustat item #71), and

Dep = depreciation and amortization expenses (Compustat item #14).

And Sloan defines Earnings (EARN)= operating income after depreciation (Compustat item #178) and cash flows from operations (CF)= Earnings (EARN) **–** Current Accruals (CAC).

Following Sloan (1996), I scale accruals, earnings and current accruals by average total assets(ATA), where total assets (Compustat item #6) are measured at the beginning and the end of the year, and label the resultant variables as CAC, EARN, and CF.

After 1988, I can retrieve operating cash flow directly from S/CF under SFAS 95, so the current accruals (CAC) are then measured as the difference between earnings (EARN) and operating cash flows from S/CF. So I define:

After year 1988, CF= operating cash flow under SFAS NO. 95 (Compustat item #308),

CAC= EARN-CF, and

EARN= operating income after depreciation (Compustat item #178).

Again, they are deflated by average total assets (ATA).

Annual raw buy-and-hold returns (RET) are calculated as the summation of ln (1+monthly stock return) for twelve months period where ln is natural log. I then anti-log the results of the above expression and subtract one to yield buy-and-hold returns (RET). Note that Ret is twelve-month annual returns ending three months after the firm's fiscal year end because the annual report filing deadline is three months in the US. Thus, RET can reflect complete dissemination of accounting information in financial statements of the current fiscal year.

Following Sloan(1996), I calculate size-adjusted abnormal returns (SizeR) as the difference between a firm's annual raw buy-and-hold return and the annual raw buy-and-hold return for the same twelve-month period on the size deciles (market-capitalization-based (Market Cap) portfolio deciles) to which the firm belongs. I use CRSP annual size deciles breakpoints to classify each firm into a size decile based on its market value of equity at the beginning of the fiscal year in which the twelve-month period begins. So the future abnormal return ($SizeR_{(t+1)}$) can reflect unexpected gain (loss) resulting from accrual anomaly.

3.2.2 Decompositions of current accruals

To obtain normal (nondiscretionary) current accruals and abnormal (discretionary) current accruals, following Teoh et al. (1998a), I use the cross-sectional adaptation of the modified Jones (1991) model (also used by successive researchers - e.g., Xie (2001); Francis et al. (2004); Chan et al. (2006); Pincus et al (2007)).

An ordinary least squares regression of current accruals for a given year is regressed on the change in sales for that year using all firms grouped in the same two-digit SIC code. Again, all variables including the intercept term in the cross-sectional regression are scaled by average total assets (ATA) to reduce heteroskedasticity:

$$CAC_{jt} = a_0(1/ATA_{jt}) + a_1(\Delta Sales_{jt}/ATA_{jt}) + \varepsilon_{jt}, \qquad (2)$$

where j firms belong in the same two-digit SIC code for industry classification and $\Delta Sales_{jt}$ is the change in sales revenues in year t (Compustat item #12) for firm j.

The normal current accruals (NCAC), expressed as the portion of current accruals dictated by firm sales growth, is viewed as independent of managerial control (discretion), that is, earnings management. Then it is computed as predicted values of the Jones model:

$$NCAC_{jt}= \hat{a}_0(1/ ATA_{jt}) + \hat{a}_1((\Delta Sales_{jt}-\Delta A/R_{jt})/ ATA_{jt}), \qquad (3)$$

where $\Delta A/R_{jt}$ is the change in trade receivables in year t (Compustat item #2) for firm j.

I exclude the increase in accounts receivables from sales growth for normal current accruals to prevent the possibility of credit sales manipulation due to manager's discretion, allowing generous credit policies to achieve higher-than-normal sales. I thus estimate the modified Jones model in cross-section for each two-digit SIC code and year combination and denote the predicted values as normal current accruals.

The abnormal current accruals (DCAC) are the difference between current accruals and normal current accruals, denoted as the residual values of the modified Jones model. The abnormal current accruals can be interpreted as the portion of current accruals subject to earnings management:

$$DCAC_{jt} = CAC_{jt} - NCAC_{jt} \tag{4}$$

3.2.3 The Mishkin (1983) Test

Abel and Mishkin (1983) explain rational expectations (or market efficiency) meaning that the market's expectation of any variable equals the true expectation, which implies that the market's forecast error must be unpredictable. Sloan (1996), and Dechow and Sloan (1997), apply this test to test naïve expectations hypotheses by incorporating the concept of accrual overweighting to demonstrate inefficient capital markets due to investors' naïve expectations on the accruals components of current earnings. I infer overweighting of accruals if investors attribute a higher valuation coefficient to accruals than the weight implied in the association between accruals and future earnings.

As done in earlier research by others, I jointly estimate a forecasting specification for future earnings and the valuation pricing specification:

$$EARN_{(t+1)} = \gamma_0 + \gamma_1 CF_t + \gamma_2 CAC_t + \mu_{(t+1)}, \tag{5}$$

$$SizeR_{(t+1)} = \alpha + \beta(EARN_{(t+1)} - \gamma_0 - \gamma^*_1 CF_t - \gamma^*_2 CAC_t) + e_{(t+1)}, \tag{6}$$

For decompositions of current accruals conducted in the Mishkin Test:

$$EARN_{(t+1)} = \gamma_0 + \gamma_1 CF_t + \gamma_2 NCAC_t + \gamma_3 DCAC_t + \mu_{(t+1)}, \quad (7)$$

$$SizeR_{(t+1)} = \alpha + \beta(EARN_{(t+1)} - \gamma_0 - \gamma^*_1 CF_t - \gamma^*_2 NCAC_t - \gamma^*_3 DCAC_t) + e_{(t+1)}, \quad (8)$$

where all variables are defined as before. Equation (5) and equation (7) are forecasting equations that estimate the forecasting coefficients (γ_s) of current earnings components for predicting future earnings. Equations (6) and equation (8) are valuation equations that estimate the valuation coefficients (γ^*_s) that investors (market participants) assigns to current earning components.

I estimate coefficients jointly by using an iterative weighted generalized nonlinear least squares estimation procedure, proceeding in two stages. In the first stage, I jointly estimate coefficients for equations (5) and (6), as well as equations (7) and (8), without imposing constraints on γ_s and γ^*_s. In the second stage, I impose rational pricing constraints where $\gamma^*_q = \gamma_q$ (q=1, 2, 3). The test statistic is a likelihood ratio distributed asymptotically chi-square (q) under the null hypotheses:

$$2*n*\ln(SSR^c / SSR^u)$$

Where q=the number of constraints imposed by market efficiency,

n=the number of sample observations in each equation,

ln=natural logarithm operator,

SSR^c=the sum of squared residuals from the constrained regressions in the second stage,

SSR^u=the sum of squared residuals from the unconstrained regressions in the first stage.

In this pooled time series and cross-sectional 'stacked' regression, note that the intercept term (γ_0) as γ_0=1/ATA is close to 0 and is excluded from the test.

The intuition of this test is quite straightforward. It is to test whether the market has rational forecasts of growth in earnings and its components. Sloan (1996), by introducing accruals overweighting, shows that stock prices act as if investors do not fully anticipate the lower persistence of the accrual component of current earnings pertaining to future earnings. Baumon and Dowen (1988) and La Porta et al. (1997) argue that prices reflect the overoptimistic earnings forecasts of financial analysts, which also implies that the earnings expectations implicit in market prices are biased, owing to accrual overweighting. Sloan concludes by showing the evidence from the Mishkin test, which is consistent with investors relying on biased estimates of accrual overweighting from 1962 to 1991.

In order to show that accrual overweighting still exists, in this paper, I modify Sloan's definition of accruals to eliminate the measurement errors after 1988 and perform the Mishkin test to check whether the investors, during the period 1964-2003, will be systematically surprised when accruals turn out to be less persistent than expected. The existence of the accrual anomaly will support my research interests in the relation between R^2 and accruals by centering on whether the firm-specific variations are driven by unexpected earnings attributable to accrual overweighting.

I report the results in Table 1a, 1b. The results in Table 1b use decile ranking to control for outliers. Consistent with Sloan (1996), in Panel A of Table 1a, I observe U.S. stock prices overweight accrual persistence from 1964 to 2003. That is, for current accruals, the valuation coefficient (γ^*_2=0.8797) is statistically higher than the forecasting coefficient (γ_2=0.7291) where the likelihood ratio statistic (untabulated) is 153.11, rejecting the null that $\gamma_2 = \gamma^*_2$. In panel A of Table 1b, the test yields similar results. I use decile ranking instead of actual value (e.g., γ^*_2=0.6613> γ_2=0.5411, marginally significant level=0.000 as the likelihood ratio=147.60). The results suggest that the market overweighs (or overprices) current accruals relative to its ability to forecast earnings one year ahead, and, in the future, as a result, the systematic shock brought by accruals overweighting will lead to more idiosyncratic volatility.

Given the existence of accrual anomaly, to further examine if accrual overweighting is attributable to abnormal current accruals, following Teoh et al. (1998a), I decompose current accruals into normal current accruals and abnormal current accruals by using a modified Jones model and perform a capital market efficiency test. In panel B of table1a, consistent with Xie (2001), the abnormal current accruals variable is the least persistent (γ3=0.7209), compared to normal current accruals (γ_2=0.7585) and operating cash flows (γ1=0.8089), although the difference between normal current accruals and abnormal current accruals is not quite as obvious as evidence shown in Xie's (2001) paper[4].

In panel B of Table1a, the valuation coefficients for normal current accruals (γ^*_2=0.9159) and abnormal current accruals (γ^*_3=0.8728) are all significantly higher than the forecasting coefficients (γ_2=0.7585, γ_3=0.7209). Even though γ^*_2 and γ^*_3 are almost equally 21 percent higher than γ_2 and γ_3, respectively, higher likelihood ratio statistics for $\gamma_3 = \gamma^*_3$ (130.65 for $\gamma_3 = \gamma^*_3$; 33.315 for $\gamma_2 = \gamma^*_2$), rejecting the null hypothesis of rational pricing for abnormal current accruals, suggest the accruals overweighting is stronger on abnormal current accruals. Moreover, in panel B of table 1b, with decile ranking of financial variables used to control for outliers, the likelihood ratio statistics of 16.287 and 185.281 both reject the null of $\gamma_2 = \gamma^*_2$ and $\gamma_3 = \gamma^*_3$ respectively, indicating that the market assigns higher weights to current accruals, especially abnormal current accruals, relative to its ability to forecast earnings one year ahead. In panel B of Table1a, for operating cash flows, the valuation coefficient (γ^*_1=0.8182) is also close to the forecasting coefficient (γ_1=0.8089) and the null hypothesis of $\gamma_1 = \gamma^*_1$ can not be rejected .The decile ranking of financial variables, in panel B of Table 1b, gives the same conclusion that cash flow is neither underweighting nor overweighting. My results in the Mishkin test (panel B in Table 1a and 1b), show that accrual overweighting is due largely to abnormal current accruals.

3.2.4 The Abnormal Returns Test

The Mishkin test results provide evidence on the existence of accrual anomaly and indicate that accrual overweighting is largely due to abnormal current accruals. Consequently, high (low) accruals firms will earn negative (positive) abnormal returns in the future. Following Sloan (1996), I perform the abnormal returns test to assess whether abnormal returns can be earned in the subsequent year by taking a long position in the lowest rank of current accruals (abnormal current accruals) and a short position in the highest rank of current accruals (abnormal current accruals). If the abnormal return can be predicted in the future by utilizing the existence of accrual overweighting, this not only will further support the assertion that the market overprices accruals but also implies that future firm-specific variations can be predicted for those extreme-accruals firms.

Each year, I rank current accruals (abnormal current accruals) for each firm into deciles and form a hedge portfolio (year t) by taking a long position in lowest rank of current accruals (abnormal current accruals) and a short position in the highest rank of current accruals (abnormal current accruals) for earning future abnormal returns (t+1, t+2, and t+3).

Panel A of Table 2 reports the results based on current accruals ranking. Consistent with Sloan (1996), the hedge portfolio yields positive abnormal returns of 8.4 percent (t=7.21), 4 percent (t=2.7), and insignificant 4.6 percent (t=1.86) in year t+1, t+2, and t+3, respectively. The untabulated results indicate that the abnormal returns to the hedge portfolio in year t+1 are continuously positive for most of the 40 (1964-2003) sample years[5], which implies current accrual anomaly systematically increases future idiosyncratic risk, particularly in year t+1.

Panel B of Table 2 reports the results based on abnormal current accruals ranking. Consistent with Xie (2001) that the market overpricing of total accruals is largely due to abnormal accruals, the hedge portfolio yields positive abnormal returns of 9.2 percent (t=8.43), 5.7 percent (t=3.83), and 3.9 percent (t=2.31) in year t+1, t+2, and t+3, respectively, while the abnormal returns (untabulated) are all insignificantly different from zero, based on normal current accruals ranking.

To sum up, first, given that the Mishkin test confirms that accrual overweighting is due largely to abnormal current accruals, the hedge portfolio deriving from the accrual anomaly, based on abnormal current accrual ranking, yields larger and more significant abnormal returns. Second, overweighting of either total current accruals or abnormal current accruals yields significant, continuous future abnormal returns, which suggests that the firm-specific variations, and R^2, can be systematically predicted for those extreme-accrual firms.

3.2.5 The formation of R^2

In this paper, in order to map the relationship between current accrual anomaly and future R^2 one on one, I refer to R^2 of the market model per firm per year in the form

$$(r_{jt}-rf_t)= \alpha_{jm} + \beta_{jm}(r_{mt}-rf_t) +\varepsilon_{jt} \quad , \qquad (9)$$

where r_{jt} is a daily stock return in time t for firm j, rf_t a market daily risk-free rate in time t, t a daily time index, and r_{mt} is a value-weighted daily market index in time t. All of these variables are supplied by the CRSP daily return file. Note that if the firm's fiscal year end is December, the $R^2_{(t+1)}$ of the asset pricing model will be calculated for the period from April of year t+1, to March of year t+2. Since my sample consists of firms with both December year-end and non-December fiscal year-end, the R^2 of the market model is calculated for the period of over 252 trading days starting three months after fiscal year end, with a minimum of 30 daily stock returns within the year.

I also examined other methods of calculating R^2 but found that the $R^2{}_s$ they produce are highly correlated with the R^2 I used above. Thus, I will use the R^2 discussed above for the remaining analysis. Panel A of Table 3a shows the spearman rank correlation (all significant at $p<0.01$, two-tailed t) between my R^2 used above and

(1) R^2 of the market model, based on the equally-weighted market index and daily stock returns, is 0.982;

(2) R^2 of the market model, based on the value-weighted market index and monthly stock returns (e.g. twelve observations to obtain annual R^2 per firm, minimum of six observations required), is 0.841;

(3) R^2 of the market model, based on the equally-weighted market index and monthly stock returns, is 0.843.

These three other measures will be used in performing the robustness check discussed later and reveal similar results.

In order to examine the hypothesis regarding the relation between R^2 and accruals, my measurement of R^2 of the market model has to be transformed to be suitable as a dependent variable in regressions. Following Morck et al. (2000), when performing regressions analysis later, I use R^2 as a proxy of adjusted R^2 (all R^2 in this paper refer to adjusted R^2 unless used as a dependent variable) because it is bounded within the interval [0, 1]. I then adopt a standard econometric method and apply logistic transformations to R^2 as

$$R = \log (R^2 / 1 - R^2) \tag{10}$$

In Eq. (10), R maps R^2 from the interval [0, 1] to Φ, the set of real numbers from negative to positive infinity.

Since R^2 ($=\sigma^2_m / (\sigma^2_m + \sigma^2_\varepsilon)$) can be decomposed into market-wide variation, σ^2_m, and firm-specific variation, σ^2_ε, a lower R^2 can reflect a high level of firm-specific variation or a low level of market-wide variation, or both. It would be meaningful and useful to interpret the behavior of R^2 with these measures. Therefore, γ, the logistic transformation of R^2, can be further expressed as:

$$R = \log (\sigma^2_m / \sigma^2_\varepsilon) = \log (\sigma^2_m) - \log (\sigma^2_\varepsilon) = M - E \tag{11}$$

Figure 1 displays the relative firm-specific variation and market-wide variation in my US sample from 1964 to 2003. Obviously, the high level of firm-specific variation relative to the low level of market-wide variation is associated more with firm-specific information captured in stock prices than with market-wide factors, except for the financial crisis occurring in 1987, when R^2 is near 0.3, about three times larger than other years average. This evidence helps explain that accounting accruals could affect the pattern of R^2 through firm-specific variation. As unexpected stock price movement occurs due to accrual overweighting, significant, continuous future abnormal returns will be earned, as shown in the abnormal returns test.

3.3. Testing of Research Hypotheses

3.3.1. Tests of H1

The first hypothesis is that R^2 falls as misperception of accrual overweighting increases. In order to measure the degree of misperception, Francis et al. (2005) first use accruals quality (AQ) as the proxy for information uncertainty. They use the absolute value of abnormal accruals to measure accrual quality (AQ). In my paper, I then use the absolute value of accruals to measure the misperception by examining firm's accrual quality. R^2 is calculated in terms of stock return variations rather than stock returns level. Therefore, R^2 can be decomposed into firm-specific information risk and market-wide information risk. The accounting accruals have to be unsigned to measure information risk. That is, the misperception, a proxy for information risk associated with a key accounting number - earnings, increases as accrual quality (AQ) deteriorates (Francis et al., 2005), measured by higher absolute values of accruals. Firms with higher information risk, or poor accrual quality, probably have lower R^2 through more firm-specific information risk than market-wide information risk.

In my main hypothesis, firm-specific information risk is expected to increase in the future, affecting R^2. More misperception of accrual overweighting due to poorer accrual quality increases the effects of future information shocks on stock returns. My hypothesis hence builds on the view that a high degree of information risk from accruals, a priced risk factor, represented as the uncertainty or imprecision of information used or desired by investors to price securities, will produce future shocks on stock returns ($\sigma_{\varepsilon\ (t+1)}{}^2$). As long as investors can systematically earn significant, continuous future abnormal returns, firm-specific risk is expected to rise and R^2 is expected to fall.

I examine my first hypothesis in four ways. First, the abnormal return test (section III.2.4): I provide time-series mean future R^2 formed based on absolute value of current accruals and abnormal current accrual decile ranking and relevant descriptive statistics. Second, I conduct modified cross-sectional regressions (Fama and Macbeth, 1973) of R^2 on misperception of accrual overweighting, after controlling for several factors known to affect R^2 and stock returns: firm size, firm age, book-to–market(BM), and earning to price (EP). Third, I decompose firm-specific volatility into firm risk (idiosyncratic risk) and industry risk to examine whether the relation between R^2 and accruals is due to firm risk or industry risk.

In order to investigate whether the relation between R^2 and accruals is subject to particular industry characteristics or not, I apply the methods of Fama and French (1996): I classify my sample 45,536 firm-years into 48 different industry levels and run cross-sectional regressions on industry level. Next, I decompose firm-specific volatility.

Accrual Anomaly in Decile Rank

Panel B of Table 3a reports on mean statistics of R^2, the size of the firms, CAPM betas, and number of firms ranked by current accrual and abnormal current accruals ranking. I first sort stocks into deciles based on the absolute value of accruals (or discretionary accruals). Within each decile, I report the average R^2, firm size, beta, age, book-to-market ratio and earning to price ratio. As shown in panel B of Table 3a, cacvol rank and dcacvol rank present similar patterns - adjusted R^2 is dropping as earning quality deteriorates. The firms with the lowest absolute value of discretionary accruals have average adjusted $R^2_{(t+1)}$ 12.113%, while the firms with the highest absolute value of discretionary accruals have average adjusted $R^2_{(t+1)}$ only 8.7% .

In Table 3b, firm's idiosyncratic volatility also increases as the absolute value of discretionary accruals increases. For example, for the lowest accruals decile, the idiosyncratic volatility is 15.42%; while in the highest accruals decile, the idiosyncratic volatility is as high as 36.11%. Table 3b also shows that the firms with high accruals are typically small firms, the firms with young age, a relatively high beta, a lower book to market ratio and a lower earnings to price ratio.

The third panel of table 3b shows the time series mean adjusted R^2 pattern by further ranking firms by sizes of firms in quintiles[6]. A decreasing pattern of R^2 is only found in the smallest firms, consistent with the second panel showing that poorest accrual quality firms are smallest (in average). But it also raises another possibility or hypothesis, discussed next, that large firms have higher R^2 than small firms due partially to accruals because we can observe that as accrual quality deteriorates, the R^2 gap between smallest-size and largest-size portfolios is enlarged. In order to control for the size effect in my analysis, I perform cross-sectional regressions.

Cross-Sectional Regressions

To further check the robustness of the relation between R^2 and accruals, panel B of Table 3c reports the means of the coefficient estimates from modified cross-sectional regressions (Fama and Macbeth, 1973) of R^2 and its decomposed components on current accruals in absolute values and a variety of control variables known to affect returns and R^2. A separate cross-sectional regression is first estimated each year and then takes the means of estimated coefficients for forty years in my sample, along with t values based on the time-series residuals of the estimated coefficients. The major cross-sectional regressions are performed in two stages and described as:

$$Size_t = \alpha_0 + \alpha_1 Cacvol_t + \mu_t \quad (12)$$

$$R_{(t+1)} = M_{(t+1)} - E_{(t+1)} = ß0 + ß_1 * Cacvol_t + ß_2 * Age_t + ß_3 * Size_t^r + ß_4 * BM_t + ß_5 * EP_t + \varepsilon_{(t+1)} \quad (13)$$

Where $Cov(Cacvol_t, Size_t^r) = 0$,

$R_{(t+1)} = \log (R^2_{(t+1)}/1 - R^2_{(t+1)})$,

$M_{(t+1)} = \log (\sigma^2_{m(t+1)})$,

$E_{(t+1)} = \log (\sigma^2_{\varepsilon(t+1)})$,

$Cacvol_t$= the absolute value of current accruals,

Age_t= the number of years firm survived at time t and listed in NYSE/AMEX,

$Size_t$= the natural log of the market value of common equity measured at fiscal year end (Computstat item #25 times #195) for each firm,

$Size_t^r$= residual values of OLS regression (12) at first stage,

BM_t = book to market ratio, is the ratio of the fiscal year-end book value of equity (Compustat item #60) to the fiscal year-end market value of equity for each firm,

EP_t = earning to price ratio, is the ratio of operating income after depreciation (Compustat item #178) to the fiscal year-end market value of equity for each firm.

Since accrual is highly correlated (panel A of table3c) with firm size, I run a two-stage regression. I perform OLS regression (12) of size on cacvol at the first stage and collect residuals, $Size_t^r$, orthogonal to the accruals, used in equation (13) at the second stage.

As expected, the results, reported in panel B of table 3c generally confirm those reported in table 3a and 3b using decile portfolios of current accrual ranking and abnormal current accrual ranking in absolute values. The strong and significantly negative coefficient on accruals-cacvol (-3.16, t-statistics=-5.43) is unaffected by including control variables in cross-sectional regressions. The coefficients from decomposed variations (firm-specific variation ($E_{(t+1)}$) and market-wide variation ($M_{(t+1)}$)) on accruals show that the decreasing R^2 caused by accruals is entirely due to increasing firm-specific variation (cacvol=3.77, t-statistics=18.51) while market-wide variation hardly affects it (cacvol=0.61, t-statistics =1.13). This further supports my view, that given that the volatilities of the stock market returns are quite stable (Campbell et al., 2001), because of the occurrence of increasing shocks on unexpected deteriorating earnings, R^2 is decreasing due to investors' misperception of the persistence of accrual components of earnings, resulting in negative abnormal size-adjusted returns. In particular, by decomposing current accruals (cacvol) into normal current accrual (ncacvol) and abnormal current accruals (dcacvol), the significantly negative coefficient on dcacvol (-2.51, t-statistics=-4.06) also confirms the previous analysis showing that the decrease of R^2 on the misperception of accrual overweighting is largely due to abnormal current accruals. With the negative correlations between current accruals and both firm size (-0.16) and firm age (-0.15) observed in panel A of table 3c, the predicted signs on age and size are positive and then confirmed, but only the size factor is statistically significant (size=0.51, t-statistics=27.55). This indicates that larger firms have moved more closely with the overall market. It's not surprising to see that because large firms move more in line with the market index, but it's interesting that smaller-size firms with poor accrual quality (table 3b) seem to be very volatile, given the negative coefficient of $E_{(t+1)}$ on $size^r$ is -0.26, (t-statistics=-20.06); large firms seem to be less volatile and increase more with market-wide variation (0.26, t-statistics=-10.3), where both effects enlarge the difference of R^2 by size, due partially to accruals. Hence I would like to analyze the behavior of R^2 by considering size effect in my next hypothesis.

The coefficients on firm age, insignificant in my main regression, yet significant and small in accrual- decomposition regression, suggest the presence of multicollinearity, which is usually suspected if one does not detect significant results as expected. But it does not seem to be a major problem because (1) the coefficient is the smallest of all estimated coefficients (2) as noted above, the accrual-decomposed regression contains a smaller sample. In untabulated results, I perform an additional OLS regression of age on accruals at the first stage, yielding almost identical results to those shown before. Obviously firm age here does not enter into the determination of R^2. The remaining estimated coefficients of other control variables only deliver minor significant effects on future R^2 in my main regression (-0.1 on BM, 0.35 on EP).

One thing that needs to be further investigated is that the coefficient of R^2 on accruals at time period t+2 and at time period t+3 (table 3c1) is still significantly negative (see appendix). The evidence of the persistence of R^2 on accruals raises two possibilities: (1) the autocorrelation problem regarding R^2. It is well known that daily stock returns generate significant short-run serial correlation, which might affect my main results because R^2 is computed by using daily stock returns. Therefore, I will construct R^2 based on monthly stock returns for which autocorrelation is much weaker and see if the results still hold. Table 3e reports the results obtained by performing a sensitivity test. The coefficients on accruals in table 3e are all significantly negative at the 0.01 level, suggesting that the persistence of significant negative influence of R^2 on accruals is not materially due to autocorrelation of R^2. (2) Earnings Management. The evidence is consistent with Teoh et al. (1998). They examine the long-term underperformance of seasoned equity issues by pre-issue earnings management, measured by abnormal current accruals (discretionary accruals). Consistent with Teoh et al. (1998), the coefficients on abnormal current accrual in absolute values (dcacvol) are all significantly negative at year t+2 and year t+3 in table 3c1. Even when I use monthly stock returns (in untabulated results), the coefficients of R^2 on accruals are still significantly negative at the 0.05 level for years t+1 and t+2. The results in table 3c and 3c1 regarding accrual-decomposition regressions indicate that through earnings management, where earnings are manipulated under manager's discretion on accruals, unexpected deterioration of net income continuously occurs, caused by not only investors optimistically overweighting accruals but also by the manipulation of accruals themselves, resulting in non-sustainable future earnings. Lack of persistence of accrual components of earnings seems to have a persistent effect of lowering R^2 under manager's discretion on accruals.

Accrual Anomaly at Industry Level

To check the robustness of the negative relation of R^2 on accruals, I would also like to see if the results still hold at industry level, and in the meantime, that the results can also be used in the next section for firm-specific decomposition. I use the Fama and French (1997) industry classification scheme for forty-eight industries and apply the SIC code to classify my sample firms (classification data are available at "mba.tuck.dartmouth.edu/pages/faculty/ken.french/ ").

For the formation of R^2, I use industry-level daily returns against the daily market index with value-weighted values, adjusted risk-free rate, one-month T-bill rate. Next, I classify firms in my sample into 48 industries by SIC code[10] and then value-weighted means of cacvol and other control variables are calculated for each industry. Thus, the cross-sectional regression is designed in each year to have 48 industry-level R^2, accruals, and other control variables with 40-year cross-sectional regressions described as:

$R_{ind}(t+1)=ß_0+ ß_1*cacvol(t)_{ind}+ ß_2*age(t)_{ind}+ ß_3*Size^r(t)_{ind} + ß_4*BM(t)_{ind}+ ß_5*EP(t)_{ind} +\varepsilon_{ind(t+1)},$

- (14)

where $R_{ind}(t+1)= \log (R^2_{(t+1)}/1- R^2_{(t+1)})=M_{ind}(t+1)- E_{ind}(t+1)$, subscript $_{ind}$ indicates industry level. Notice that $R^2_{(t+1)}$ is calculated for one year starting three months after the industry's average fiscal year end, by which time financial reports of publicly owned firms listed in NYSE/AMEX are released. Only 34-year cross-sectional regressions from 1970 to 2003 are selected because prior to 1970 fewer than 30 industries are excluded from my final sample, and smaller sample size per year would decrease explanatory power.

I report the results in table B of table 3d. It's encouraging to see that the coefficient on industry-level of cacvol is still significantly negative ($cacvol_{ind}$=-4.49, t-statistics=-2.03) although it is significant at the 0.05 level.

As expected, the industry-level volatility ($cacvol_{ind}$=-8.42, t-statistics=7.33) increases more than market-wide volatility. ($cacvol_{ind}$=3.92, t-statistics=2.42). As for year t+2 and year t+3, the coefficients of R^2 on $cacvol_{ind}$ are not significant, as shown in Panel b of table 3d1 and table 3d2 in the appendix. Average industry age (age_{ind}) is negatively significant in all three years, indicating that young and new industries tend to have higher industry-level R^2 compared to traditional and old industries, quite contrary to the relation at firm level. To sum, the evidence suggests that not only is there a strong negative relation of R^2 to accruals at firm level, but also the negative relation is strong enough to let some industries where firms have relatively poor accrual quality have lower R^2 in the future.

One might be curious about what industries have greater misperception of accrual anomaly (that is, higher cacvol) or poorer accrual quality (higher dcacvol). Not surprisingly, they are very similar. The top three industries- Construction, Computers, and Banking – and the bottom two industries- Insurance and utilities- are similar as to misperception of accrual anomaly and accrual quality. It might not be surprising that earnings management would occur more often in industries like construction, computer, and banking than in insurance or utilities. Here I note also that the strong significantly negative relation of R^2 to accruals at firm level is not subject to industry effect (stated in the next section), even though there's a significantly negative relation of R^2 to accruals at industry level, a firm in the insurance industry with poor accrual quality will decrease R^2, just like a firm with similarly poor accrual quality in the computer industry.

Firm-Specific Volatility Decomposition

By now, it is clear that the significantly negative relation of R^2 to accruals is largely due to poor accrual quality, measured by absolute value of abnormal accruals, and the relation even pertains to year t+2 and t+3. The plausible explanation of this persistence is earnings management. In addition, the decreasing trend of R^2 due to accruals can be largely explained by increasing trend of firm-specific volatility. In order to better understand the behavior of R^2 and firm-specific volatility, I decompose firm-specific volatility further into firm risk and market risk to check whether increase in firm risk itself (idiosyncratic risk) or market risk, or both, determine the increasing trend of firm-specific volatility.

To see that, I apply and modify Campbell et al.(2001) edition of volatility decomposition. First, I rewrite the formation of CAPM R^2 in equation (9) - $(r_{jt}-rf_t)= \alpha_{jm} + \beta_{jm}(r_{mt}-rf_t) +\varepsilon_{jt}$ to:

$$r_{jt}= \alpha_{jm} + \beta_{jm}r_{mt} +\varepsilon_{jt}, \tag{15}$$

where r_{jt} and r_{mt} are adjusted for risk-free rate. The industry level R^2 in equation (14) can be calculated in the form of:

$$r_{it=}\ \alpha_{im}+\ \beta_{im}r_{mt}\ +\varepsilon_{it}, \tag{16}$$

where r_{it} is industry i's of 48 industries daily returns at time t and daily market returns, r_{mt} , both are adjusted for risk-free rate. β_{im} denotes the beta for industry I with respect to market return, and ε_{it} denotes the industry-specific residual. And CAPM R^2 of firm returns on industry returns is described as

$$r_{jt}= \alpha_{ji} + \beta_{ji}r_{it} +\mu_{jt}= \alpha_{ji} + \beta_{ji}*(\ \alpha_{im}+ \beta_{im}r_{mt} +\varepsilon_{it}) + \mu_{jt}=\alpha + \beta r_{mt} + \beta_{ji}\ \varepsilon_{it} + \mu_{jt} \tag{17}$$

where $\alpha= \alpha_{ji} + \beta_{ji}\alpha_{im}$ and $\beta=\beta_{ji}\beta_{im}$. $ß_{ji}$ is the beta of firm j in industry i with respect to its industry and μ_{jt} is the firm-specific residual. Here μ_{jt} is orthogonal to industry return r_{it} and I also assume that μ_{jt} is also orthogonal to the components r_{mt} and ε_{it} so that the beta of firm j with respect to market, $\beta_{jm}= \beta=\beta_{ji}\beta_{im}$. By assumption that all covariance terms in equation (17) are set to zero, so the variance decomposition in equation (17) is:

$$Var(r_{jt})= \beta^2Var(r_{mt}) + \beta^2jiVar(\varepsilon_{it}) + Var(\mu_{jt}), \tag{18}$$

And the variance of firm return in equation (15) is written as:

$$Var(r_{jt})= \beta^2Var(r_{mt}) + Var(\varepsilon_{jt}), \tag{19}$$

Where $\beta_{jm}= \beta$ by assumption. With equation (18) and equation (19), I can get firm-specific variation decomposition described as:

$$Vol_{firm}= Vol_{industry}+Vol_{idio}, \tag{20}$$

Where $Vol_{firm}= Var(\varepsilon_{jt})$ is firm-specific variation, $Vol_{industry}= \beta^2jiVar(\varepsilon_{it})$ denotes industry risk, and $Vol_{idio}= Var(\mu_{jt})$ denotes firm risk or idiosyncratic risk. So the stock return variations can be decomposed into:

$$Vol_{return}=Vol_{market}+ Vol_{firm} = Vol_{market} + Vol_{industry}+Vol_{idio,} \tag{21}$$

Where Vol_{market} denotes market-wide variation.

To estimate industry risk, first I can obtain beta estimates of β_{jm} from equation (15) per firm-year observation and $ß_{im}$ from equation (16) per industry-year observation I performed in previous section of the formation of R^2 by 48-industry classification. Second, given $\beta_{jm}= \beta=\beta_{ji}\beta_{im}$, I can estimate $\beta^2 ji =(\beta_{jm}/ \beta_{im})^2$ first, and industry risk can be estimated as:

$$Vol_{industry}= (\underline{\beta_{jm}}/ \underline{\beta_{im}})^2 Var(\underline{\varepsilon_{it}}), \tag{22}$$

where $Var(\underline{\varepsilon_{it}})$ is the squares of firm-specific residuals obtained from equation (15) per firm-year observation and $Cov(Vol_{industry}, Vol_{idio})=0$.

To estimate firm risk, I can add industry dummies into my main cross-sectional equation by controlling for industry effect to obtain:

$$R_{(t+1)}=ß_0+ ß_1*cacvol_t+ ß_2*age_t+ ß_3*Size_t^r+ ß_4*BM_t+ ß_5*EP_t+(ß_6*ind_1+ \ldots\ldots.+ ß_{53}*ind_{48})+ \varepsilon_{(t+1)} \tag{23}$$

Where $ind_i=1$ only if firm j is in industry i for i=1 to 48, otherwise $ind_i=0$. Thus, the firm risk can be estimated by the squares of residuals ($Var(\mu_{jt})$) obtained from equation (23).

Panel A of table 3d reports the results of coefficient estimates in equation (23) for firm risk and panel C of table 3d shows the results of coefficient estimates for firm-specific volatility decomposition. Table 3d1 and 3d2 in the appendix are similar to table 3d but the dependent variables are at year t+2 and t+3. By controlling for industry dummies (panel A of table 3d), the estimated coefficient of R^2 to accruals is still significantly negative and this relation pertains to year t+2 and t+3, while the estimated coefficient of market risk to accruals is insignificant. This evidence supports my first hypothesis and the negative relation between R^2 and accruals is robust and it is not subject to firm age, size, BM, or EP, and as well as not to industry. Panel C of table 3d summarizes volatility decomposition where M(t+1), E(t+1), $E_{firm}(t+1)$, and $E_{industry}(t+1)$

denote market-wide variation (Vol_{market}), firm-specific variation (Vol_{firm}), firm risk (Vol_{idio}), and industry risk ($Vol_{industry}$) at year t+1 with logistic transformation, respectively.

From panel C of table 3d, I can conclude that: a) the decreasing trend of R^2 due to accruals is dominated by the increasing trend of firm-specific variation; b) the increasing trend of firm-specific variation is subject largely to firm risk ($E_{firm}(t+1))= Var(\mu_{j(t+1)})$); c) industry-specific risk has no effect on the trend of R^2. As for the estimated coefficient of $E_{ind}(t+1) =\log(\sigma^2_{im(t+1)})$ on cacvol, 1.27 (t-statistics=6.81), it is consistent with panel B of table 3d at industry level when measuring industry-to-market volatility. But when I use estimates of industry risk measure at firm level ($E_{industry}= \log((ß_{jm}/ ß_{im})*\sigma^2_{im})$ at year t+1, the coefficients of $E_{industry}(t+1)$ on cacvol and M(t+1) on cacvol are almost identical (0.53, 0.61, respectively) and insignificant, which imply that industry effect cannot be the explanation of the positive relation of firm-specific variation to accruals or the negative relation of R^2 to accruals.

In panel C of table 3d1 and 3d2 in appendix at year t+2 and t+3, as discussed before, the persistence of R^2 on accruals caused largely by earnings management is further supported by the dominance of firm risk on firm-specific variation where the coefficients of $E_{firm}(t+2)$ on cacvol and $E_{firm}(t+3)$ on cacvol (3.15, t-value=13.48 at year t+2; 2.97, t-value=17.68 at year t+3) are all positively significant relative to firm-specific variation. The estimated coefficients of market risk ($E_{industry}$) on cacvol are all insignificant for all three years t+1, t+2, and t+3.

I rank firms into one hundred portfolios based on current accrual in absolute values (cacvol) in my sample containing 45,536 firm-year observations in NYSE/AMEX between 1964 and 2003 and each portfolio contains at least 450 firms. Then as shown in Figure II, I plot the time-series mean R^2 and decomposed volatility through 100 portfolios of firms by accrual rank. In Panel A of Figure II, in general, results shown in Panel A are consistent with previous evidence and confirm my hypothesis that the R^2 will drop as the degree of misperception of accrual overweighting increases, and the pattern is much more obvious as accrual rank starts after 70^{th} portfolio as firm-specific variation is sharply increasing, leading R^2 to fall while market-wide variation is clearly unchanged. As in panel B of Figure II, the firm-specific variation (from panel A) is decomposed to firm risk (Vol_{idio}) and industry risk ($Vol_{industry}$), where the increasing trend of firm-specific variation is basically mimicked by the trend of idiosyncratic risk and industry risk has no clear pattern as accrual rank increases. The graphical analysis explains that the behavior of R^2 and firm-specific variation changes dramatically for firms with higher accruals, and further supports my empirical evidence on estimates of cross-sectional regression. As investors face a higher degree of information uncertainty concerning accruals, their misperception of accrual overweighting will let them disappointed in the future with incoming unexpected deteriorating earnings. This will increase firm-specific variation (corruptive risk-return relation) and further decrease R^2 consistently, due largely to the explanation of earnings management. The strong negative relation of R^2 and accruals is not subject to industry effect and other control variables. Therefore, my first hypothesis can not be rejected.

3.3.2. Examination of Notion1

My first notion is that higher (lower) R^2 for larger-size (smaller-size) firms can be explained by accruals. Roll (1998) investigates the relation of R^2 and size by showing that portfolio-diversification effect is not the explanation of why larger firms have higher R^2. In this paper, by incorporating the evidence of a) a negative relation of R^2 and accruals and b) the association of poorer accrual quality with smaller firm size, I have come up with the notion that lower R^2 occurred in small firms and higher R^2 occurred in large firms could be mainly explained by accounting accruals. Previous cross-sectional analysis indicates that firm size is very strong positive and statistically significant but only found significance at the 0.05 level for industry size on industry level (Panel B of table3d). Accruals, therefore, could help explain why larger firms display higher R^2 and smaller firms display lower R^2 without considering industry effect. The decomposed components of R^2 - firm-specific variation and market-wide variation - at firm level provide us another picture – namely, that possibly smaller firms, usually associated with poor accrual quality (second panel of table 3b), have more firm-specific variation relative to market-wide variation. Larger-size firms, usually associated with good accrual quality, have more market-wide variation ($size^r$=0.25, t-statistics=10.3) relative to firm-specific variation. This explains, at least partially, why larger (smaller) firms have higher (lower) R^2.

To check that, I define good accrual quality (Good AQ) firms by assigning them to the first half of accrual rank (1-50 portfolios) illustrated in Figure II and poor accrual quality (Poor AQ) firms to the second half, 51-100 portfolios.[11] (1) The mean R^2 trend from year 1964 to 2003 for both Good AQ and Poor AQ firms and the difference in R^2 are depicted in panel A of Figure III. This shows that poor AQ firms generally exhibit somewhat lower R^2, relative to good AQ firms, especially in the 20 years starting 1983. Clearly, the difference in R^2 of good AQ firms minus poor AQ firms is mostly positive, and perhaps a little cyclical. (2) The firm-specific variation (SSE) and market-wide variation (SSR) of good AQ firms minus poor AQ firms are further depicted in Panel B of Figure III, showing that the difference in R^2 is subject to firm-specific variation, not market-wide variation. Together, the two graphs in Figure III give evidence that poor AQ firms have lower R^2 resulting from higher firm-specific variation than good AQ firms while the market-wide variation levels for both types of firms are basically the same, which implies that good accrual quality can not explain why larger firms have higher R^2.

Therefore, one can only states that smaller firms, with high accruals (poor AQ), have lower R^2, compared to larger firms. Accruals only partially explain why smaller firms have lower R^2.

To further examine the robustness of the firm size effect on the behavior of R^2 due to accruals, I assign all the firms each year to quintiles (size 1 to 5) based on fiscal year-end market capitalization in my sample and conduct the same cross-sectional regressions analysis within each size quintile. Panel C of table 3c reports the results. As expected, and consistent with graphical analysis in Figure III, firms with poor accrual quality (usually smaller firms) have statistically lower R^2 (cacvol=-3.39, t-statistics=-3.79) and the higher R^2 of larger firms are not due to accruals. Table 3c1 in the appendix provides the similar results as in year t+2 and t+3. To sum up, accruals do explain why R^2s differ; with firm size considered, I do not find support for my first notion with an explanation that only for smaller firms with lower R^2 is due to accruals, not for larger firms.

3.3.3. Examinations of Notion2-5

Various important explanations for the phenomenon of accrual anomaly that might affect the significantly negative effect of R^2 have been developed by previous research. Notions 2-5 will be tested by conducting similar cross-sectional regression analysis as shown in panel B of table 3c with additional key variables suggested by these hypotheses.

First, to test notion 2, that the significantly negative relationship between R^2 and accruals can be influenced by value-glamour anomaly, I follow Desai et al. (2004). I use a key variable, OCFP, operating cash flow deflated by fiscal year end stock price (CF/ Compustat item #199), capturing both value-glamour anomaly and accrual anomaly effect, as an additional control variable in my main regression (13). Panel B of table 3f presents the results. When controlling operating cash flow-to-stock price, even though the coefficient on OCFP is significantly negative

(OCPF=-4.61, t-statistics=-3.61), obviously the value-glamour anomaly does not affect my major results in H1 with cacvol=-3.00 (t-statistics=-5.28) where the negative relation of R^2 to accruals still holds after controlling for value-glamour anomaly (variable OCFP).

Next, on notion 3, that the significantly negative relationship between R^2 and accruals can be influenced by earnings management, I have already examined this relation and found evidence of earnings management. Here I would like to go further and distinguish between short term and long term effects of earnings management. Following Teoh et al. (1998a), continuing from equation (2)-(4), total accruals (TAC) as the sum of current accruals (CAC) and long-term accruals (LAC), I can get:

$$\begin{aligned} TAC &= CAC + LAC \\ &= \text{Net Income} - CF \end{aligned} \tag{2-1}$$

where net income is Compustat item #172 deflated by average total assets (ATA). For long-term accruals, I first estimate total accruals. The equation is equation (3), except that the dependent variable is TAC and property, plant, and equipment form an additional independent variable deflated by ATA as in the Jones Model:

$$TAC_{jt} = b_0(1/ATA_{jt}) + b_1(\Delta Sales_{jt}/ATA_{jt}) + b2(\ PPE_{jt}/ATA_{jt}) + \ \varepsilon_{jt}\ , \tag{3-1}$$

where PPE_{jt} is Compustat item # 7. Again, the predicted value of equation (25) is normal or nondiscretionary total accruals (NTAC) and the abnormal or discretionary total accruals (DTAC) are the difference between total accruals (TAC) and normal total accruals (NTAC), denoted as the residual values of the modified Jones model in equation (25). Then I use NTAC to obtain:

$$NLAC_{jt} = NTAC_{jt} - NCAC_{jt}\ , \tag{4-1}$$

and use DTAC to get :

$$DLAC_{jt} = DTACjt - DCAC_{jt}\ . \tag{4-2}$$

Therefore, by decomposing total accruals into normal and abnormal total accruals, I can have:

$$TAC_{jt}=CAC_{jt} + LAC_{jt} = NCAC_{jt} +DCAC_{jt} +NLAC_{jt} + DLAC_{jt}. \quad (4\text{-}3)$$

I incorporate decomposed total accrual components in equation (4-3) in absolute values into my main cross-sectional regression (13) to analyze whether short-term (dcacvol) or long-term (dlacvol) earnings management is the explanation for the significantly negative relation between R^2 and accruals. I report the results in panel A of table 3f. For four decomposed components of total accruals, only the coefficient of R^2 to dcacvol is significantly negative (dcacvol=-2.42, t-statistics=-3.94). The evidence supplements hypothesis H1 by establishing that the negative relation between R^2 and accruals is largely explained by earnings management of short-term current accruals, resulting in investors facing higher degree of misperception of accrual anomaly. So I support notion3 of earnings management as an explanation of H1.

Notion 4 involves the concept of bankruptcy risk developed by Khan (2005). He states that the size-adjusted future abnormal returns (8.4%) obtained by performing hedge portfolio strategy in table 2 is normal because, he argues, accrual anomaly is not mispricing, but rather is a return commensurate with greater bankruptcy risk. To measure bankruptcy risk, following Zach (2003), I compute Altman's Z (1968) (ALTZ) as follows:

$$ALTZ= 1.2*WC/TA + 1.4*RE/TA +3.3*EBIT/TA + 0.6*MVE/TL + S/TA , \quad (24)$$

Where WC/TA = working capital/ total assets (Compustat item #179/ item #6),

RE/TA = retained earnings/total assets (item #36/ item #6),

EBIT/TA = earnings before interest and taxes/total assets (item #(18+16+15)/ item #6),

MVE/TL = market value of equity/total liabilities (item #(199*25)/ item #181),

S/TA = sales/total assets (item #12/ item #6).

High (low) values of the Z-score represent firms with lower (higher) likelihood of bankruptcy. Controlling for bankruptcy risk, ALTZ, panel C of table 3f indicates that the coefficient of R^2 to accruals remains significantly negative, consistent with my main results, while the coefficient on ALTZ is of positive significance at the 0.05 level. Thus bankruptcy risk itself cannot explain the negative relation between R^2 and accruals, notion 4 is not supported.

Lastly, notion 5 concerns arbitrage risk as analyzed by Mashruwala et al. (2006). They state that lack of close substitutes poses limits to arbitrage, which keeps arbitrageurs from driving away accrual-related mispricing because the abnormal returns to the accrual anomaly are gathered in stocks with high arbitrage risk, and hence, accrual anomaly remains. In my main regression (13) shown in panel D of table 3f, I control for arbitrage risk. I interact cacvol with ARB, a proxy for arbitrage risk, calculated as residual variance from equation (9) of CAPM market model of stock daily returns over 48 months ending two months after fiscal year end[12].

The significantly negative coefficient on cacvol (-3.15, t-statistics=-4.19) indicates that the negative relation between R^2 and accruals is not subject to arbitrage risk and further implies that even if it is easy for arbitrageurs to arbitrage their position on accrual-related mispricing with close substitutes, this does not prevent earnings management from producing the mispricing accrual-related assets persistently. Earnings manipulation, leading to unexpected deteriorating earnings and increasing firm-specific variation in the future, is the main cause for lower R^2. The evidence in panel D of table 3f proves that the negative relation between R^2 and accruals is robust and is not influenced by arbitrage risk.

To sum up, both the empirical evidence and the graphical analysis support my main hypothesis. The significantly negative relation between R^2 and accruals is robust and persist, and is not affected by (1) firm size, firm age, and other control variables like BM and EP; (2)

industry risk, and of course, market-wide variation; (3) value-glamour anomaly, bankruptcy risk, and arbitrage risk. Further, this paper supports a corruptive risk-return relationship for newly listed firms. Moreover, the accrual anomaly, largely due to earnings management, does explain why R^2 differs through firm-specific variation (figure II, III), which further is more consistent with the evidence in Campbell (2001) that average stock return volatilities have been increasing over time from 1962 to 1997 in the US.

4. Sample Formation and Variables Measurement in a Global Setup

4.1. Sample Formation and Measurement of Variables

To form accruals, R^2, and other variables analyzed in a global setup, I select all firms with available data 1990-2007 on the Global Vantage Industrial/Commercial (GVIC) for global firms accounting information and Global Vantage Issues (GVI) for global stock returns information. To assemble my candidates, I will

(1) select accounting standards in accordance with ISAC, OECD, or GAAP, each of which is close to United States accounting standards;

(2) delete financial firms (SIC codes 6000-6999) because of peculiarities in the accruals for such firms;

(3) require at least 20 firms per year and 500 firm-years in my final sample. The range is from 505 firm-years in Mexico to 41,144 firm-years in the USA between 1990 and 2005 (I use two additional years 2006-2007 for measurement of future R^2);

(4) delete extreme accrual values when ABS(Accruals/Total Assets)>1 for outliers or mistakes occurring in international data;

(5) delete fewer than six observations in any one-digit SIC code and year combination when calculating abnormal accruals by using the Jones model;

(6) delete R^2 of the standard market model with less than 12 observations for both two-year monthly stock returns and value-weighted monthly market index.

Since previous papers (Ball et al. 2000; Land and Lang 2003) use the Global Vantage database (GVI and GVIC) and delete outliers for possible data error, here I winsorize extreme values at the 1st and 99th percentiles. Finally, 31 countries including the USA are included in my international empirical analysis: Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, Hong Kong, Indonesia, India, Italy, Japan, Korea, Mexico, Malaysia, Netherlands, Norway, Philippines, Singapore, Spain, South Africa, Switzerland, Sweden, Taiwan, Thailand, the United Kingdom, and the United States.

Following Ball et al. (2000) and Pincus et al.(2007) for each country, I define Net income (NI): it is operating income (GVIC item #14). I define current accruals (ACC) as:

$$ACC = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD) - Dep, \quad (25)$$

where ΔCA = change in current assets (GVIC item #75),

$\Delta cash$ = change in cash and short-term investment (GVIC item #60),

ΔCL = change in current liabilities (GVIC item #104),

ΔSTD = change in debt included in current liabilities (GVIC item #94),

Dep = depreciation and amortization (GVIC item #11).

And operating cash flow (OCF) is the difference between net income (NI) and current accruals (ACC), where operating cash flow, current accruals, and operating income are deflated by average total assets. Total assets (GVIC item #89) are measured at the beginning and the end of the year. I label the resultant variables as OCF, ACC, and NI, matching CF, CAC, and EARN in the US sample.

For decomposition of current accruals, to obtain normal (nondiscretionary) current accruals (ACC)and abnormal (discretionary) current accruals (DACC), I use a OLS regression in which current accruals for a given year in each country is regressed on the change in sales for that year, for all firms grouped in the same one-digit SIC code. Again, all variables including the intercept term in the cross-sectional regression are scaled by average total assets (ATA) to reduce heteroskedasticity:

$$ACC_{jct} = a_0(1/ATA_{jt}) + a_1(\Delta Sales_{jct}/ATA_{jt}) + \varepsilon_{jct} \quad (26)$$

Where j firms belong in the same one-digit SIC code for industry classification and $\Delta Sales_{jt}$ is the change in sales revenues in year t (GVIC item #1) for firm j in country c.

The normal current accruals (NACC) and abnormal current accruals (DACC) are computed as predicted values and residuals of the modified Jones model:

$$NACC_{jct}= \hat{a}_0(1/ ATA_{jct}) + \hat{a}_1((\Delta Sales_{jct}-\Delta A/R_{jct})/ ATA_{jct}) \quad (27)$$

$$DACC_{jct}= CAC_{jct} - NCAC_{jct} \quad (28)$$

For the formation of R^2, I apply CAPM equation (9) of a typical market model using monthly stock returns, instead of daily stock returns, against a monthly value-weighted market index in two years starting from filing deadlines of financial statements after fiscal year-end[13] for each country for two reasons. First, daily stock returns in some developing countries are very sluggish and sticky. Second, previous analysis in table 3a on selection of R^2 and table 3e on sensitivity test results all indicate that analysis using monthly stock returns gives similar results compared to daily stock returns. Also, in order to increase explanatory power, twenty-four monthly stock returns are used to calculate two-year R^2. The filing deadlines vary country by country; they are reported in table 4a. The deadlines are based on the timing of availability of financial statements and I assume that firms file their financial statements on a timely basis[14]. The final sample of 126,475 firm-years across 31 countries, including United States, between year 1990 and 2005 (since the calculation of R^2 and my analysis require two years data after my sample years), totaling 16 years, will be tested for the relationship of R^2 to accruals.

4.2. Descriptive Statistics

Table 4a reports the summary statistics for all the countries in my sample. As expected and consistent with Morck et al. (1998), higher R^2 are mostly found in emerging countries while lower R^2 are mostly found in developed countries. The five lowest R^2 are found in Denmark, United States, Australia, UK, and Canada; while the five highest R^2 are found in India, Spain, Malaysia, Taiwan, and Greece. Whereas in the domestic US sample I observe a negative relationship between R^2 and accruals, the cross-country data seems to show no apparent relationship between R^2 and the absolute value of accruals. Also shown in table 4a, where countries are sorted by R^2, the firms in developed counties are older than those of emerging markets. For example, the oldest firms are found in USA and Canada, and the youngest, in Taiwan and Korea. Companies in Denmark, Norway, Japan, Switzerland, South Africa, Finland, Hong Kong, Indonesia, Malaysia, and Taiwan have a relatively low book-to-market ratio; while those of Canada, Singapore, and Greece have a relatively high BM.

4.3. Empirical Design and Hypothesis Testing of H2

Since I am interested in the cross-country difference in the relation between R^2 and accruals, within each country, I run a cross-sectional regression of firm's R^2 on the absolute value of accruals and other control variables. I construct a similar cross-sectional analysis by country as follows:

$$R(t+1)=M(t+1)-E(T+1)= ß_0+ ß_1*accvol_{jct} + ß_2*age_{jct}+ ß_3*Size_{jct}^r+ ß_4*BM_{jct}+ ß_5*EP_{jct} +\varepsilon_{jc(t+1)}, \tag{29}$$

$$R(t+1)=M(t+1)-E(T+1)= ß_0+ ß_{11}*naccvol_{jct}+ ß_{12}* daccvol_{jct} + ß_2*age_{jct} +ß_3*Size_{jct}^r+ ß_4*BM_{jct}+ ß_5*EP_{jct} +\varepsilon_{jc(t+1)}, \tag{30}$$

where $Size_{jct}^{r}$ is the residuals (μ_{jct}) of size of firm j in a given country c at time period t as second stage, from first stage of OLS regression: $Size_{jct} = \alpha_0 + \alpha_1 accvol_{jct} + \mu_{jct}$. The dependent variables are defined as $R(t+1) = \log(R^2_{(t+1)}/(1-R^2_{(t+1)}))$, $M_{(t+1)} = \log(\sigma^2_{m(t+1)})$, and $E_{(t+1)} = \log(\sigma^2_{\varepsilon(t+1)})$.

In other words, equations (29) and (30) will be implemented in each country of my sample, 31 countries in all, in order to test my hypothesis (H2) that the accounting accruals is the explanation of lower R^2 for developed countries.

Test of H2

Panels A, B, and C of table 4b present the results of the coefficient estimates of ACCVOL, NACCVOL, and DACCVOL in equation (29) and (30), which use firm-level data on an individual country basis.

As shown in Table 4b, only nine out of thirty-one countries in my sample, including the United States, show a significantly negative relationship of R^2 to accruals and they are Australia, UK, Canada, Japan, Germany, Netherlands, South Africa, France, and USA. The evidence is consistent with Pincus et al. (2007) who find accrual anomaly only in four out of 20 countries: USA, Australia, UK, and Canada. In this paper, I find evidence suggesting that countries with accrual anomaly, mostly found in developed countries, will have lower R^2 mostly through firm-specific variation. It is surprising to see that the significantly negative relationship between R^2 and accruals occurs mostly in developed countries, clustered in countries with lower R^2, where their capital markets are considered to be the most efficient markets.

Twenty two of thirty-one countries in my sample display no significant effect of accruals on R^2, which suggests one cannot explain why emerging countries have higher R^2 through accruals. To check further the explanatory power of accruals on R^2 at the country level, I use medians of all firm-level independent variables in a country as country-level independent variables to conduct pooled cross-country time-series OLS regression analysis with 432 country-years between 1990 and 2005. As reported in panel B of table 4C, the coefficient of absolute value of accruals is negative but is not significant. The absolute value of discretionary accruals is positively significant in explaining idiosyncratic volatility, but also fails to explain R^2. Consistent with Brown and Kapadia (2006), firm age is negative and significant in explaining the adjusted R^2.

To test the influence of accruals on R^2 a bit further, I compare developed countries and developing countries. By separating countries into two groups, excluding USA, 15 countries with low-R^2 (from DEK to FRA) (sample of 222 firm-years), and another 15 countries with high-R^2 (from SWE to GRC) (sample of 194 firm-years), I conduct the same cross-country OLS for these two groups. Untabulated results indicate, surprisingly, that no influence of accruals on R^2 for either group of countries. Therefore, the empirical results do not support my hypothesis H2. However, they do provide an explanation: the effects of accruals on R^2 are clustered largely in developed countries with relatively low R^2 and accruals decrease R^2 in most advanced countries. These factors partially explain the difference in R^2 between developed and developing countries. Somehow, the relatively low R^2 in most advanced countries reflect greater inefficiency in terms of accrual anomaly.

To further study this evidence, inspired by Pincus et al.(2007), I study the cross-country systematic differences in governmental and institutional structures and accounting standards, in the hope that these differences might help us explain the influence of accruals on R^2. In the next section, we propose several conjectures based on previous research and develop a simple empirical test to show whether these differences across countries can explain the relation between R^2 and accruals.

5. The Occurrence of Accruals Significantly Decreasing R^2 and Differences Between Countries in Governmental and Institutional Structures and Accounting Standards

5.1. Conjectures Development

The adjusted R^2 captures the relative variation in market-wide and firm-specific variation. While accounting accruals representing the method the firms use to disclose their specific information, the cross-country differences in institutional and corporate law structure could have an impact on relation between R^2 and accruals.

I identify four categories: (1) A country's legal tradition: common law versus civil law; (2) law enforcement: rule of law and corruption; (3) Investor rights; (4) Shareholder Ownership; (5) Accounting standards[16]. Previous researches suggest plausible systematic differences across countries that lie behind accruals significantly decreasing R^2. Since there is no strong theory in this area so far, I assume the following conjectures are independent of each other.

(1). A country's legal tradition

La Porta et al. (1998) classify country's legal tradition into two groups: civil law versus common law. Ball et al. (2000) characterize the 'shareholder' and 'stakeholder' corporate governance models of common and civil law countries respectively as resolving information asymmetry by public disclosure and private communication. In civil law counties, more diversified investors including shareholders, creditors, customers, suppliers are represented by the board. In contrast, under the common law the board is selected only by shareholders. This implies that in civil law countries a wider range of investors can access firm information; hence asymmetric information can be more easily resolved in civil law countries. Since the accruals anomaly is due to investors overreacting to the information in accruals, a higher degree of information asymmetry may mitigate the accrual mispricing in common law countries. Hence, my first conjecture is:

C1: The occurrence of accruals significantly decreasing R^2 is more likely in countries with a common law tradition than in countries with a civil law system

(2) Law enforcement: rule of law and corruption

La Porta et al. (1997) state that civil law countries have weaker investor protections, higher ownership concentration, and smaller and narrower capital markets than common law countries in their sample of 49 countries. They use the character of legal rules and the quality of law enforcement to measure investor protection. Different legal systems reflect different laws' stance towards investor rights and the quality of law enforcement determines how well investor rights are protected in practice. For instance, these rights give investors the power to claim their returns on their investment from managers.

Shareholders can expect to receive dividends (given sufficient earnings) because they can vote out the directors who do not pay them, and creditors can expect to be paid because they have the power to repossess collateral. Without these rights or with poorer rights due to inefficient law enforcement or little protection by government, managers would have more power to act in their own interests. Higher quality of law enforcement is usually associated with a strong tradition of rule of law and a low degree of government corruption. Strong protection of investor's rights can prevent managers from cooking earnings and thus reduce uncertainty of information. Following La Porta et al.'s (1997) measures of law governing investor protection (rule of law pertains to law enforcement proper and corruption deals with government's stance towards firms), I construct my second conjecture:

C2: The occurrence of accruals significantly decreasing R^2 is greater in countries with a weak tradition of rule of law and a high level of corruption.

(3) Investor Rights

La Porta et al. (1998) use an anti-director rights index to capture the voting rights of minority shareholders. They measure how strongly the legal system favors minority shareholders against the manager in the corporate decision making process. Following Pincus et al. (2007), I center on anti-director index to examine minority shareholder rights, served as my investor rights measures. Thus, in a country with poorer investor rights, managers of firms will have more chances to act in their own interest and increase the probability of earnings management. My third conjecture is:

C3: The occurrence of accruals significantly decreasing R^2 is greater in countries with weaker investor rights.

(4) Shareholder Ownership

La Porta et al., (1997) found that firms in countries with weaker investor protection have more concentrated ownership of their shares, replacing legal protection, since small shareholders rights are more likely to be expropriated by managers in such countries. Therefore, countries where share ownership is widely dispersed (most often common law countries with better investor protections), investors rely on reported earnings and earnings forecasts from financial analysts to evaluate firms' financial performance. Hence earnings management is more likely to occur in a country with lower concentration of ownership because a greater focus on earnings increases the incentives for managers to manage earnings. My fourth conjecture is:

C4: The occurrence of accruals significantly decreasing R^2 is more common in countries with lower concentration of shareholder ownership.

(5) Accounting standards

Accounting systems always play an important and crucial role in corporate governance. Since investors may wish to evaluate firms' financial performances under a given accounting system before they invest, the quality of accounting standards will determine how wisely investors interpret financial accounting information even if found on adequate disclosures. It's reasonable to assume that accrual mispricing is more likely to occur in a country with low quality of accounting standards since managers have more chances to mislead investors with poor information on reported earnings and its' "omitted" components, measured by number of items missing from total reporting elements.

Thus, my last conjecture is:

C5: The occurrence of accruals significantly decreasing R^2 is greater in countries with low quality of accounting standards.

5.2. Variable measurement

Using data based on La Porta et al. (1997), in table 5a, I report descriptive statistics of country-level variables for 30 countries, excluding China[17], and define the following variables as having possible influence on the occurrence of accrual anomaly affecting future R^2:

Legal$_c$ -Common=1 if country c's legal tradition is a common law system, and 0 if a civil law system,

Corrupt$_c$ -Corruption Index=an index of assessment of the corruption in government in country c, a measure of investor protection, varying from 0 to 10, with lower scores indicating that "high government officials are likely to demand special payments" and "illegal payments are generally expected throughout lower levels of government" in the form of "bribes connected with import and export licenses, exchange controls, tax assessment, policy protection, or loans",

Rule_law$_c$ -Rule of law=varying from 0 to 10, with lower scores indicating weak tradition of law and order, as well as weak investor protection,

InvRights$_c$ -Investor rights=an aggregate measure of minority shareholder rights in country c, varying from 0 to 5, with lower scores indicating poor investor rights, based on anti-director index,

OwnConcen$_c$-Ownership concentration=means for country c of the percentage of common shares owned by three largest stockholders in the ten largest privately owned non-financial firms,

Account$_c$ -Accounting Standards=measure of quality of accounting standards, varying from 0 to 90, lower scores represent low quality.

In Table 5a, ten of the 30 countries have a common law tradition and the rest have a civil law tradition. Countries with Scandinavian origins, like Netherlands, Finland, Norway, and Sweden, as well with Denmark, Canada, and Switzerland all have a corruption index of 10, the lowest degree of government corruption, while Indonesia and Philippines are both considered the worst in this respect with scores below 3. They also have the least tradition of law and order, with scores under 4 for rule of law. These scores make them the countries with the poorest investor protection. USA and Canada are considered to be countries favoring minority shareholders, having the highest rights against manager or the dominant shareholders with the investor rights index of 5 while Italy, Mexico and Belgium have the lowest rights for minority shareholders. USA, UK, Japan, and Taiwan have the lowest ownership concentration (20 percent or below) while Greece and Mexico are the highest with over 60 percent. With inclusion of ninety items in their annual reports to measure accounting standards, Greece, Italy, Brazil, and Austria only cover 50 items, while Sweden has the highest quality of accounting standards with a score of 83.

5.3. Results

I use logit regression analysis with a dummy dependent variable (AADR), the occurrence of accruals significantly decreasing R^2, to explore my cross-country conjectures about institutional, governmental, and accounting factors influencing possible systematic differences across countries. There are thirty countries in my sample, twenty-eight in the full model. The dummy dependent variable is equal to 1 for each country- USA, Australia, UK, Canada, Japan, Germany, Netherlands, South Africa, and France found as the occurrence of accruals significantly decreasing R^2 in Table4b.

By examining the effect of the occurrence of accruals significantly decreasing R^2 on possible cross-country systematic differences in market-wide variation and firm-specific variation, I first investigate which of the independent variables are associated with AADR, and then estimate a full model with all factors included:

$$AADR_c = ß_0 + ß_1{*}Legal_c + ß_2{*}Corrupt_c + ß_3{*}Rule\_law_c + ß_4{*}InvRights_c + ß_5{*}OwnConcen_c + ß_6{*}Account_c + \varepsilon_c \quad (31)$$

I also perform regression analysis with another two dummy dependent variables: the occurrence of accruals significantly increasing firm-specific variations (AADE) and the occurrence of accruals significantly affecting market-wide variations (AADM) (Germany and South Africa-accrual anomaly are significantly decreasing, instead of increasing, market-wide variations), on possible cross-country systematic differences, and they (AADE,AADM) are equal to one if significant. For sign specification, I expect a positive coefficient for $Legal_c$, and negative coefficients for the rest of the factors.

In panel A of Table 5b, first, AADR is positively and significantly correlated with AADM (r=0.59), suggesting that the occurrence of accruals decreasing R^2 is closely associated with market-wide variation rather than firm-specific variation in cross-country analysis, consistent with the cross-country OLS results. Second, for the first row of correlations in panel A, some of the signs are not expected: AADR is positively and significantly correlated with corruption (Corrupt) and investor rights (InvRights), which I expect to be negative in my conjectures, and AADR is positively but not significantly correlated with rule of law (Rule_law) and accounting standards (Account), which I also anticipate a negative sign. Only the signs of legal tradition (Legal) and Ownership Concentration (OwnConcen) meet my expectation for conjectures C1 and C4.

Panel B of table 5c presents the logit regression estimates for individual and full models. An interesting sign appears for the factor government corruption (Corrupt). Either in the individual or the full model, a significantly positive coefficient on Corrupt(=3.16, Chi-square=4.69 in the full model) does not meet my expectation but yet is the most significant among all the factors, which suggests that the occurrence of accruals significantly decreasing R^2 is more likely in a country with a low level of government corruption. Two plausible explanations for the result are the following: (1) In countries with a high level of government corruption, more likely to be countries with poorer investor protection, managers have fewer incentives to manage earnings if the marginal revenue of attracting external finance is less than the marginal cost of special payments or bribes demanded by government officials. Marginal revenue is even shrinking as poorly protected investors don't trust or underweight reported earnings for frequent or pervasive usage of earnings management. This view is further supported in Pincus et al. (2007), providing evidence that in civil law countries, with relatively poorer investor protection than common law countries, investors even underweight (underprice) corporate earnings. (2) As in La Porta et al. (1998), they conclude that common law countries protect the investors the most and French civil law countries protect them the least. If investors are mostly protected in common law countries, managers will have more incentives to manage earnings because the higher probability of earnings management on shareholder model (C1) might overcome the lower probability of earnings management on lower level of government corruption in common law countries. Panel B of table 5b shows a negative coefficient on Corrupt (=-0.83) for dependent variable AADE and a positive coefficient on Corrupt (=1.59) for dependent variable AADM, which suggests that a high level of government corruption might increase the likelihood of earnings management resulting in increasing firm-specific variation but is overcome by market-wide factors to drive R^2 up, although they are insignificant. And in panel A of table 5b, corruption is negatively and significantly correlated with ownership concentration, implying that countries with a high level of corruption usually have concentrated ownership, which allows investors to have more access to inside information or better understand the persistence of accruals. Both effects will be likely to change to a significantly positive coefficient on Corrupt for dependent variable AADR.

Panel B of table 5b also reveals that, as predicted, there is a reliably positive and significant coefficient on Legal (=8.33); a reliably negative and significant coefficient on Ownconcen (=-0.34). One must interpret the coefficient on Account with caution because of the change of signs. Although in the full model there's a negative and significant coefficient on Account (=-0.37, Chi-square=3.75), as expected, the coefficient is positive and insignificant in individual model. Recall that muliticollinearity is generally viewed as a problem if one does not detect significant results as predicted (Belsley et al. 1980). In view of the explanations mentioned above, the results in panel B of table 5b for significant institutional and governmental coefficient estimates should be reliable. Therefore, I conclude that the occurrence of accruals significantly decreasing R^2 is more likely to occur in a country with a common law tradition, low level of government corruption, or accounting standards and/or where shareholder ownership is widely dispersed. A country with low concentration of share ownership is more likely to increase firm-specific variation (Ownconcen=-0.19, Chi-square=2.67) and further decrease R^2 by accruals, and a country with a common law tradition increases the likelihood of "accrual anomaly affecting R^2" largely through market-wide variations (Legal=8.70, Chi-squares=2.83). While, as expected, a country with a civil law tradition (Legal=0), most with higher R^2, reduces the probability of the influence of accruals on R^2 and rarely shows an effect of accruals on market-wide variations (political or social factors, considered to be market-wide factors, are probably better measures of systematic differences in civil law countries here).

6. Robustness Check

In this section, I perform two tests to check the robustness of my major findings for the US dataset: The significantly negative relation between R^2 and accruals is persistent and is not subject to (1) firm size, firm age, and other control variables like BM and EP; (2) industry risk, and of course, market-wide variation; (3) value-glamour anomaly, bankruptcy risk, and arbitrage risk. My major findings survive in these two tests. For the first, I incorporate the three-factor Fama-French model into my formation of R^2 (equation (9)):

$$(r_{jt}-rf_t)= \alpha_{jm} + \beta_{jm}(r_{mt}-rf_t) + s_j SMB_t + h_j HML_t + \varepsilon_{jt}, \tag{32}$$

Where SMB_t, HML_t the monthly returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market.

R^2s calculated from equation (32) replace original R^2s and enter into my analysis and the major results indicated above still hold (coefficient of Cacvol =-1.48, p-value=0.02 in panel B of table 3c) for the significantly negative relationship between R^2 and accruals, but the significance will be stronger (i.e., at the 0.01 level) if I employ daily returns.

Second, in the global dataset, instead of using 24-month stock returns to calculate future R^2, I use 12-month stock returns and 36-month stock returns. The occurrence of accruals significantly decreasing R^2 still occurs most often in developed countries (except for South Africa when studied using 12-month stock returns), clustered in countries with lower R^2 and in cross-country logit regression analysis gives qualitatively unaltered results for my finding in a global setup.

6.1. Evidence from ADR

So far I have found strong domestic evidence that the uncertainty of accounting information which is proxied by the absolute value of accruals can predict the next period adjusted R^2. But using international data, I find only eight out of thirty-one countries in our sample that have similar evidence. An interesting question is whether the cross-listed firms, like ADRs, have absolute value of accruals and relation to R^2 similar to what I observed in the US. ADRs represent foreign stock ownership, but are traded in U.S and in U.S. currency. In order to be listed as ADRs, foreign firms must meet SEC disclosure and enforcement standard. By analyzing ADRs, I hope to further examine whether the dependence of accruals on R^2 is related to differences in institutional and accounting features differences across countries. It would be interesting to see whether the domestic main results can be extended to ADR, especially for those countries with no occurrence of accruals significantly decreasing R^2.

I select my ADR sample from the CRSP and Compustat merged database with a total of 3,479 firm-years from 1989 to 2004, containing 28 countries ADRs, listed in panel A of Table 6. I classify ADRs into four groups: group1 (group2) includes those ADRs from countries with non-occurrence (occurrence) of absolute value of accruals-R^2 relation at home; group3 (group4) includes those ADRs from countries with non-occurrence (occurrence) of absolute value of accruals having relation with firm-specific variation at home. For each ADR, I compute R^2 by regressing of daily return of ADR against CRSP value-weighted market index. We compute accruals using information from Compustat. The results are reported in Table 6. In panel A, if I pool all the ADRs together, the evidence is similar to that of domestic evidence, i.e. that absolute value of accruals (discretionary accruals) is negatively related to next period R^2. The estimated coefficient is -3.76 and significant at 1% level. This is similar to domestic US evidence (with estimated coefficient is -3.16). Interestingly, for group 1 (non-occurrence), the estimated coefficient on absolute value of (discretionary) accruals is still not significant, which is also the case in their home countries. For group 2 (occurrence), the absolute value of (discretionary) accruals of those ADRs still have power in predicting R^2. The estimated coefficient is -3.98 and significant at 1%. Similar evidence is found for firm-specific variation, for group3 (non-occurrence) ADRs, the absolute value of accruals still cannot predict the next period firm-specific variation; but for group 4 (occurrence) ADRs, the absolute value of accruals can positively predict the firm-specific variation.

In summary, I find that ADRs of firms from countries with non-occurrence of R^2 on accruals still have no apparent relation between R^2 and accruals. Somehow, the evidence of ADRs supplements my international findings. In group 1 (non-occurrence), absolute value of accruals (discretionary accruals) is positively related to next period firm-specific variations but not enough to lower R^2. The estimated coefficient is 3.97 and significant at 1%. Here I propose two plausible explanations: first, the financial performances of ADRs are essentially performed in their home countries, where still under local institutional and governmental influences; even they are required to make additional financial disclosures to be allowed to be traded in U.S. markets. Second, in panel B of Table 6, I compare the magnitude of accruals of ADRs and those of domestic firms by conducting nonparametric median tests. I find the magnitude of accruals in group 1 is smaller than that of the domestic sample but with a larger R^2, which decreases the importance of the accruals in predicting R^2.

7. Conclusion

In this paper I have characterized the behavior of R^2 and its decomposed variations (firm-specific variation and market-wide variation) with regard to the accrual anomaly (Sloan 1996), domestically and internationally. In the United States study, I show that accrual anomaly does help explain why R^2 decreases through time by answering the question "what factors cause an upward trend of firm-specific variations not captured by market-wide variations?". Particularly, the lack of persistence of accruals seems to have a persistent effect of lowering R^2 through firm-specific variations relative to market-wide variations, supported with the explanation of earnings management. The evidence is also consistent with Teoh et al. (1998) that long-term underperformance of seasoned equity offerings (resulting in persistent shocks on firm-specific variations and R^2) is based on investors naively extrapolating pre-issue manipulated earnings. I also provide empirical evidence of accrual anomaly, answering my second question "What factor can explain a negative low-return high-risk relationship for the newly listed firms?" by commenting that, with the existence of accrual anomaly, given higher risk embedded in newly listed firms, investors' expected returns will decline, even becoming negative.

My major results in US sample of 45,536 firm-years between 1964 and 2003 are as follows. First, the effect of accruals significantly decreasing R^2 through firm-specific variations relative to market-wide variations is robust and is not subject to (1) size, firm age, and other control variables; (2) industry risk and market risk; (3) alternative explanations of accrual anomaly: value-glamour anomaly, bankruptcy risk, and arbitrage risk. Second, earnings management is the most probable reason why R^2 decreases through time in terms of accruals. Third, by providing graphical analysis with two types of portfolios: Good Accrual Quality and Poor Accrual Quality, I show that the difference of R^2 between two portfolios is subject to firm-specific variations and not by size, although larger firms having higher R^2 than smaller firms is due partially to accruals. Fourth, the robustness of accruals significantly decreasing R^2 is even affected by industry level, not surprisingly, the poorest accrual quality industries are construction, computers, and banking while insurance and utility industries are unlikely to incur accrual anomaly.

For the global setup, my major findings, based on data for 126,475 firm-years between 1990 and 2005 for 31 countries, are as follows. First, the occurrence of accruals significantly decreasing R^2 is clustered largely in developed countries with relatively low R^2 and they are USA, Australia, UK, Canada, Japan, Germany, Netherlands, South Africa, and France, while the dependence of R^2 on accruals in most advanced countries partially explains the difference in R^2 between developed and developing countries. Second, without accrual anomaly, the actual R^2 of developed countries should be higher in terms of market efficiency. In developed countries, with part of firm-specific variation reflecting inefficient firm-specific information (accruals) and we might be cautious in answering that the more efficient the capital market is, the lower R^2 is. Third, since the influence of accruals on R^2 at country level is very limited, by turning the attention to cross-country systematic differences, I find that the occurrence of accruals significantly decreasing R^2 is more likely to occur in a country with a low level of government corruption, a common law tradition, low quality of accounting standards, or where shareholder ownership is widely dispersed.

Last, ADRs analysis helps us to further examine the systematic effects of institutional and governmental structures on the relation of R^2 and accruals, and thus supplements my international evidence.

However, it is possible to have wrong signs due to multicollinearity problems among the factors (presumably endogenous) and the absence of strong theory for cross-country differences. But it will be insightful and useful to further understand why the occurrence of accruals affecting R^2 occurs in most developed countries but not in developing countries.

Notes

1.To avoid survivorship bias, I retain the firms that cease to exist after my sample years in my sample. The downward survivorship bias stemmed from those nonsurviving firms are adjusted in my sample by assigning missing value the year when exiting the market.
2.The un-tabulated analyses reveal that the results in my paper still hold for both pre-1988 and post-1988 periods, which suggest that in my study measurement errors, such as merger, acquisitions, and divestitures, will not significantly affect my main results.
3. I find that after year 1988, either actual values or decile ranking, operating cash flows is significantly overweighed, while before 1988, as consistent with Sloan, operating cash flows is underweighted. That explains why, taking both samples together, operating cash flows is neither overweighting nor underweighting given the null hypothesis is not rejected.
4. Three factors may explain the difference. First, Xie's sample includes additional Nasdaq markets and my sample only covers NYSE and AMEX. Second, the sample period is also different, where Xie's sample is from 1971-1992 and mine is 1964-2003. Third, Xie use Subramanyam's (96) definitions of total accruals, but my paper use Sloan's definition of current accruals.
5 There are only two negative abnormal returns occurred in year 1966 and 1981 while the abnormal returns based on the ranking of abnormal current accruals are all positive for each of the 40 sample years.
9. The reason I use quintile rank instead of decile rank is limited number of firms in decile-rank portfolio will reduce explanatory power on R^2.
10 Due to certain industries with peculiarity in the accruals such as financial firms, there's only 41 out of 48 industries existed in my final sample.
11 If the accrual quality is based on abnormal current accrual in absolute values, the results in Figure III are identical.
12 I also try on monthly returns in performing sensitivity test in table 3e with additional cacvol*ARB variable and produce similar results(Aka., significantly negative on cacvol) and the same conclusion of H3d.
13 The filing deadlines in average is about 6 months. As with Alford et al. (1993) and Fama French (1998), I calculate 6 months after fiscal year end for all countries in my sample, the results are unchanged.
14 A few countries (BZR, FIN, AUT, and BEL) are assigned filing deadlines of financial statements of 6 months after fiscal year end, the average of filing deadlines, because of lack of information on them.
15 I also employ other analytic variables, OCFP, ALTZ, and ARB into equation (29), similar to analysis conducted in table 3f to see which alternative explanation affects the relationship between accrual anomaly and future R^2 globally, and the results are basically unchanged, similar to conclusion conducted in table3f that earnings management is a key explanation of my findings.
16 Hung(2001) also states that firms have more opportunities to manage earnings in countries that permit a higher use of accrual accounting. Unfortunately, I only have limited accrual index developed by Hung (2001) in19 of 31 countries and discarded in my conjectures.
17 In La Porta (1997), they examine 49 countries in their sample by different law system origin: common law (English origin), French civil law, German civil law, and Scandinavian civil law origin where China is not on the list.

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Figure I- The average stock returns variation decomposition

Total stock returns variation is decomposed into market-wide variation, $\sigma^2_{m,}$ and firm- specific variation, σ^2_{ε}, based on 45,536 observations from 1964 to 2003. Each bar represents annual average variation based on daily stock returns, where returns and value-weighted market index of the market model include dividends.

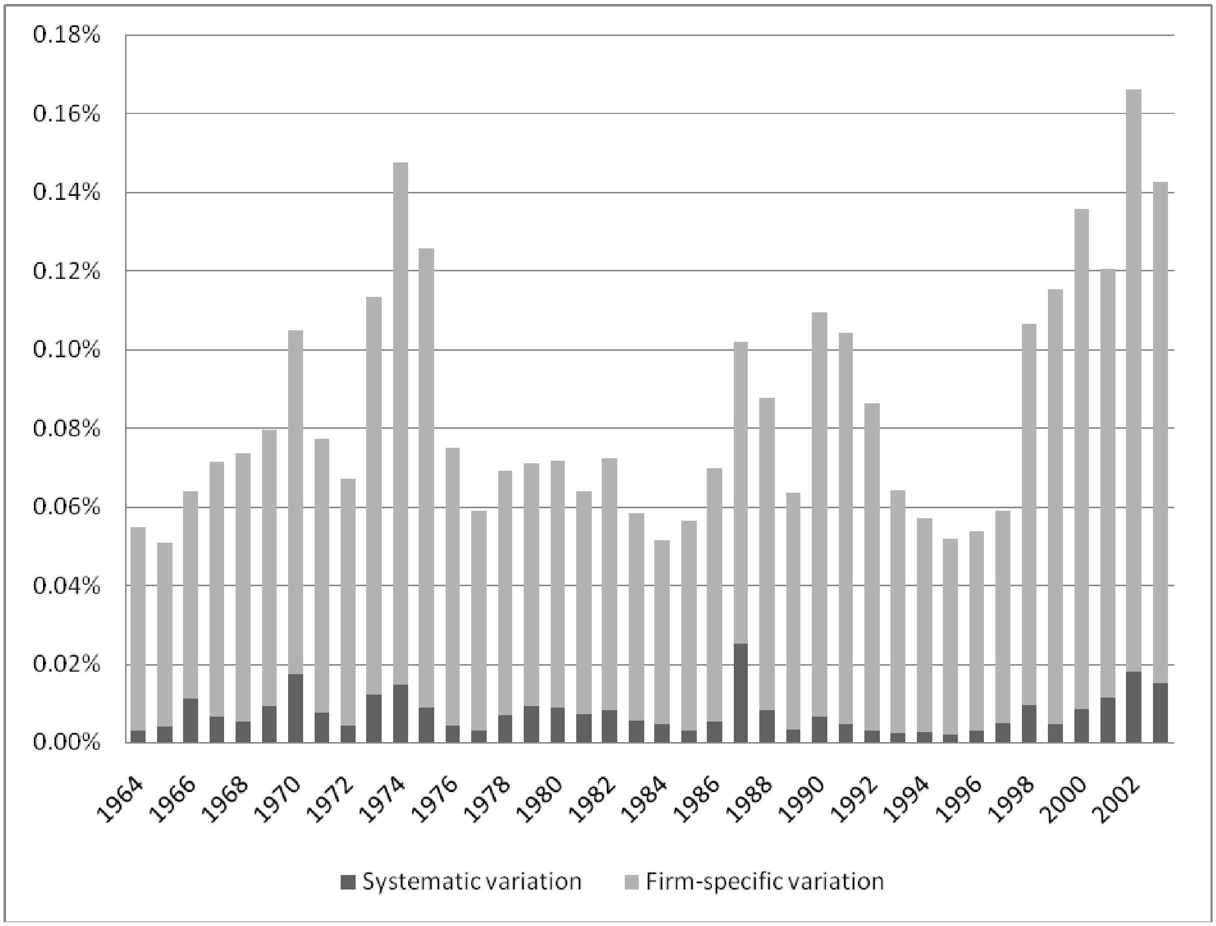
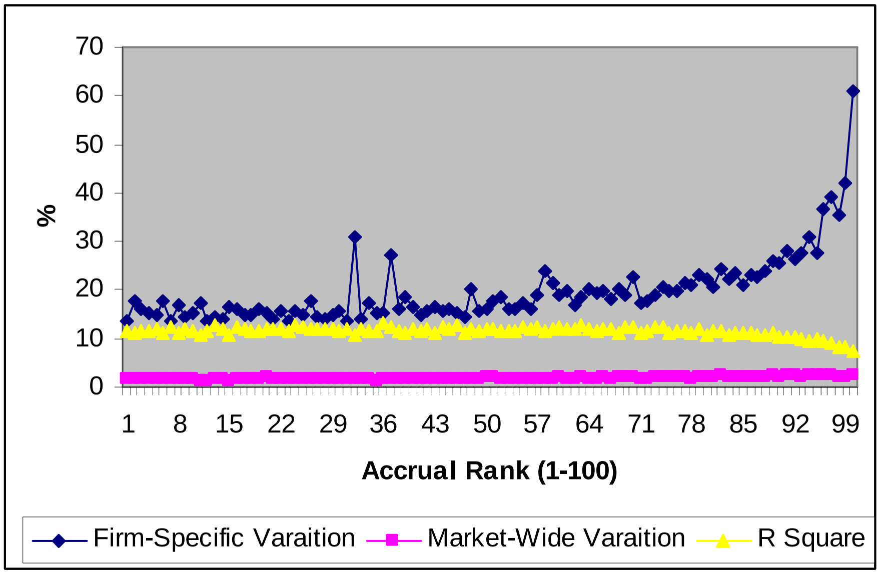


Figure II - Time-series mean future R^2 and its decomposed volatilities on Accrual Anomaly

Total stock returns variation is decomposed into market-wide variation, $\sigma^2_{m,}$ and firm- specific variation, σ^2_{ε}. The firm specific variation is further decomposed to firm (idiosyncratic) risk, Vol_{idio}, and market risk, Vol_{market}, calculated and estimated using equation (22) and (23), based on 45,536 firm-years between 1964 and 2003. The accrual rank is formed into 100 portfolios annually based on the ranking of current accruals in absolute values.

Panel A: The Future R^2 and its decomposed variation on Accrual Anomaly



Panel B: The Future Firm-Specific Variation Decomposition on Accrual Anomaly

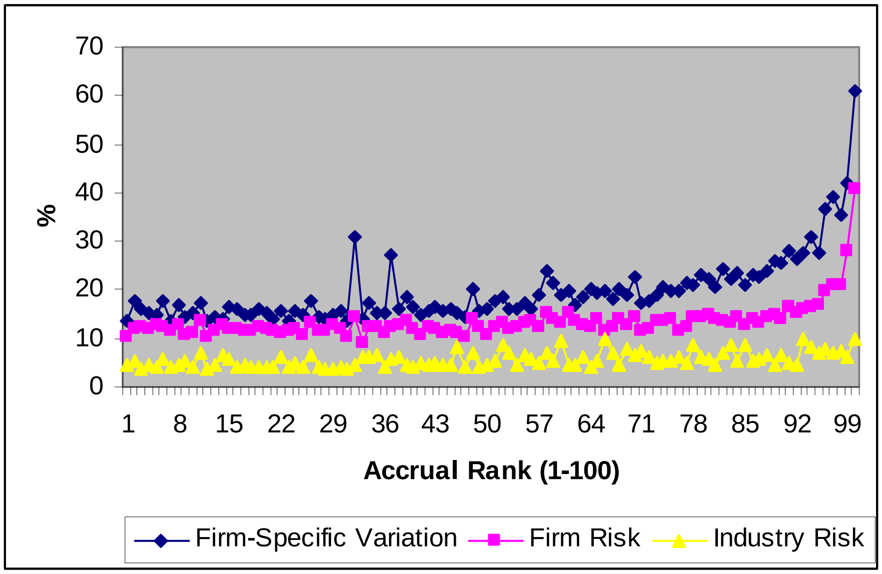
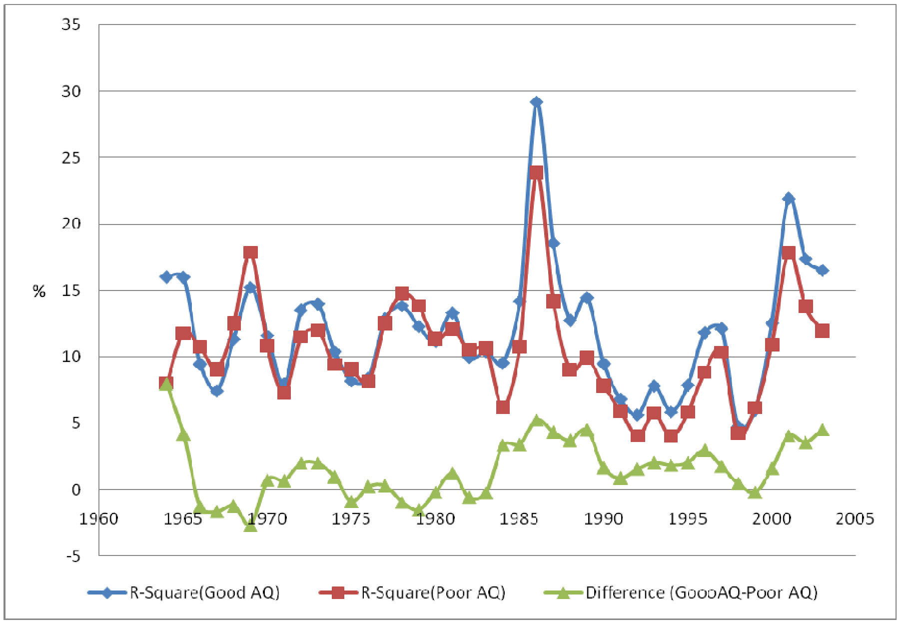


Figure III - The Mean One-Year-Ahead R^2 and Its Decomposed Variations for Good AQ Firms and Poor AQ Firms between Year 1964 and 2003

Good accrual quality (AQ) firms are ranked 1-50 of 100 portfolios of firms based on current accruals in absolute values and poor AQ firms are ranked another 50 portfolios of firms from 51 to 100.

Panel A: The mean future R^2 between good AQ firms and poor AQ firms



Panel B: The decomposed variation difference between good AQ firms and poor AQ firms

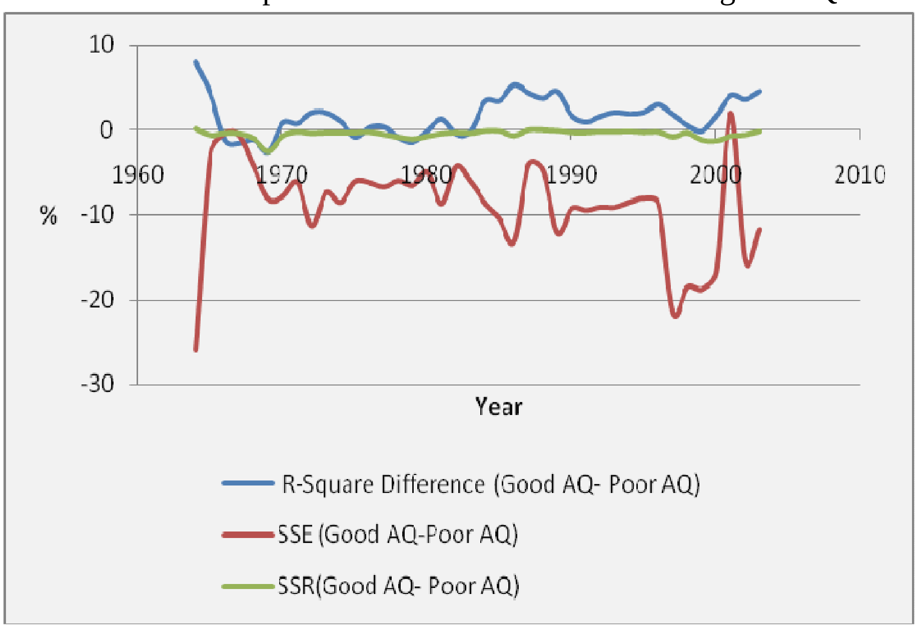


Table 1a- Mishkin Test-Capital Market Efficiency

Nonlinear Generalized Least Squares Estimation of the Market Pricing of Cash Flow from Operations, Current Accruals with Respect to Their Implications for One-Year-Ahead Earnings

Panel A: $\mathbf{EARN_{(t+1)} = \gamma_0 + \gamma_1\, CF_t + \gamma_2\, CAC_t + \mu_{(t+1)}}$ **(5)**

$\mathbf{SizeR_{(t+1)} = \alpha + \beta(EARN_{(t+1)} - \gamma_0 - \gamma^*_1 CF_t - \gamma^*_2\, CAC_t) + e_{(t+1)}}$ **(6)**

Parameter	Estimates	Asymptotic Standard Error
γ_1	0.8105	0.0027
γ^*_1	0.8203	0.0105
γ_2	**0.7291**	0.0041
γ^*_2	**0.8797**	0.0164
β	1.6556	0.0305

Test of Rational Pricing of Earning Components: $\gamma_1 = \gamma^*_1$ and $\gamma_2 = \gamma^*_2$

Likelihood ratio statistics 164.754

Marginal significance level 0.000

Panel B: $\mathbf{EARN_{(t+1)} = \gamma_0 + \gamma_1\, CF_t + \gamma_2\, NCAC_t + \gamma_3\, DCAC_t + \mu_{(t+1)}}$ **(7)**

$\mathbf{SizeR_{(t+1)} = \alpha + \beta(EARN_{(t+1)} - \gamma_0 - \gamma^*_1\, CF_t - \gamma^*_2\, NCAC_t - \gamma^*_3\, DCAC_t) + e_{(t+1)}}$ **(8)**

Parameter	Estimates	Asymptotic Standard Error
γ_1	0.8089	0.0027
γ^*_1	0.8182	0.0107
γ_2	**0.7585**	0.0092
γ^*_2	**0.9159**	0.0364
$\gamma 3$	**0.7209**	0.0045
$\gamma^* 3$	**0.8728**	0.0179
β	1.6503	0.0305

Test of Rational Pricing of Earning Components $\gamma_1 = \gamma_{*1}$ and $\gamma_2 = \gamma^*_2$ and $\gamma 3 = \gamma^*_3$

Likelihood ratio statistics 169.078

Marginal significance level 0.000

Equation (5) and (6), same as Equation (7) and (8), are jointly estimated using an iterative weighted generalized nonlinear least squares estimation procedures based on 45,536 observations from 1964 to 2003. Due to missing values for dependent variables, the number of observations drops to 43,256 in Panel A and to 42,168 in Panel B;

Size-adjusted abnormal returns (SizeR) is the difference between a firm's annual raw buy-and-hold return (Ret) and the annual raw buy-and-hold return for the same twelve-month period on the market-capitalization-based (Market Cap) portfolio decile to which the firm belongs;

The return cumulation period begins four months after the fiscal year end in which financial variables are measured;

Earnings(EARN) = income from continuing operations divided by average total assets.

Cash flows(CF) = operating cash flow under SFAS NO. 95 after 1988, or the difference between earnings and current accruals before 1988.

Current Accruals(CAC)= the difference between earnings and cash flows after 1988, or the Sloan's(96) definition of current accruals before 1988.

Normal Current Accruals (NCAC) and Abnormal Current Accruals (DCAC) are denoted the predicted values and residual values of the modified Jones(91) model estimating in cross-section for each two-digit SIC code and year combination.

Table 1b- Mishkin Test-Capital Market Efficiency

Nonlinear Generalized Least Squares Estimation of the Market Pricing of Cash Flow from Operations, Current Accruals with Respect to Their Implications for One-Year-Ahead Earnings by using decile rankings of financial statement variables

Panel A: $EARN^{dec}_{(t+1)} = \gamma_0 + \gamma_1 CF^{dec}t + \gamma_2 CAC^{dec}t + \mu_{(t+1)}$ **(5)**

$SizeR_{(t+1)} = \alpha + \beta(EARN^{dec}_{(t+1)} - \gamma_0 - \gamma^*_1 CF_t^{dec} - \gamma^*_2 CAC^{dec}t) + e_{(t+1)}$ **(6)**

Parameter	Estimates	Asymptotic Standard Error
γ_1	0.7565	0.0035
γ^*_1	0.7415	0.0132
γ_2	**0.5411**	0.0041
γ^*_2	**0.6613**	0.0164
β	0.063	0.0011

Test of Rational Pricing of Earning Components: $\gamma_1 = \gamma_{*1}$ **and** $\gamma_2 = \gamma^*_2$
Likelihood ratio statistics 199.726
Marginal significance level 0.000

Panel B: $EARN^{dec}_{(t+1)} = \gamma_0 + \gamma_1 CF^{dec}t + \gamma_2 NCAC^{dec}t + \gamma_3 DCA^{dec}t + \mu_{(t+1)}$ **(7)**

$SizeR_{(t+1)} = \alpha + \beta(EARN^{dec}_{(t+1)} - \gamma_0 - \gamma^*_1 CF^{dec}t - \gamma^*_2 NCAC^{dec}t - \gamma^*_3 DCAC^{dec}t) + e_{(t+1)}$ **(8)**

Parameter	Estimates	Asymptotic Standard Error
γ_1	0.7097	0.0037
γ^*_1	0.7134	0.014
γ_2	0.2196	0.0033
γ^*_2	0.2561	0.0124
γ_3	**0.4499**	0.0037
γ^*_3	**0.5878**	0.0141
β	0.063	0.0011

Test of Rational Pricing of Earning Components $\gamma_1 = \gamma_{*1}$ **and** $\gamma_2 = \gamma^*_2$ **and** $\gamma_3 = \gamma^*_3$
Likelihood ratio statistics 252.050
Marginal significance level 0.000

Equation (5) and (6), same as Equation (7) and (8), are jointly estimated using an iterative weighted generalized nonlinear least squares estimation procedures based on 45,536 observations from 1964 to 2003. Due to missing values for dependent variables, the number of observations drops to 43,256 in Panel A and to 42,168 in Panel B;
The decile rankings and decile returns are supplied by CRSP;
The 'dec' superscript indicates a decile rank;
The variables are defined in table 1a.

Table 2- Hedge Portfolio Analysis

Time –series Means of Size-Adjusted Abnormal Returns in Three Years Based on Portfolio Accrual(Current Accruals or Abnormal Accrual) Ranking. Sample Consists of 45,536 Firm-years between 1964 and 2003

Portfolio Ranking[a]	Panel A: Current Accruals year t+1	year t+2	year t+3		Panel B: Abnormal Accruals year t+1	year t+2	year t+3
Lowest	0.060 (6.44)**	0.049 (4.99)**	0.044 (2.32)*		0.067 (7.23)**	0.057 (5.95)**	0.043 (5.31)**
2	0.036 (5.13)**	0.042 (5.51)**	0.013 (2.31)*		0.038 (5.38)**	0.027 (3.94)**	0.042 (2.9)**
3	0.054 (7.36)**	0.041 (5.85)**	0.002 (0.23)		0.047 (6.29)**	0.034 (4.51)**	0.012 (1.98)*
4	0.024 (4.14)**	0.036 (5.98)**	-0.002 (0.14)		0.034 (5.31)**	0.032 (4.9)**	0.002 (0.38)
5	0.024 (3.92)**	0.024 (4.06)**	0.001 (1.13)		0.017 (2.83)**	0.016 (2.78)**	0.002 (1.20)
6	0.021 (3.25)**	0.017 (2.95)**	-0.006 (-0.83)		0.021 (3.45)**	0.02 (3.4)**	0.021 (3.12)**
7	0.017 (2.95)**	0.024 (3.98)**	0.021 (2.34)*		0.007 (1.21)	0.025 (4.05)**	0.001 (0.12)
8	0.012 (1.87)	0.02 (3.01)**	-0.014 (-0.3)		0.003 (0.45)	0.012 (1.23)	-0.002 (-0.38)
9	-0.01 (-0.85)	0.015 (2.18)*	0.012 (1.88)		0.003 (0.38)	0.026 (2.17)*	-0.003 (-0.09)
Highest	**-0.024** (-3.03)**	0.009 (1.10)	-0.002 (-1.32)		**-0.025** (-2.67)**	0.000 (0.21)	0.004 (1.27)
Hedge	**0.084** (7.21)**	0.04 (2.7)*	0.046 (1.86)		**0.092** (8.43)**	0.057 (3.83)**	0.039 (2.31)*

The size-adjusted abnormal returns (SizeR) is the difference between a firm's annual raw buy-and-hold return ending three months after the fiscal year end and the annual raw buy-and-hold return for the same twelve-month period on the market-capitalization-based (Market Cap) portfolio decile (that is, size decile) to which the firm belongs.

The * and ** denote significance at the 0.05 and 0.01 level, respectively, based on a two-tailed t-test for the time series (40 years) of annual portfolio abnormal size-adjusted returns.

[a] Portfolio deciles are formed annually based on the ranking of current accruals and abnormal current accruals for Panel A and Panel B, respectively. The hedge portfolio is formed in year t by taking a long position in the lowest decile portfolio and a short position in the highest decile portfolio based on current accruals and abnormal current accruals, respectively.

Table 3a

Selection of R^2 and mean stats of $R^2_{(t+1)}$, firm size, and CAPM beta ranked by absolute values of current accruals (Cacvol) and abnormal current accruals (Dcacvol)

Panel A: Spearman correlations between various measures of adjusted R square

	$R^2_{paper,daily,vw}$	$R^2_{daily,ew}$	$R^2_{monthly,vw}$	$R^2_{monthly,ew}$
$R2_{daily,ew}$	0.982			
$R2_{monthly,vw}$	0.841	0.852		
$R2_{monthly,ew}$	0.843	0.855	0.991	1

Panel B: Time–series means of future R^2, firm size, and CAPM beta ranked by absolute values of current accruals and abnormal current accruals

Cacvol Rank	$R^2_{(t+1)}$ observations	Size (beta)	Dcacvol Rank	$R^2_{(t+1)}$ observations	Size (beta)
1(lowest)	11.214 4537	5.614 (0.739)	1(lowest)	12.113 4366	5.83 (0.77)
2	11.358 4554	5.672 (0.752)	2	11.876 4384	5.802 (0.775)
3	11.6 4563	5.753 (0.743)	3	11.978 4389	5.766 (0.766)
4	11.468 4552	5.652 (0.75)	4	11.857 4381	5.667 (0.766)
5	11.444 4554	5.63 (0.763)	5	11.572 4386	5.605 (0.776)
6	11.606 4564	5.578 (0.776)	6	11.246 4392	5.461 (0.791)
7	11.555 4556	5.485 (0.814)	7	11.254 4384	5.403 (0.815)
8	11.131 4559	5.369 (0.824)	8	10.93 4385	5.203 (0.847)
9	10.582 4558	5.099 (0.866)	9	10.131 4388	4.961 (0.852)
10(highest)	8.873 4539	4.565 (0.898)	10(highest)	8.7 4370	4.484 (0.898)

R^2, in this paper, is calculated by annual buy-and-hold returns ending three months after the fiscal year end on its market indices(value weighted) by using 252 daily stock returns.

Each firm has its own estimated beta and R^2, based on one-year daily rolling regression, which at least contains 30 daily observations per year.

Size=the natural log of the market value of common equity (in millions of dollars) measured by ending-year price times outstanding shares.

The number of observations on abnormal current accrual rank is smaller than on current accrual rank is due to the outliers in Jones model discussed in section 3.1.

Table 3b

Time series means of selected variables ranked by abnormal current accruals

Portfolio Abnormal Current Accruals Deciles Ranked in absolute values

Dcacvol	Lowest	2	3	4	5	6	7	8	9	Highest
$AdjR^2_{(t+1)}$	12.113	11.876	11.978	11.857	11.572	11.246	11.254	10.93	10.131	8.7
$R^2_{(t+1)}$	12.463	12.227	12.328	12.208	11.923	11.599	11.607	11.285	10.489	9.064
$\sigma m^2_{(t+1)}$	1.637	1.642	1.718	1.721	1.733	1.781	1.905	1.963	2.083	2.249
$\sigma\varepsilon^2_{(t+1)}$	15.42	16.302	16.375	15.783	16.558	21.673	19.021	21.159	23.8	36.11
CF_t	0.123	0.121	0.121	0.118	0.118	0.119	0.12	0.12	0.112	0.088
$Ncacvol_t$	0.026	0.026	0.027	0.027	0.027	0.027	0.028	0.03	0.032	0.046
$dcacvol_t$	0.003	0.009	0.015	0.021	0.028	0.037	0.048	0.064	0.089	0.173
N	4366	4384	4389	4381	4386	4392	4384	4385	4388	4370
β	0.77	0.775	0.766	0.766	0.776	0.791	0.815	0.847	0.852	0.898
age	17.078	17.116	17.031	17.178	16.691	16.383	16.156	15.246	14.8	12.83
Size	5.83	5.802	5.766	5.667	5.605	5.461	5.403	5.203	4.961	4.484
BM	0.895	0.848	0.897	0.699	0.867	0.880	0.862	0.858	0.830	0.80
EP	0.183	0.192	0.189	0.184	0.184	0.187	0.178	0.176	0.164	0.088
Size Portfolios	$AdjR^2_{(t+1)}$									
Smallest	2.98	2.67	2.50	2.27	2.57	2.71	2.49	2.73	2.72	2.46
2	6.67	6.56	7.03	6.82	6.37	7.09	6.72	7.14	7.22	6.77
3	9.99	9.43	9.57	9.84	10.71	10.64	10.50	10.44	10.82	11.01
4	13.00	13.1	12.94	13.72	13.77	13.97	14.1	14.95	15.28	15.81
Largest	21.08	20.71	20.79	21.29	21.48	21.14	22.94	23.27	23.70	23.06

Sample consists of **43,825** firm-years between 1964 and 2003 in NYSE/AMEX, the sample is smaller because of outliers deleted in modified Jones model when calculating abnormal accruals.

$\mathbf{R^2}$ in this paper are all referred to adjusted R^2, unless they are denoted as a dependent variable, a proxy of adjusted R^2 because it is bounded within the interval [0, 1].

$\boldsymbol{\sigma m^2_{(t+1)}}$**,** market-wide variations in t+1, are calculated by $\sigma\varepsilon^2_{(t+1)}*(R^2_{(t+1)}/1-R^2_{(t+1)})$, adjusted for degrees of freedom.

$\boldsymbol{\sigma\varepsilon^2_{(t+1)}}$, firm-specific variations in t+1, are measured by the squares of standard deviations of residuals from a market model that uses 252 daily returns on value weighted market returns starting from three months after fiscal year-end, adjusted for degrees of freedom.

β =CAPM betas, measured from a market model that uses 252 daily returns on value weighted market returns starting from three months after fiscal year-end .

Age is the number of years firm survived and listed in NYSE/AMEX.

Size is the natural log of the market value of common equity measured at fiscal year end (Computstat item #25 times #195) for each firm.

BM, book to market ratio, is the ratio of the fiscal year-end book value of equity (Compustat item #60) to the fiscal year-end market value of equity for each firm.

EP, earning to price ratio, is the ratio of operating income after depreciation (Compustat item #178) to the fiscal year-end market value of equity for each firm.

Size Portfolios are firm portfolios ranked in quintiles by the sizes of firms

Table 3c
Cross-sectional Regression Tests of Future R^2 on Accrual Anomaly
Sample consists of 45,536 firm-years between 1964 and 2003.

Panel A: Spearman correlations for cross-sectional regression variables:

	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	cacvol	ncacvol	dcacvol	age	size	BM	EP
$R_{(t+1)}$	1	-0.30	0.86	-0.07	-0.13	-0.04	0.14	0.48	-0.02	0.03
$E_{(t+1)}$		1	0.23	0.24	0.26	0.20	-0.32	-0.50	0.01	-0.08
$M_{(t+1)}$			1	0.06	0.01^n	0.06	-0.03	023	-0.02	-0.01
cacvol				1	0.28	0.82	-0.15	-0.16	0.00^n	-0.14
ncacvol					1	0.14	-0.20	-0.30	0.01^n	-0.04
dcacvol						1	-0.12	-0.12	0.00^n	-0.11
Age							1	0.47	-0.04	-0.07
Size								1	-0.06	-0.15
BM									1	-0.01^n
EP										1

Panel B: Cross-sectional Regressions of future $R_{(t+1)}$, $E_{(t+1)}$, $M_{(t+1)}$ on absolute values of current accruals (cacvol)
(or decomposed components: normal current accruals (ncacvol) and abnormal current accruals (dcacvol)), and control variables.

Dependent Variable	$R_{(t+1)}$	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	Predicted Sign	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
Cacvol	-3.40 (-5.82)**	**-3.16** **(-5.43)****	**3.77** **(18.51)****	**0.61** **(1.13)**	Negative			
Ncacvol					+/-	**-0.2** **(-0.27)**	2.84 (9.31)**	2.64 (3.48)**
Dcacvol					Negative	**-2.51** **(-4.06)****	3.58 (13.70)**	1.07 (1.99)
Age		0.03 (0.6)	-0.17 (-6.27)**	-0.14 (-3.61)**	Positive	0.09 (3.24)**	-0.21 (-9.37)**	-0.12 (-3.29)**
$Size^r$		0.51 (27.55)**	-0.26 (-20.06)**	0.25 (10.3)**	Positive	0.50 (24.52)**	-0.24 (-20.04)**	0.26 (10.12)**
BM		-0.1 (-3.22)**	-0.1 (-4.11)**	-0.2 (-4.73)**	+/-	-0.14 (-3.47)**	-0.08 (-3.46)**	-0.22 (-4.41)**
EP		0.35 (2.36)*	-0.82 (-8.86)**	-0.47 (-2.5)**	+/-	0.34 (2.23)*	-0.79 (-9.43)**	-0.46 (-2.48)*

Panel C: Cross-sectional Regressions of future $R_{(t+1)}$ on absolute values of current accruals and control variables for five portfolios of firms formed annually by assigning firms to quintiles based on firm size.

	Dependent Variable is $R_{(t+1)}$ for :				
	Size=smallest	2	3	4	Largest
Cacvol	**-3.39** **(-3.79)****	-2.32 (-1.4)	-0.62 (0.71)	1.54 (1.03)	7.17 (0.94)

$R_{(t+1)} = \log(R^2_{(t+1)}/(1-R^2_{(t+1)}))$
$E_{(t+1)} = \log(\sigma^2_{\varepsilon(t+1)})$
$M_{(t+1)} = \log(\sigma^2_{m(t+1)})$
$Size^r$ here is residual values of OLS regression of size on absolute value of current accruals as first stage.
* denote 5% significance level
** denote 1% significance level
^{n} denote non-significance at 1% level.

Table 3d

Cross-sectional Regression Analysis of Firm-Specific Volatility Decomposition: Idiosyncratic Risk and Industry Risk

Panel A: Control for 48 industries (dummies) to measure idiosyncratic risk on accrual anomaly.

$R_{(t+1)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$+(ß$_6$*ind1+ …….+ ß$_{53}$*ind48)+ $\varepsilon_{(t+1)}$

Dependent Variable	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
Cacvol	**-3.77** **(-6.41)****	2.95 (16.14)**	-0.82 (-1.6)
Age	-0.01 (-0.11)	-0.11 (-4.64)**	-0.11 (-3.18)
$Size^r$	0.53 (24.84)**	-0.26 (-22.72)	0.27 (11.13)
BM	-0.05 (-1.70)	-0.12 (-2.59)*	-0.17 (-3.76)**
EP	0.44 (2.11)*	-0.65 (-2.56)*	-0.21 (-1.58)

Panel B: Cross-industry level $R^2_{(t+1)}$ on value-weighted aggregate accruals at industry level to measure industry-to-market volatility.

$R_{ind}(t+1)$=ß$_0$+ ß$_1$*cacvol(t)$_{ind}$+ ß$_2$*age(t)$_{ind}$+ ß$_3$*Size^r(t)$_{ind}^1$+ ß$_4$*BM(t)$_{ind}$+ ß$_5$*EP(t)$_{ind}$ +$\varepsilon_{ind(t+1)}$

Dependent Variable	$R_{ind}(t+1)$	$E_{ind}(t+1)$	$M_{ind}(t+1)$
$Cacvol_{ind}$	**-4.49** **(-2.03)***	8.42 (7.33)**	3.92 (2.42)*
Age_{ind}	-0.08 (-3.62)**	0.04 (3.02)**	-0.04 (-2.90)**
$Size_{ind}^r$	0.16 (2.33)*	-0.14 (-3.02)**	0.02 (0.5)
BM_{ind}	-0.09 (-0.3)	-0.24 (-1.72)	-0.34 (-1.56)
EP_{ind}	2.26 (2.77)**	-1.44 (-4.65)**	0.82 (1.30)

Panel C: Firm-specific volatility(E) decompositions on accrual anomaly at firm level: Idiosyncratic risk (E_{firm}) and industry risk($E_{industry}$)

$R_{(t+1)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$ +$\varepsilon_{(t+1)}$

Dependent Variable	R(t+1)	E(t+1)	**E_{firm}(t+1)**	**E_{ind}(t+1)**	**$E_{industry}$(t+1)**	M(t+1)
Cacvol	**-3.16** **(-5.43)****	**3.77** **(18.51)****	**2.95** **(16.14)****	1.27 (6.81)**	**0.53** **(0.94)**	**0.61** **(1.13)**
Age	0.03 (0.59)	-0.17 (-6.19)**	-0.11 (-4.64)**	-0.05 (-2.74)**	-0.17 (-3.68)**	-0.14 (-3.59)**
$Size^r$	0.51 (27.53)**	-0.26 (-20.26)**	-0.26 (-22.72)**	-0.01 (-1.45)	0.26 (11.53)**	0.25 (10.26)**
BM	-0.09 (-3.13)**	-0.11 (-4.26)**	-0.12 (-2.59)*	0.01 (0.31)	-0.14 (-2.04)*	-0.20 (-4.72)**
EP	0.34 (2.23)*	-0.78 (-8.36)**	-0.65 (-2.56)*	0.02 (0.08)	-0.15 (-0.53)	-0.44 (-2.38)*

$R_{(t+1)}=\log(R^2_{(t+1)}/(1-R^2_{(t+1)}))$,

$E_{(t+1)}=\log(\sigma^2_{\varepsilon(t+1)})$, $E_{ind}=\log(\sigma^2_{im})$, $E_{industry}=\log((ß_{jm}/ß_{im})*\sigma^2_{im})$,

$M_{(t+1)}=\log(\sigma^2_{m(t+1)})$,

R_{ind} is 48-industry R^2 measured as CAPM of value-weighted industry returns on value-weighted market return, both adjusted for risk free rate.

$Size^r$ here is residual values of OLS regression of size on absolute value of industry-levelcurrent accruals as first stage.

* denote 5% significance level

** denote 1% significance level

Table 3e
Cross-sectional Regression Analysis of Sensitivity Test: Daily Returns versus Monthly Returns

$$R_{(t+1)}=ß_0+ ß_1*Cacvol_t+ ß_2*Age_t+ ß_3*Size_t^r+ ß_4*BM_t+ ß_5*EP_t +\varepsilon_{(t+1)}$$

	Year T+1			**Year T+2**			**YearT+3**		
	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	$R_{(t+2)}$	$E_{(t+2)}$	$M_{(t+2)}$	$R_{(t+3)}$	$E_{(t+3)}$	$M_{(t+3)}$
Daily									
Cacvol	**-3.16 (-5.43)****	**3.77 (18.51)****	**0.61 (1.13)**	**-3.30 (-5.98)****	**3.97 (18.32)****	**0.67 (1.56)***	**-3.75 (-5.71)****	**3.76 (19.42)****	**0.01 (0.01)**
Monthly									
Cacvol	**-1.23 (-2.81)****	**3.62 (17.92)****	**2.39 (6.40)****	**-1.54 (-3.32)****	**3.74 (19.17)****	**2.20 (5.48)****	**-1.55 (-3.57)****	**3.47 (16.73)****	**1.92 (3.86)****
Age	-0.02 (-0.45)	-0.20 (-12.65)**	-0.22 (-4.38)**	-0.12 (-1.32)	-0.18 (-7.91)**	-0.30 (-3.48)**	-0.03 (-0.76)	-0.19 (-9.14)**	-0.22 (-6.22)**
$Size^r$	0.21 (11.65)**	-0.24 (-17.72)**	-0.03 (-1.16)	0.20 (11.03)**	-0.23 (-16.32)**	-0.03 (-1.55)	0.19 (10.85)**	-0.22 (-22.3)**	-0.02 (-1.35)
BM	-0.11 (-2.82)**	-0.09 (-3.42)**	-0.20 (-3.57)**	-0.04 (-0.51)	-0.10 (-2.26)*	-0.14 (-2.72)**	-0.12 (-1.65)	-0.04 (-1.36)	-0.16 (-3.01)**
EP	0.15 (0.69)	-0.77 (-4.46)**	-0.62 (-3.91)**	0.41 (1.13)	-0.81 (-4.60)**	-0.40 (-1.74)	-0.33 (-1.62)	-0.60 (-4.87)**	-0.93 (-4.29)**

Table 3f

Cross-sectional Regression of Other Possible Explanations in Affecting the Relationship of Future R^2 on Accrual Anomaly:

Panel A: Accruals Decompositions-Teoh et al. (1998)

$R_{(t+1)}$=ß$_0$+ ß$_1$*$Ncacvol_t$+ ß$_2$*$Dcacvol_t$ + ß$_3$*$Nlacvol_t$ + ß$_4$*$Dlacvol_t$ +ß$_5$*Age_t+ ß$_6$*$Size_t^r$+ ß$_7$*BM_t+ ß$_8$*EP_t +$\varepsilon_{(t+1)}$

Dependent Variable	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
NCacvol	-0.52 (-0.86)	2.68 (7.78)**	2.16 (3.87)**
Dcacvol	**-2.42** **(-3.94)****	**3.29** **(12.44)****	**0.87** **(1.51)**
Nlacvol	-0.17 (-0.54)	-0.66 (-3.00)**	-0.83 (-2.10)*
Dlacvol	-0.21 (-0.61)	1.60 (8.06)**	1.39 (4.14)**
Age	0.10 (3.46)**	-0.21 (-7.04)**	-0.12 (-2.93)**
$Size^r$	0.50 (23.56)**	-0.24 (-20.23)**	0.26 (9.58)**
BM	-0.14 (-3.71)**	-0.09 (-3.79)**	-0.23 (-4.26)**
EP	0.34 (2.25)*	-0.74 (-8.62)**	-0.40 (-2.04)*

Panel B: Value-Glamour Accruals-Desai et al. (2004)

$R_{(t+1)}$=ß$_0$+ ß$_1$*$Cacvol_t$+ ß$_2$*Age_t+ ß$_3$*$Size_t^r$+ ß$_4$*BM_t+ ß$_5$*EP_t +$OCFP_{t+}$ $\varepsilon_{(t+1)}$

Panel C: Bankruptcy Risk (Altman Z) – Khan (2005)

$R_{(t+1)}$=ß$_0$+ ß$_1$*$Cacvol_t$+ ß$_2$*Age_t+ ß$_3$*$Size_t^r$+ ß$_4$*BM_t+ ß$_5$*EP_t + ß6*$ALTZ_t$ +$\varepsilon_{(t+1)}$

Panel D: Arbitrage Risk-Mashruwala et al. (2006)

$R_{(t+1)}$=ß$_0$+ ß$_1$*$Cacvol_t$+ ß$_2$*Age_t+ ß$_3$*$Size_t^r$+ ß$_4$*BM_t+ ß$_5$*EP_t + ß$_6$* (Cacvol*ARB)+$\varepsilon_{(t+1)}$

	Panel B			Panel C			Panel D		
	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
Cacvol	**-3.00** **(-5.28)****	**3.40** **(14.14)****	**0.40** **(0.74)**	**-3.28** **(-5.43)****	**3.66** **(17.34)****	**0.39** **(0.66)**	**-3.15** **(-4.19)****	**-0.05** **(-0.08)**	**-3.20** **(-2.96)****
Age	0.03 (0.69)	-0.16 (-4.80)**	-0.13 (- 3.02)**	0.03 (0.77)	-0.20 (-7.73)**	-0.17 (-4.49)**	0.02 (0.43)	-0.19 (-5.88)**	-0.17 (-2.56)*
$Size^r$	0.50 (25.73)**	-0.25 (-19.04)**	0.25 (9.55)**	0.51 (27.99)**	-0.26 (-21.7)**	0.25 (11.04)**	0.51 (30.52)**	-0.22 (-19.6)**	0.29 (14.43)**
BM	-0.11 (-3.71)**	-0.10 (-3.87)**	-0.21 (-4.74)**	-0.07 (-2.43)*	-0.07 (-1.55)	-0.14 (-2.20)*	-0.09 (-3.02)**	-0.04 (-0.99)	-0.13 (-2.14)*
EP	0.42 (2.96)**	-0.86 (-8.42)**	-0.44 (-2.52)*	0.36 (2.10)*	-0.58 (-3.19)**	-0.22 (-0.72)	0.42 (2.73)**	-0.36 (-1.66)	0.06 (0.20)
OCFP	**-4.61** **(-3.61)****	**3.81** **(2.64)***	**-0.80** **(-0.42)**						
ALTZ				**0.02** **(2.62)***	**-0.01** **(-1.27)**	**0.01** **(1.64)**			
Cacvol*ARB ($*10^4$)							**0.03** **(0.66)**	**0.37** **(5.78)****	**0.40** **(4.32)****

Table 4a

The Time-Series Means of Future R^2, Accruals and Its Decomposed Components in Absolute values, and Control Variables Across Countries, sorted by R^2. Sample Consists of 126,475 Firm-Years Over 1990 and 2005.

Country	ISO	Filing Deadline[1]	N	Future R^2(%)	$Accvol_t$	$Naccvol_t$	$Daccvol_t$	Firm age	Firm Size[2]	BM	EP
Denmark	DNK	6	1,013	16.4	0.074	0.041	0.06	7.38	4.85	0.34	0.10
USA	USA	3	41,144	16.4	0.077	0.041	0.06	8.37	5.80	0.84	0.12
Australia	AUS	4	4,025	17.0	0.087	0.041	0.077	5.78	4.29	4.23	-0.90
UK	GBR	6	11,210	17.5	0.078	0.044	0.065	7.44	4.86	5.49	3.89
Canada	CAN	4	4,419	17.7	0.084	0.051	0.062	7.06	5.20	9.15	5.36
Japan	JPN	3	24,052	17.8	0.053	0.041	0.044	8.21	5.10	0.33	0.08
Switzerland	CHE	6	1,543	18.1	0.066	0.049	0.052	6.86	5.76	0.32	0.09
Thailand	THA	3	2,104	20.3	0.085	0.048	0.071	6.14	3.55	0.58	0.06
Philippines	PHL	6	528	20.4	0.083	0.046	0.073	5.53	3.13	2.28	2.49
Germany	DEU	8	5,085	20.8	0.119	0.056	0.095	6.92	4.98	0.71	0.09
Brazil	BRA	6	865	21.7	0.076	0.051	0.064	6.55	8.55	1.19	0.89
Netherlands	NLD	5	1,554	22.7	0.093	0.05	0.072	7.02	5.58	0.39	0.41
S. Africa	ZAF	6	809	23.5	0.071	0.036	0.062	6.10	5.91	0.13	1.35
Finland	FIN	6	791	23.9	0.086	0.052	0.060	5.92	5.27	0.37	0.17
Norway	NOR	6	976	24.3	0.087	0.041	0.078	6.80	4.90	0.3	0.05
France	FRA	6	4,890	24.4	0.097	0.043	0.075	6.86	5.16	1.73	0.79
Sweden	SWE	6	1,842	24.5	0.077	0.032	0.066	6.44	4.82	0.87	-0.1
Austria	AUT	6	644	24.7	0.11	0.061	0.075	6.47	4.63	3.19	0.87
Belgium	BEL	6	732	25.5	0.10	0.057	0.069	6.52	5.38	5.08	2.11
China	CHN	6	3,127	26.4	0.082	0.031	0.074	7.08	5.36	0.57	0.07
Mexico	MEX	6	505	26.9	0.062	0.05	0.056	6.91	6.42	0.51	0.16
Hong Kong	HKG	6	1,058	27.3	0.071	0.034	0.067	7.02	5.33	0.36	-1.17
Indonesia	IDN	4	1,242	28.1	0.124	0.046	0.108	6.06	3.64	0.07	0.05
Korea	KOR	6	1,366	28.5	0.09	0.045	0.075	4.85	4.72	0.64	0.18
Singapore	SGP	3	2,493	29.3	0.079	0.04	0.071	6.19	4.29	0.61	0.12
Italy	ITA	4	1,309	29.5	0.088	0.044	0.068	5.74	4.94	18.2	5.25
India	IND	6	1,937	30.7	0.074	0.038	0.068	5.69	4.95	0.43	0.22
Spain	ESP	6	1,102	30.9	0.092	0.052	0.073	6.97	6.21	6.32	3.64
Malaysia	MYS	7	4,955	34.2	0.078	0.037	0.072	6.45	4.07	0.36	0.07
Taiwan	TWN	4	1,774	37.1	0.065	0.038	0.054	4.93	5.39	0.35	0.01
Greece	GRC	6	556	44.4	0.131	0.045	0.111	5.18	5.51	18.3	4.65

[1] Filing deadlines are the number of months required to release financial statements after fiscal year end.

[2] Firm size is calculated as natural logarithm of market value of market equity measured at fiscal year-end and transferred to US currency by fiscal year-end exchange rate for the purpose of comparison to other countries. All other analysis for the firm size is used in domestic currency.

Future R^2 is calculated as CAPM of a typical market model with monthly stock returns against monthly value-weighted market index in two years starting from filing deadlines of financial statements after fiscal year-end month. Current accruals (ACC) is defined in equation (25) and ACCVOL is ACC in absolute values. Normal current accruals (NACC) and Abnormal current accruals (DACC) are measured in equation (26-28) by using modified Jones model with one-digit SIC code. BM is book-to market ratio and EP is Earning-to-price ratio. ISO is international standards organizations country code.

Table 4b

Cross-sectional Regressions coefficients of future R^2, R(t+1), and decomposed components E(t+1), and M(t+1) on absolute values of current accruals (ACCVOL) or decomposed components: normal current accruals (ACCVOL) and abnormal current accruals(DACCVOL), and control variables by country, sorted by R^2.

$$R(t+1)=M(t+1)-E(T+1)= ß_0+ ß_1*accvol_t + ß_2*age_t+ ß_3*Size_t^r+ ß_4*BM_t+ ß_5*EP_t +\varepsilon_{(t+1)}$$

$$R(t+1)=M(t+1)-E(T+1)= ß_0+ ß_{11}*naccvol_t+ ß_{12}* daccvol_t + ß_2*age_t +ß_3*Size_t^r+ ß_4*BM_t+ ß_5*EP_t +\varepsilon_{(t+1)}$$

		Coefficients ($ß_1$)			Coefficients ($ß_{11}$)			Coefficients ($ß_{12}$)		
Country	ISO	Я (t+1)	E(t+1)	M(t+1)	Я (t+1)	E(t+1)	M(t+1)	Я (t+1)	E(t+1)	M(t+1)
Denmark	DNK	-1.99	3.66**	1.67	-6.71	7.16	0.45	-0.03	3.79*	3.76
USA	USA	**-0.83***	4.91**	4.09**	2.22*	3.89**	6.11**	**-1.29****	3.73**	2.44**
Australia	AUS	**-1.32^**	3.62**	2.31**	1.48	0.95	2.42^	**-1.43^**	2.68**	1.26^
UK	GBR	**-1.83****	2.84**	1.02^	-3.13**	4.47**	1.34	**-1.18****	2.24**	1.05**
Canada	CAN	**-0.91^**	2.99**	2.08**	0.62	2.72**	3.35*	**-1.35***	2.3**	0.94
Japan	JPN	**-3.4***	3.76**	0.36	-2.62	2.57*	-0.05	-0.02	3.12**	3.1^
Switzerland	CHE	4.67	4.11	8.78	-2.5	1.37	-1.12	1.75	0.32	2.07
Thailand	THA	-0.98	1.46**	0.48	3.27	1.50	4.78	-0.06	1.56**	1.51^
Philippines	PHL	0.66	0.72	1.37	-2.41	0.95	-1 .46	2.31	4.28*	6.59
Germany	DEU	**-2.23***	0.49	-1.73^	-2.16	1.51**	-0.65	**-1.67***	0.37	-1.30
Brazil	BRA	-1.74	1.30	-0.45	0.46	2.57	3.03	-2.87	-1.01	-3.88*
Netherlands	NLD	**-5.63***	0.21	-5.42	-2.61	-1.83	-4.44	-11.5	-6.64	-18.14
S. Africa	ZAF	**-2.83^**	-0.08	-2.91^	-2.91	0.97	-1.94	5.86	-1.76	4.09
Finland	FIN	-1.09	1.27	0.18	-2.86^	0.84	-2.02	-1.27	1.70	0.43
Norway	NOR	-1.03	0.72	-0.32	0.80	2.48*	3.28^	-1.1	0.71	-0.39
France	FRA	**-1.15***	1.32*	0.17	-1.79	1.93*	0.14	**-1.36****	0.99^	-0.37
Sweden	SWE	-3.23	2.26*	-0.97	8.29	1.63	9.92*	-4.85	2.60^	-2.26
Austria	AUT	0.20	-2.18	-1.98	2.36	-1.92	0.44	-2.60	-0.18	-2.78
Belgium	BEL	-3.08	0.89	-2.19	-0.05	-0.89	-0.94	-2.48	-1.12	-3.6
China	CHN	-0.14	0.34	0.20	-3.17**	-0.26	-3.42*	-0.06	0.03	-0.04
Mexico	MEX	-1.94	1.39	-0.55	-0.67	5.37	4.70	-2.38	1.75	-0.64
Hong Kong	HKG	-1.81	2.81	1.01	-4.61*	1.88	-2.73	1.79	3.29^	5.08^
Indonesia	IDN	-0.94	0.40^	-0.54	-1.74	0.15	-1.59	2.92	0.38	3.30^
Korea	KOR	-2.71	2.84**	0.13	3.54	0.04	3.58	2.37	-2.85	-0.48
Singapore	SGP	0.32	1.85**	2.18*	-1.63	2.24*	0.61	-0.37	0.93*	0.57
Italy	ITA	-2.96	1.15	-1.81	-8.04	-0.28	-8.32	1.09	-0.16	0.93
India	IND	-0.64	-0.31	-0.95	-0.35	-0.81	-1.16	-0.03	0.10	0.07
Spain	ESP	0.22	-0.13	0.09	-4.47	5.26	0.79	-0.22	0.56	0.33
Malaysia	MYS	-0.84	2.21**	1.37*	-0.57	1.88*	1.31	-0.89	2.07**	1.31
Taiwan	TWN	-0.90	1.68**	0.78	-1.31	-1.69	-2.30^	-0.59	1.11**	0.52
Greece	GRC	0.99	0.49	1.49	-1.21	-1.25	-2.46^	0.35	0.63	0.98

Table 4c

Pooled cross-country time-series regression of future R^2, R(t+1), and respective decomposed components, future firm-specific stock return variation, E(t+1) , future market-wide stock return variation, M(t+1), on accrual anomaly and control variables. Sample consists of 432 country-years between 1990 and 2005.

Panel A: Spearman correlations for cross-country OLS regression variables:

	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	accvol	naccvol	daccvol	age	size	BM	EP
$R_{(t+1)}$	1	**0.03**	**0.88****	-0.03	0.09^	**-0.11***	**-0.43****	0.15**	-0.19**	-0.23**
$E_{(t+1)}$		1	0.48**	0.03	0.02	**0.19****	**-0.05**	-0.04	-0.21**	-0.21**
$M_{(t+1)}$			1	-0.01	0.10*	**-0.00**	**-0.39****	0.13**	-0.27**	-0.31**
accvol				1	0.53**	0.75**	-0.00	-0.18**	0.03	0.02
naccvol					1	0.33**	-0.09^	-0.01	-0.15**	-0.15**
daccvol						1	-0.27**	0.14**	0.00	0.01
Age							1	-0.17**	0.10*	0.13**
Size								1	-0.33**	-0.30**
BM									1	0.97**
EP										1

Panel B: Country-level OLS regression of future R^2 and its decomposed firm-specific variations and market-wide variations on medians of country-level current accruals in absolute values and control variables.

Panel C: Country-level OLS regression of future R^2 and its decomposed firm-specific variations and market-wide variations on medians of decomposed components of current accruals in absolute values and control variables.

	Panel B				Panel C		
Dependent Variable	$R_{(t+1)}$	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	$R_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
Cacvol	-2.21 (-0.72)	-1.78 (-0.64)	0.57 (0.34)	-0.59 (-0.19)			
Ncacvol					4.08 (1.14)	-3.94 (-1.84)^	0.79 (0.19)
Dcacvol					-3.75 (-1.13)	**8.32** **(4.19)****	4.44 (1.15)
Age		-0.19 (-8.82)**	-0.01 (-0.86)	-0.20 (-7.93)**	-0.18 (-8.49)**	-0.02 (-1.48)	-0.20 (-7.94)**
$Size^r$		0.20 (1.03)	-0.26 (-2.30)*	-0.05 (-0.01)	0.17 (0.88)	-0.15 (-1.27)	0.03 (0.39)
BM		0.29 (2.43)*	-0.07 (-1.04)	0.24 (1.69)^	0.28 (2.36)*	-0.06 (-0.77)	0.24 (1.77)^
EP		-0.36 (-3.2)**	-0.01 (-0.07)	-0.38 (-2.97)**	-0.35 (-3.11)**	-0.02 (-0.33)	-0.37 (-3.02)**
N	432	432	432	432	432	432	432
R^2	0.01	0.23	0.06	0.22	0.23	0.10	0.23

Table 5a
Country Characteristics

Country	ISO	Legal Tradition	Corruption	Rule of Law	Investor Rights	Ownership Concentration(%)	Account
Denmark	DNK	civil	10	10.00	2	45	62
USA	USA	Common	8.63	10.00	5	20	71
Australia	AUS	Common	8.52	10.00	4	28	75
UK	GBR	Common	9.10	8.57	4	19	78
Canada	CAN	Common	10	10.00	5	40	74
Japan	JPN	civil	8.52	8.98	4	18	65
Switzerland	CHE	civil	10	10.00	1	41	68
Thailand	THA	Common	5.18	6.25	2	47	64
Philippines	PHL	civil	2.92	2.73	4	57	65
Germany	DEU	civil	8.93	9.23	1	48	62
Brazil	BRA	civil	6.32	6.32	3	57	54
Netherlands	NLD	civil	10	10.00	1	39	64
S. Africa	ZAF	Common	8.92	4.42	4	52	70
Finland	FIN	civil	10	10.00	2	37	77
Norway	NOR	civil	10	10.00	3	36	74
France	FRA	civil	9.05	8.98	2	34	69
Sweden	SWE	civil	10	10.00	2	28	83
Austria	AUT	civil	8.57	10.00	1	58	54
Belgium	BEL	civil	8.82	10.00	0	54	61
Mexico	MEX	civil	4.77	5.35	0	64	60
Hong Kong	HKG	Common	8.52	8.22	4	54	69
Indonesia	IDN	civil	2.15	3.98	2	58	-
Korea	KOR	civil	-	5.35	2	23	62
Singapore	SGP	Common	8.22	8.57	3	49	78
Italy	ITA	civil	6.13	8.33	0	58	62
India	IND	Common	4.58	4.17	4	40	57
Spain	ESP	civil	7.38	7.80	3	51	64
Malaysia	MYS	Common	7.38	6.78	3	54	76
Taiwan	TWN	Civil	6.85	8.52	3	18	65
Greece	GRC	civil	7.27	6.18	1	67	55

Data based on La Porta et al. (1997), country's legal tradition is either common (civil) law system. Corruption Index is an index of assessment of the corruption in government, measurement of investor protection, varying from 0 to 10, with lower scores indicating "high government officials are likely to demand special payments" and "illegal payments are generally expected throughout lower levels of government" in the form of "bribes connected with import and export licenses, exchange controls, tax assessment, policy protection, or loans". Rule of Law is an index measured for investor protection, varying from 0 to 10, with lower scores indicating less tradition for law and order. Investor Rights is an aggregate measure of minority shareholder rights, varying from 0 to 5, with lower scores indicating poor investor rights, based on anti-director index. Ownership Concentration is means of the percentage of common shares owned by three largest stockholders in the ten largest privately owned non-financial firms, Accounting Standards measure for quality of accounting standards, varying from 0 to 90, lower scores account for proxy of low quality of accounting standards.

Table 5b

Logit cross-country regressions of the occurrence of accrual anomaly significantly decreasing R^2, AADR, the occurrence of accrual anomaly significantly increasing future firm-specific variation, AADE, and the occurrence of accrual anomaly significantly affecting future market-wide variation, AADM, on cross-country institutional and governmental factors.

Panel A: Spearman correlations for cross-country institutional and governmental factors:

	AADR	AADE	AADM	Corrupt	Legal	Rule_law	InvRights	OwnConcen	Account
AADR	1	**0.26**	**0.59****	0.39*	0.31^	0.28	0.38*	-0.46**	0.26
AADE		1	0.34^	0.06	0.33	0.14	0.37*	-0.58**	0.49**
AADM			1	0.26	0.69**	0.13	0.47**	-0.19	0.50**
Corrupt				1	0.03	0.85**	0.03	-0.44*	0.47*
Legal					1	0.08	-0.64**	0.14	-0.42*
Rule_law						1	-0.11	-0.41*	0.36^
InvRights							1	-0.44*	0.41*
OwnConcen								1	-0.47**
Account									1

Panel B: logit regression estimates:

$AADR_c = ß_0 + ß_1*Legal_c + ß_2*Corrupt_c + ß_3* Rule\_law_c + ß_4* InvRights_c + ß_5* OwnConcen_c + ß_6* Account_c + \varepsilon_c$ (31)

Dependent Variable	Coef. (Chi-square)	Coef. (Chi-square)	Coef. (Chi-square)	Coef. (Chi-square)	Coef. (Chi-square)	Coef. (Chi-square)	AADR	AADE	AADM
Corrupt	**0.68^**						**3.16***	-0.83	1.59
	(3.50)						**(4.69)**	(0.45)	(1.75)
Legal		**1.39^**					**8.33^**	5.37	**8.70^**
		(2.70)					**(2.97)**	(1.68)	**(2.83)**
Rule_law			0.35				-1.08	1.26	-0.30
			(2.16)				(1.16)	(0.92)	(0.13)
InvRights				0.68*			-1.34	-0.49	-1.35
				(3.81)			(0.94)	(0.25)	(0.87)
OwnConcen					**-0.08***		**-0.34***	**-0.19^**	-0.08
					(5.32)		**(3.92)**	**(2.67)**	(0.52)
Account						0.08	**-0.37***	0.08	-0.00
						(1.85)	**(3.75)**	(0.42)	(0.00)
Adjusted R^2	0.26	0.13	0.12	0.21	0.28	0.09	0.77	0.73	0.73
N	29	30	30	30	30	29	28	28	28

Corrupt=Corruption index, varying from 0 to 100. Lower scores indicate high degree of government corruption.
Legal=legal tradition, o if civil law tradition, 1 if common law tradition.
Rule_law=rule of law, varying from 0 to 10. Lower scores indicate less tradition for law proper.
InvRights=Investor Rights, varying from 0 to 5. Lower scores indicate least minority shareholder rights.
OwnConcen=Shareholder Ownership Concentration, varying from 0 to 100(%). Low percentage indicates high ownership concentration.
Account=Accounting Standards, varying from 0 to 100. Low scores indicate low quality of accounting standards.
All factors are defined in table 5a.

Table 6: Evidence from ADR$_s$

This table reports the results from ADRs, We choose all the ADRs from CRSP and Compustat merged database. In total, I have 3479 observations from 1989 to 2004. I classify the sample into four groups: Group1(non-occurrence) includes ADRs from those countries where there is no accruals and R^2 relation. Group2 (occurrence) includes ADRs from those countries where there is accruals and R^2 relation. group3 (group4) includes those ADRs from countries with non-occurrence (occurrence) of absolute value of accruals and firm-specific variation relation. $R_{(t+1)} = \log(R^2_{(t+1)}/(1-R^2_{(t+1)}))$, $E_{(t+1)} = \log(\sigma^2_{\varepsilon(t+1)})$ and $M_{(t+1)} = \log(\sigma^2_{m(t+1)})$. Cacvol is the absolute value of current accruals, ncacvol is the absolute value of normal accruals and dcacvol is the absolute value of discretionary accruals. I also control for firm size, book-to-market ratio, earning to price. The coefficients of control variables are not reported here, but available upon request. I use ^, * and ** to denote the significant level at 10%, 5%, and 1% respectively.

Panel A: Cross-sectional regression results.

ADRs	All countries pooled			Group1[b](non-occurrence of Я $_{(t+1)}$ on cacvol)			Group2[c](occurrence of Я $_{(t+1)}$ on cacvol)		
N	3,479 (28 countries)			861 (20 countries)			2,618 (8 countries)		
	Я $_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	Я $_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$	Я $_{(t+1)}$	$E_{(t+1)}$	$M_{(t+1)}$
Cacvol	**-3.76**	**4.11**	0.34	18.26	**3.97**	22.24	**-3.98**	**4.05**	0.06
	(3.78)**	**(11.22)****	(0.39)	(1.83)	**(3.22)****	(2.01)	**(-4.08)****	**(10.90)****	(0.07)
Or									
Ncacvol	3.94	1.91	5.86	-17.32	1.30	-16.02	7.06	4.83	11.90
	(1.14)	(1.35)	(2.16)*	(-1.10)	(0.24)	(-0.80)	(2.40)*	(1.11)	(2.02)
Dcacvol	-3.47	3.52	0.05	9.45	5.54	14.99	-3.50	3.77	0.27
	(-3.84)**	(8.76)**	(0.07)	(1.76)	(2.13)*	(1.95)	(-3.94)**	(8.16)**	(0.37)

	Group3 (non-occurrence of $E_{(t+1)}$ on cacvol)			Group4 (occurrence of $E_{(t+1)}$ on acvol)		
N	949 (17 countries)			2530 (11 countries)		
Cacvol	4.57	0.82	5.38	-4.35	4.54	0.19
	(0.81)	(0.99)	(1.06)	(-4.52)**	(11.03)**	(0.18)
Or			Or			
Ncacvol	8.95	2.24	11.19	7.36	5.90	13.26
	(1.44)	(0.73)	(1.85)	(2.51)*	(1.36)	(2.08)
Dcacvol	4.15	0.94	5.09	-3.80	4.23	0.43
	(0.83)	(1.14)	(1.05)	(-4.13)**	(8.92)**	(0.48)

Panel B: Nonparametric Median Test for ADR Sample and Domestic Sample.

Sample	N	Mean R^2(%)	Mean Score for R^2
ADR (Group1)	861	12.73	0.57
ADR (Group2)	2,618	9.31	0.38
Domestic	43,525	11.59	0.51
P-value			0.000

Sample	N	Mean Cacvol(%)	Mean Score for Cacvol
ADR (Group1)	861	5.01	0.39
ADR (Group2)	2,618	6.16	0.46
Domestic	43,525	5.82	0.51
P-value			0.000

Appendix

Table 3c1

Cross-sectional Regression Tests of Future R^2 on Accrual Anomaly

Sample consists of 45,536 firm-years between 1964 and 2003.

Panel A: Cross-sectional Regressions of future $R_{(t+2)}$, $E_{(t+2)}$, $M_{(t+2)}$ on absolute values of current accruals (cacvol)
(or decomposed components: normal current accruals (ncacvol) and abnormal current accruals (dcacvol)), and control variables.

Dependent Variable	$R_{(t+2)}$	$R_{(t+2)}$	$E_{(t+2)}$	$M_{(t+2)}$		$R_{(t+2)}$	$E_{(t+2)}$	$M_{(t+2)}$
Cacvol	-3.53 (-6.21)**	**-3.30** **(-5.98)****	3.97 (18.32)**	0.67 (1.56)*				
Ncacvol						**-1.26** **(-1.51)**	3.17 (9.98)**	1.91 (2.4)*
Dcacvol						**-2.09** **(-3.77)****	3.37 (12.31)**	1.28 (2.52)*
Age		0.05 (0.75)	-0.19 (-7.14)**	-0.13 (-2.20)*		0.12 (3.7)**	-0.23 (-13.65)**	-0.11 (-3.05)**
$Size^r$		0.49 (22.51)**	-0.25 (-20.10)**	0.24 (9.23)**		0.48 (20.24)**	-0.23 (-20.65)**	0.25 (9.02)**
BM		-0.04 (-0.96)	-0.12 (-3.24)**	-0.16 (-5.01)**		-0.12 (-2.76)**	-0.08 (-3.75)**	-0.20 (-3.83)**
EP		0.22 (0.93)	-0.91 (-8.22)**	-0.69 (-2.76)**		0.09 (0.58)	-0.87 (-9.08)**	-0.78 (-3.60)*

Dependent Variable is $R_{(t+2)}$ for :

	Size=smallest	2	3	4	Largest
Cacvol	**-4.35** **(-3.35)****	**-4.83** **(-4.37)****	-2.94 (-1.91)	0.34 (0.18)	2.83 (0.91)

Panel B: Cross-sectional Regressions of future $R_{(t+3)}$, $E_{(t+3)}$, $M_{(t+3)}$ on absolute values of current accruals (cacvol)
(or decomposed components: normal current accruals (ncacvol) and abnormal current accruals (dcacvol)), and control variables.

Dependent Variable	$R_{(t+3)}$	$R_{(t+3)}$	$E_{(t+3)}$	$M_{(t+3)}$		$R_{(t+3)}$	$E_{(t+3)}$	$M_{(t+3)}$
Cacvol	-3.87 (-6.86)**	-3.75 (-5.71)**	3.76 (19.42)**	0.01 (0.01)				
Ncacvol						-1.78 (-1.7)	3.13 (10.87)**	1.34 (1.23)
Dcacvol						-2.62 (-3.91)**	3.14 (17.26)**	0.51 (0.87)
Age		0.17 (1.81)	-0.19 (-7.58)**	-0.02 (-0.14)		0.21 (2.10)*	-0.23 (-13.18)**	-0.02 (-0.27)
$Size^r$		0.48 (15.33)**	-0.24 (-21.99)**	0.24 (6.84)**		0.47 (14.89)**	-0.22 (-20.21)**	0.24 (7.46)**
BM		-0.06 (-1.03)	-0.11 (-4.50)**	-0.17 (-2.38)*		-0.09 (-1.28)	-0.07 (-2.80)**	-0.16 (-2.72)**
EP		-0.23 (-0.76)	-0.96 (-6.66)**	-1.19 (-3.03)**		-0.25 (-0.73)	-0.9 (-7.56)**	-0.15 (-2.91)**

Dependent Variable is $R_{(t+3)}$ for :

	Size=smallest	2	3	4	Largest
Cacvol	-3.76 (-3.54)**	-2.67 (-1.02)	-3.16 (-1.91)	0.91 (0.36)	0.80 (0.46)

Table 3d1

Cross-sectional Regression Analysis of Firm-Specific Volatility Decomposition: Idiosyncratic Risk and Industry Risk

Panel A: Control for 48 industries (dummies) to measure idiosyncratic risk on accrual anomaly.

$R_{(t+2)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$+(ß$_6$*ind1+ …….+ ß$_{53}$*ind48)+ $\varepsilon_{(t+2)}$

Dependent Variable	$R_{(t+2)}$	$E_{(t+2)}$	$M_{(t+2)}$
Cacvol	-3.68 (-8.33)**	3.15 (13.48)**	-0.53 (-1.79)
Age	0.05 (0.73)	-0.12 (-4.83)**	-0.08 (-1.35)
Size^r	0.51 (18.88)**	-0.25 (-22.21)**	0.26 (9.11)**
BM	-0.09 (-2.4)*	-0.12 (-1.89)	-0.22 (-2.45)*
EP	0.03 (0.15)	-0.79 (-3.1)**	-0.76 (-1.80)

Panel B: Cross-industry level $R^2_{(t+1)}$ on value-weighted aggregate accruals at industry level to measure industry-to-market volatility.

R_{ind}(t+2)=ß$_0$+ ß$_1$*cacvol(t)$_{ind}$+ ß$_2$*age(t)$_{ind}$+ ß$_3$*Size^r(t)$_{ind}$[1]+ ß$_4$*BM(t)$_{ind}$+ ß$_5$*EP(t)$_{ind}$ +$\varepsilon_{(t+2)}$

Dependent Variable	R_{ind}(t+2)	E_{ind}(t+2)	M_{ind}(t+2)
Cacvol$_{ind}$	-4.03 (-1.96)	8.65 (7.08)**	4.62 (3.02)**
Age$_{ind}$	-0.08 (-3.64)**	0.04 (3.29)**	-0.04 (-3.27)**
Size$_{ind}^r$	0.15 (2.0)	-0.14 (-3.35)**	0.01 (0.03)
BM$_{ind}$	-0.01 (-0.05)	-0.23 (-1.80)	-0.24 (-1.59)
EP$_{ind}$	2.53 (3.46)**	-1.32 (-4.39)**	1.2 (2.10)*

Panel C: Firm-specific volatility(E) decompositions on accrual anomaly at firm level: Idiosyncratic risk (E_{firm}) and industry risk(E_{ind})

$R_{(t+2)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$ +$\varepsilon_{(t+2)}$

Dependent Variable	R(t+2)	E(t+2)	E_{firm}(t+2)	E_{ind}(t+2)	$E_{industry}$(t+2)	M(t+2)
Cacvol	-3.30 (-5.98)**	**3.98** **(18.34)****	**3.15** **(13.48)****	1.34 (7.75)**	**1.02** **(2.38)***	0.68 (1.57)
Age	0.05 (0.73)	-0.19 (-7.11)**	-0.12 (-4.83)**	-0.04 (-2.87)**	-0.17 (-2.55)*	-0.13 (-2.24)*
Size^r	0.50 (22.58)**	-0.25 (-20.27)**	-0.25 (-22.21)**	-0.01 (-1.25)	0.26 (10.91)**	0.24 (9.21)**
BM	-0.04 (-1.00)	-0.13 (-3.36)**	-0.12 (-1.89)	0.01 (0.29)	-0.11 (-2.10)*	-0.17 (-5.13)**
EP	0.23 (1.04)	-0.85 (-7.96)**	-0.79 (-3.1)**	0.08 (0.39)	-0.47 (-1.64)	-0.62 (-2.66)*

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$R_{(t+2)} = \log(R^2_{(t+2)}/(1-R^2_{(t+2)}))$

$E_{(t+2)} = \log(\sigma^2_{\varepsilon(t+2)})$

$M_{(t+2)} = \log(\sigma^2_{m(t+2)})$

R_{ind} is 48-industry R^2 measured as CAPM of value-weighted industry returns on value-weighted market return, both adjusted for risk free rate.

Size^r here is residual values of OLS regression of size on absolute value of current accruals as first stage.

* denote 5% significance level

** denote 1% significance level

Table 3d2

Cross-sectional Regression Analysis of Firm-Specific Volatility Decomposition: Idiosyncratic Risk and Industry Risk

Panel A: Control for 48 industries (dummies) to measure idiosyncratic risk on accrual anomaly.

$R_{(t+3)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$+(ß$_6$*ind1+ …….+ ß$_{53}$*ind48)+ $\varepsilon_{(t+3)}$

Dependent Variable	$R_{(t+3)}$	$E_{(t+3)}$	$M_{(t+3)}$
Cacvol	-4.45 (-6.19)**	2.97 (17.68)**	-1.48 (-2.17)*
Age	0.13 (1.73)	-0.13 (-5.48)**	0.01 (0.07)
Size^r	0.50 (17.63)**	-0.24 (-22.3)**	0.26 (8.73)
BM	0.04 (0.99)	-0.08 (-3.55)**	-0.04 (-0.78)
EP	0.34 (0.68)	-0.64 (-5.43)**	-0.3 (-0.61)

Panel B: Cross-industry level $R^2_{(t+1)}$ on value-weighted aggregate accruals at industry level to measure industry-to-market volatility.

R_{ind}(t+3)=ß$_0$+ ß$_1$*cacvol(t)$_{ind}$+ ß$_2$*age(t)$_{ind}$+ ß$_3$*Size^r(t)$_{ind}^1$+ ß$_4$*BM(t)$_{ind}$+ ß$_5$*EP(t)$_{ind}$ +$\varepsilon_{(t+3)}$

Dependent Variable	R_{ind}(t+3)	E_{ind}(t+3)	M_{ind}(t+3)
Cacvol$_{ind}$	-3.18 (-1.50)	8.42 (6.69)**	5.23 (3.34)**
Age$_{ind}$	-0.08 (-4.09)**	0.05 (3.56)**	-0.04 (-3.76)**
Size$_{ind}^r$	0.15 (2.33)*	-0.15 (-3.64)**	-0.00 (-0.00)
BM$_{ind}$	0.14 (0.73)	-0.20 (-1.62)	-0.06 (-0.56)
EP$_{ind}$	2.58 (3.64)**	-1.36 (-4.73)**	1.23 (2.25)*

Panel C: Firm-specific volatility(E) decompositions on accrual anomaly at firm level: Idiosyncratic risk (E_{firm}) and industry risk(E_{ind})

$R_{(t+3)}$=ß$_0$+ ß$_1$*cacvol$_t$+ ß$_2$*age$_t$+ ß$_3$*Size$_t^r$+ ß$_4$*BM$_t$+ ß$_5$*EP$_t$ +$\varepsilon_{(t+3)}$

Dependent Variable	R(t+3)	E(t+3)	E_{firm}(t+3)	E_{ind}(t+3)	$E_{industry}$(t+3)	M(t+3)
Cacvol	-3.75 (-5.71)**	**3.76 (19.42)****	**2.97 (17.68)****	1.30 (7.97)**	**0.11 (0.2)**	0.01 (0.02)
Age	0.17 (1.77)	-0.19 (-7.59)**	-0.13 (-5.48)**	-0.04 (-2.66)	-0.05 (-0.56)	-0.02 (-0.19)
Size^r	0.48 (15.42)**	-0.24 (-22.11)	-0.24 (-22.3)**	-0.01 (-0.98)	0.26 (9.52)	0.24 (6.86)**
BM	-0.05 (-0.93)	-0.11 (-4.87)**	-0.08 (-3.55)**	0.02 (0.46)	-0.1 (-2.98)**	-0.17 (-2.40)*
EP	-0.22 (-0.73)	-0.9 (-6.74)**	-0.64 (-5.43)**	0.05 (0.33)	-0.81 (-2.96)**	-1.12 (-2.91)**

$R_{(t+3)} = \log(R^2_{(t+3)}/(1-R^2_{(t+3)}))$

$E_{(t+3)} = \log(\sigma^2_{\varepsilon(t+3)})$

$M_{(t+3)} = \log(\sigma^2_{m(t+3)})$

R_{ind} is 48-industry R^2 measured as CAPM of value-weighted industry returns on value-weighted market return, both adjusted for risk free rate.

Size^r here is residual values of OLS regression of size on absolute value of current accruals as first stage.

* denote 5% significance level

** denote 1% significance level

Chapter II

Return-Volume in the Tail: Evidence from Six Emerging Markets

1. Introduction

In this paper, I study the interdependence of stock market return and trading volume for six emerging economy, is: Argentina, Chile, Malaysia, Mexico, Singapore and Thailand. I use the bivariate threshold model (see Ledford and Tawn (1996) and Longin and Solnik (2000)) to study the relation of adjusted absolute return to trading volume when the observations exceed certain thresholds.

The driving forces of stock volatility, trading volume, and their correlation have been of lasting interest in financial economics. There are several reasons why this issue is important. First, the price-volume relation provides us with insight into financial market structure. Various theoretical and empirical works have linked trading volume to the information inflow to the market and to differences of opinion among investors. The observed trading volume includes both liquidity-driven trading and information-driven trading. If we assume that liquidity trading comes to the market at a constant rate, the price change of stocks is mainly caused by new information arriving in the market. On the other hand, the more diverse the opinions of different investors, the larger the new volume of trade will be. Correctly identifying price-volume relations can lead us to understand the mechanism of information flow transmission, the dissemination of information to price determination and the extent to which market prices convey information. Secondly, if the dynamic structure of the price-volume relation can be jointly determined, incorporating the price-volume relation will improve forecasting return and volatility. Thirdly, the return-volume relation can provide us with additional information about the empirical distribution of stock returns. It is a well-known fact that the empirical distribution of stock price departs from the normal distribution. The well-known “Mixture of Distribution Hypothesis” proposes that the price data are governed by a conditional stochastic process with a changing variance parameter determined by a latent random variable proxy for the arrival of information flow. So the link between trading volume and conditional volatility can provide the explanation why empirical distribution of stock returns appears to exhibit excess kurtosis.

Although there is a rich literature about theoretic and empirical work on price-volume relations, few studies have been focused on the price-volume relation during extreme price and volume movements. Moreover, almost all of these focus on the U.S. or other developed countries. According to the Wall Street adage that “It takes volume to make price moves”, if a large price change is observed, the trading volume should also be large. But this is not always true, as shown by (Balduzzi, Kallal and Longin (1996)). They use the data of stock-market prices and transaction volume on the day of minimal daily returns for each year from 1885 to 1990. They find that large minimal returns show little correlation with transaction volume. Marsh and Wagner (2000) study price-volume dependence empirically in seven international equity markets. They fit a GARCH-M model to examine the overall return-volume relation under "normal" market conditions and a bivariate extreme value model to examine the relation under conditions of market stress. Their main findings indicate that the dependence decreases for large extreme return and volume observations.

To my knowledge, there have been no studies of the emerging markets of return-volume dependence during extreme price movements. This paper intends to fill the gap. Given the complexity of the return-volume relation, further evidence and insights should be obtainable through an investigation of an alternative set of financial markets, especially, a set of emerging markets. In this paper, I use the data from six emerging markets: Singapore, Malaysia, Thailand, Mexico, Chile and Argentina. Broadly speaking, the information flows in emerging markets are not equivalent to those in the more developed markets and also there are significant institutional differences across the markets. From the statistical point of view, the empirical distribution of asset returns of emerging markets usually has a higher mean, higher volatility, and much more significant excess kurtosis and skewness than those of developed countries. As the financial markets have become more and more globalized, how to invest and hedge emerging market risk is an important issue for both individual and institutional investors. In practice, the risk of extreme downside movements in emerging markets has more killing power than in developed markets. All these facts suggest that a separate study on the price-volume relation by using emerging markets data is necessary and will be interesting.

The issue of the price-volume relation in the tail of price movement is very interesting. As one of the well-known characteristics of the empirical distribution of asset returns is “fat-tail”, which means there is extra probability mass in the tail area, the behavior of stock price and trading volume during extraordinary events such as financial crises needs to be carefully examined.

The importance of price-volume relation during extreme observations comes from several aspects. First, study of the price-volume relation during extreme price movements can provide a valuable vehicle for understanding the underlying information-driven or liquidity-driven trading story. Theoretically, during a financial crash, the same trading volume may lead to very different price changes, depending on how information is interpreted by market participants. For example, if the selling pressure is due to some investors having private information, a reasonable amount of trading volume should be observed with the price movement. In this case, we should observe a consistent correlation between trading volume and price change during normal market conditions and market crashes. In another scenario, if the financial crisis is caused by the arrival of some public information, such as the deterioration of fundamentals of the economy, then, there is no reason to expect a high volume of trade, although price will drop sharply.

Secondly, some people argue that the information contained in volume data can improve the modeling of expected return and conditional variance. However, the decreased price-volume relation in the tail can cast doubt on the ability of trading volume to serve as a proxy for information inflow during financial market stress.

Thirdly, the price-volume relation in the tail is important because it can help us understand the fundamentals underlying financial crises. As argued by Gennotte and Leland (1990), in the absence of significant news, a small amount of hedge trading can cause crashes due to the reduced liquidity of the financial markets. So the price-volume dependence is smaller during extreme price movements than observed during other periods. Chen, Hong and Stein (2000) find that trading volume can help to forecast negative skewness (i.e., financial crisis) of the aggregate market.

Previous work provides us with empirical evidence that return and volume dependence during extreme price movements is smaller than in normal periods. There are at least three arguments in the literature as to why price-volume dependence may break down in the tail. First, Campbell, Grossman and Wang (1993) argue that large price movements are not necessarily associated with a large trading volume. Suppose one observes a fall in stock prices. This could be due to public information that has caused all investors to reduce their valuations of stocks. In this case, all investors have the same belief or expectation, and there is no reason to expect a large amount of trading. In an Arrow-Debreu setting with complete markets, the prices of securities can change dramatically as new information comes to the market. These price changes instantaneously incorporate the news and do not require a large trading volume. Secondly, Marsh and Wagner (1999) argue that volume data may be a bad proxy for the underlying information process. The noisiness in the volume data is more severe where there is a large amount of trading. As the correlation between price change and volume depends on an unobservable directing process, their relation could break down as one of them becomes more noisy. The third explanation is based on Gennotte and Leland (1990). These authors show that information differences among market participants can cause financial markets to be relatively illiquid. As a consequence of diminished liquidity, a small amount of trading can trigger a large price movement. This situation is more likely to happen in small, non mature financial markets such as emerging markets, where market illiquidity is one of the major concerns.

My methodology is to use bivariate extreme value theory to model the price-volume relation during extreme price and volume movements. Generally speaking, extreme value theory studies the limiting distribution of the underlying random variables without prior knowledge of the true distribution. Balduzzi, Kallal and Longin (1996) use simple OLS to show that minimum returns have little correlation with transaction volume. But, as pointed out by Longin and Solnik (1999), and Ang and Chen (2000), it is not reliable to directly compare the estimated correlations conditional on different values of one or two underlying variables, and thus results based on simple linear regression may be misleading. As the correlation coefficients can be precisely pinned down only when the underlying distribution is specified, I apply the recent results from extreme value theory to the study of price- volume relation.

Consistent with previous work, I find for five out of six emerging markets that the dependence between absolute return and adjusted abnormal trading volume is significantly reduced during periods of extreme price movements. I find these results still hold even when I decompose the total samples according to the directions of price change. The results from a simple OLS regression indicate that the correlation between return and volume is asymmetrical, i.e., that the correlation is larger for positive returns than for negative ones. For four out of six countries in the sample, the results from the bivariate threshold model show that during extreme price movements, this asymmetry of the correlation still holds.

The rest of paper is organized as follows: Section 2 provides a short review of the mixture of distribution model and other recent works on the return-volume relation. Section 3 gives information on data, summary statistics and the adjustment of daily trading volume series. In section 4, I perform preliminary analysis of overall price-volume relations. Section 5 outlines the general framework for the bivariate threshold model. Section 6 provides estimation procedure and empirical results for the price-volume relation during extreme price and volume movements. Finally, section 7 presents the conclusion of the paper.

2. Brief Review of Mixture of Distribution Model and Other Recent Works on Price-Volume Relation

There is a large amount of literature on the price-volume relation, but the results are mixed. Karpoff (1987) provides an excellent survey of early theoretical and empirical findings in this area. Theoretically, stock price changes when new information arrives. Thus, if the trading volume is also linked to the information flow entering the markets, a relation of price-volume obtains. Corresponding to the three different views of volume related to the information flow, there are three branches of literature that theoretically explain the price-volume relation.

The first approach views information flow as a latent variable that impacts trading volume. Pioneered by Clark (1973) and followed by Epps and Epps (1976) and Tauchen and Pitts (1983), the popular "mixture of distribution hypothesis" (MDH) suggests that price change and trading volume are governed by the same stochastic process. The resulting bivariate distribution of price and volume is based on a latent random variable. Although MDH does not provide any guidance on the distribution characteristic of this latent variable, the restriction on the moment equation can easily be derived. As a consequence, a GMM can be employed to test the MDH. In keeping with this direction, Andersen (1996) extends the MDH by considering the behavior of noisy traders. The results of his empirical tests show that modified MDH outperforms the standard MDH.

The second branch of the literature focuses on differences of opinion among investors. Shalen (1993) shows that dispersion among investors can be a factor that contributes to a positive correlation between volume and absolute change in prices. By setting up a two-period noisy rational expectation model, she shows the dispersion of expectations measures both the additional volatility and the expected volume of trade associated with noisy information. Thus, the dispersion in beliefs can cause a positive correlation between price change and trading volume.

The third group of papers develop rational expectation models with private information flows and noisy or liquidity traders. This literature is represented by the work of Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990). Their works all predict a positive relation between information arrival and trading volume. Foster and Viswanathan's intraday test results indicate that very actively traded firm's trading volume is associated with higher stock volatility.

All three streams of literature predict a positive price-volume dependence. Among them, MDH is the most popular. The empirical testing of price-volume dependence can also be divided into three streams. The first group of papers tests the validity of MDH or modified MDH. As MDH does not provide any information on the underlying process, the direct tests of MDH become difficult. (1) Richardson and Smith (1994) develop a general procedure for testing whether price and volume data conform to MDH. They apply a GMM test based on the moment restrictions on price change and volume. Their estimation procedure is independent of any distributional parameterization of the mixing variable. (2) Tauchen and Pitts (1983) work out the exact joint distribution of price change and volume by assuming that the mixing variable is lognormally distributed. (3) Lamoureux and Lastrapes (1990) treat the volume data as an exogenous variable and plug contemporary volume data directly into the GARCH model to test whether volume can be a proxy for the information flow. Their results show that volume data has explanatory power with respect to the stock volatility. Their methodology can be treated as an indirect proof of MDH. In a subsequent paper, (4) Lamoureux and Lastraped (1994) use endogenous volume data and a signal-extraction procedure to uncover the underlying mixing variable, exploiting the information in stock price and trading volume data. But their results indicate that contemporaneous squared returns and volume are noisy predictors of future return volatility. (5) Bollerslev and Jubinski (1999) examine the behavior of equity trading volume and volatility for the individual firms comprising the S&P 100 Composite Index. Using multivariate spectral methods, they find that the term fractionally "integrated process" best describes the long-run temporal dependences of both series. Interestingly, they find the long-run hyperbolic decay rates appear to be common across each volume-volatility pair. In (6) another paper, Liesenfeld (1998) tests the MDH by a simulated maximum likelihood method on the return and volume data from the German stock market. The results show that dynamic bivariate mixture models can not account for the persistence in the stock price variance.

The second branch of the literature tests the linear or non-linear causal relation between price change and trading volume. Rolalski (1978) examines whether security prices and volume are causally related. Hiemstra and Jones (1994) perform linear and non-linear Granger causality tests to examine the dynamic relation between stock return and trading volume and they find significant bidirectional nonlinear causality. This relation exists even after controlling for the volatility persistence in returns.

The third branch of the literature uses nonparametric or semiparametric techniques to study the price-volume relation. The representative works in this group includes: Gallant, Rossi and Tauchen (1992, 1993) and Tauchen, Zhang and Liu (1996). These papers estimate the conditional joint density function of return and volume based on past observations; they apply the dynamic impulse response analysis technique to study the interrelation between volatility, volume and leverage. Consistent with the findings of Hiemstra and Jones (1994), they find that price-volume dependence to be nonlinear. Yet their relation is not asymmetric. According to the results, volume responds nonlinearly to price shocks, and damps very slowly back to baseline. On the other side, volume shocks affect stock prices, but the effects are very transient and are confined to higher order (higher than two) conditional moments. The results imply that price-volume dependence holds true in general, but not exactly as predicted by MDH. MDH suggests that the distributions of both price change and trading volume are governed by the common observed stochastic case. If this assumption holds, the price-volume relation should be symmetric. In other words, the work of Gallant, Rossi and Tauchen (1992, 1993) and Tauchen, Zhang and Liu (1996) casts doubt on MDH.

The above papers investigate the contemporary relation between price change and trading volume. Campbell, Grossman and Wang (1993) take another direction and study the relation between aggregate stock market trading volume and the serial correlation of daily stock returns. They find that the first daily autocorrelation of stock returns is lower on high volume days than on low-volume days. They set up a theoretical model and derive noninformational trading from shifts in the risk aversion of some traders. They find their model fits the empirical relation between trading volume and autocorrelation of asset returns. In another paper, Wang (1994) develops a competitive stock trading model in which traders are heterogenous in their information and private investment opportunities. He shows that informational and non-informational trading lead to different dynamic relations between trading volume and stock returns.

Recently, there have been more empirical works on the price-volume relation. Llorente, Michaely, Saar and Wang (2000) use data from individual stocks to test the theoretical prediction about the relation of trading volume and the autocorrelation of asset returns. They find that in periods of high trading volume, stocks with much speculative trading tend to have positive return autocorrelation and stocks with little speculative trading tend to exhibit negative return autocorrelation. Their empirical returns conform to the prediction of Wang (1994).

Gervais,Kaniel and Mingelgrin (2000) show that relatively high trading volume contains important information about subsequent stock returns. Specifically, periods of extremely high (low) volume tend to be followed by positive (negative) excess returns. they term this effect "high volume return premium". They also find that the traditional theoretical models cannot provide a good explanation for their findings.

In another recent paper, Chen, Hong and Stein (2000) find that trading volume can predict the negative skewness of daily returns. This result is consistent with the model of Hong and Stein (1999), which predicts that negative asymmetries are more likely to occur when there are large differences of opinion among investors.

The current paper provides empirical evidence about price-volume dependence for the extreme observations in six emerging markets. Overall, I find a positive relation between price change and trading volume for all the markets in the sample. This finding agrees with the prediction of MDH. But the positive correlation between absolute return and trading volume decreases as the threshold increases, and this relation is asymmetric if I divide the data according to the directions of price change. The MDH framework can not provide an explanation for these findings.

3. Data, Summary Statistics and Volume - Adjustment

3.1. Data

The markets are: Singapore, Malaysia, Thailand, Mexico, Chile and Argentina. The reason for choosing these countries is that among all the emerging markets they have a relatively long history of trading volume data available.

The daily closing price and trading volume data for these six countries are obtained from Datastream International Inc. Except for Argentina, the data sample is from January 1, 1990 to December 31, 2000, a total of 2,870 observations. For Argentina, although the pricing data are available from January, 11, 1990, the volume data are only available after June 13, 1993. So I have a shorter data sample for Argentina, a total of 1,939 observations. I exclude all non-trading days from the sample. The price index in local currency for each country is converted into U.S. dollars according to the official exchange rate between the currency of the corresponding country and the U.S. dollar. The continuously compounded percentage return or log return in U.S. dollars is calculated as 100 times the log difference between the current and previous day's closing prices. I take the natural logarithm of the daily volume to improve the stationary properties of the data.

3.2. Volume Adjustments

In order to apply the extreme value theory to study the relation of price change and trading volume in the tail, the time series of data should be stationary and serially uncorrelated. But, as is a well-known fact, trading volume data have a time trend and are serially correlated. So, for the first step, I detrend the log-volume series first by subtracting a 60-day backward moving average from each current observation. The output from this method is a series of stationary abnormal trading volumes.

In the second step, an uncorrected stationary volume series is obtained through seasonal adjustment and ARMA estimation. Again, it is well-known that trading activities display a systematic calendar effects (e.g., see Gallant, Rossi and Tauchen (1992) and other). I choose two groups of dummy variables: day-of-the-week dummy and dummy variables for each of the months. Besides using the season dummies, I fit the detrended volume series into an $ARMA(p,q)$ model. The order of autoregressive component p and the moving average component q are chosen according to Akaike's Information Criterion (AIC), which attempts to reduce the risk of overfitting the model. The residual from the final $ARMA$ model is a stationary, serially uncorrected time series which will be used in the model as the volume series.

Finally, as the absolute value of daily return is another input for our bivariate extreme model, the serial correlation of absolute value of daily return has to be adjusted. Again, we apply the $ARMA(p,q)$ model to generate a stationary, uncorrected return series.

3.3. Summary Statistics

Table 1 displays the summary statistics of daily return and log-volume series. The means of daily returns are close to zero for all six countries. The daily standard deviation varies between 1.28% for Singapore and 2.27% for Thailand. The excess kurtoses for daily return of all six emerging markets are large and positive, indicating that returns have more mass in the tail areas than would be predicted by a normal distribution. Of these six countries, Argentina, Mexico and Singapore show negative skewness for market returns, while the others show positive skewness. For Argentina and Singapore, the hypothesis of skewness equal to zero can not be rejected.

The mean values of the adjusted trading volume are close to zero for all six countries. This is because I detrend the raw volume series by subtracting from each observation the past

60 -day moving average. The standard deviation of the volume data varies between 0.304 for Malaysia and 0.510 for Mexico. The excess kurtosis for the volume series is also positive and significant. Except in the case of Argentina, the skewness of volume series is positive. The values obtained for excess kurtosis and skewness strongly reject the hypothesis that adjusted volume is normally distributed.

I report the cross correlations between return, absolute return, squared return and adjusted trading volume. Consistent with the results of the mixture of distribution model, the correlation coefficients are all positive. The correlation between absolute return and trading volume is the strongest among the three types of returns for all six countries.

4. Preliminary Analysis

4.1. Simple OLS

For a preliminary test of price-volume relation, I use standard OLS to estimate the following equation:

$$V_t = \beta_0 + \beta_1 | r_t | + \beta_2 D_t | r_t | + \beta_3 r_{t+1} + \varepsilon_t$$

where V_t is the daily trading volume at time t, $|r_t|$ is the absolute value of daily return at time t. $D_t = 1$ if $r_t < 0$, and $D_t = 0$ if $r_t \geq 0$. β_0 is a constant.

β_1 measures the relation between absolute price change and trading volume, irrespective of the direction of price change.

The estimated value of β_2 measures the asymmetry in the price-volume relation. If the short positions are more costly than the long positions, investors should require a greater price change to transact in short positions. Hence, investors in short positions will be less responsive to price changes than those in long positions. This leads to an expectation that the dependence of volume on positive returns will be greater than that of volume on negative returns. So I predict that β_2 should be negative.

β_3 measures the relation between current absolute return and last-period trading volume. If the past information about trading activity can help predict future price movements, then β_3 should be significant.

The estimation results of OLS are shown in Table 3. For the overall regressions, the R^2 varies between 0.097 for Singapore and 0.025 for Chile. Consistent with my prediction, the estimated values of β_1 are significant and positive for all six countries. This confirms the early results from Table 2 that the absolute value of return and contemporary trading volume are positively correlated.

The asymmetric relations appear to exist for all six countries, as the estimated values of β_2 are negative and highly significant. The negative value of β_2 indicates that the slope of the negative returns is smaller than the slope for positive returns. In other words, the value of β_2 is the difference of slope coefficients of trading volume on absolute return between positive and negative price changes. The relatively higher cost for short position compared to long position trading is one of the factors that explain the asymmetric relation between absolute return and trading volume. Jennings, Starks and Fellingham (1981) provide another explanation. In their model, there are two kinds of traders: optimists and pessimists. They show that the pessimist traders trade less than the optimist traders. Since the price decreases as a result of pessimists' selling and increases as a result of optimists' buying, the trading volume is lower when price decreases than when price increases.

The estimated values of β_3 are only significant for Thailand. (and are insignificant for the rest of the five countries.) The value of β_3 is positive for Argentina and is negative for the other five countries. These results imply that information contained in past volume data does not have much power to predict stock price movement for further periods.[1]

Overall, the simple OLS estimation provides us with some preliminary results on the relation between return and adjusted trading volume. The contemporaneous absolute return and abnormal trading volume are linearly correlated. This relation is asymmetric, indicating that the correlation between positive return and volume is larger than that between negative return and volume. Finally, the lagged period of trading volume does not contain much information to predict further price movement. In the next section, I follow the model of Lamoureux and Lastrapes (1990) to test the relation between second moment of stock return and trading volume.

4.2. GARCH Model

GARCH models the conditional variance of asset return as a function of past squared residuals and lagged conditional variance. The GARCH model has been shown to be a good fit for many financial time series. The mixture of distribution model provides an explanation for the GARCH properties of conditional volatility series. Based on the mixture of distribution hypothesis, asset return and trading volume are driven by the same latent information process. If the information process is serially correlated, then the conditional variance of asset return follows a GARCH

[1]Gervais, Kaniel and Mingelgrin (1999) document that stocks with high trading volume will tend to appreciate over the next period. They use firm level data and longer portfolio formation periods than those employed in the present study.

process.[2] In general, although the data on trading volume include both informational and noisy trading, volume data are likely to contain information about price change.

So, following Lamoureux and Lastrapes (1990), I estimate the GARCH (1,1) model using the data from six emerging markets:

$$r_t = \mu + \varepsilon_t \quad where \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = p_0 + p_1\varepsilon_{t-1}^2 + p_2 h_{t-1}$$

$$h_t = p_0 + p_1\varepsilon_{t-1}^2 + p_2 h_{t-1} + q * vol_t$$

where r_t is the asset return. μ is the estimated mean value of asset return. ε_t is the innovation from the asset return and h_t is the conditional variance,which is a function of its lagged value (h_{t-1}) and past squared residual (ε_{t-1}^2) . First, I estimate the GARCH model without volume data. Secondly, I plug the contemporaneous volume data into the GARCH model. If volume and volatility are governed by the same underlying information variable, we should expect q to be significant and positive. Moreover, the GARCH coefficient (p_2) should be reduced if trading volume is a proxy for the serially correlated information variable.

[2]For detail, see Lamoureux and Lastrapes (1990, 1994).

Table 4 shows the estimated coefficients of the GARCH model with and without trading volume. In order to avoid the problem due to non-normality in the return residuals, I use a Quasi-MLE estimation, which was proposed by Bollerslev and Wooldridge (1992). The estimated GARCH coefficients and their standard errors are estimated according to Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm.

Without the volume variable, the GARCH coefficients p_1 and p_2 are significant and $p_1 + p_2$ close to but smaller than 1, indicating a high degree of persistence of the conditional volatility. When the contemporary abnormal trading volume is plugged into the conditional volatility equation, the estimated values of q are significant and positive for all six countries, which is consistent with the results of Lamoureux and Lastrapes (1990) and Marsh and Wagner (1999), who both use data from the U.S. and six other developed countries. The likelihood ratio test for the restricted model (GARCH model without volume) vs. the unrestricted model (GARCH with trading volume) yields a test statistic which is $\chi^2(1)$. Except for Argentina, (where the likelihood ratio test statistics are significant at the 5% level; all the others are significant at the 1% level.), thereby favoring the unrestricted model (GARCH with volume) and rejecting the restricted model (GARCH without volume).

As many previous studies have shown, GARCH effects may result from the time dependence in the rate of information flow. If the stock volatility and trading volume are driven by the same information process, as assumed by the mixture of distribution hypothesis, the volume coefficient in the GARCH model should be significant and positive, and the persistence of conditional volatility measured by $p_1 + p_2$ should be reduced. In Table 4, I see how the coefficient changes with and without the volume variable and the coefficients of autoregressive conditional volatility p_2 are reduced for all six countries. The measure of the persistence of conditional volatility $p_1 + p_2$ is only slightly reduced for five out of six countries when volume information is included in the equation. For Chile, the persistence even increases slightly when volume data is included in the GARCH model. This is different from the results of Lamoureux and Lastrapes (1990), using data from U.S. individual stocks. They found that the GARCH effects almost disappear.

Estimation from the GARCH model provides us with empirical evidence that conditional volatility and abnormal trading volume are positively correlated. The theoretical explanation of this finding is that volume and volatility are both driven by a common, unobservable factor, which is determined by the arrival of new information. An autoregression of conditional volatility is reduced when volume is introduced as an explanatory variable. But the GARCH coefficients remain significant in the presence of the volume variable and the persistence of conditional volatility is not significantly reduced in any of the six countries. One possible explanation is that because I use index level data. The information content of volume data from index level is not as precise as for data from individual firms.

5. Bivariate Threshold Model

5.1. Model Setup

In the previous section, I used OLS and the GARCH models to study the overall relation between return and volume. The relation between return and trading volume under extreme price and volume trading conditions is also important and interesting. Dalduzzi, Kallal and Longin (1995) is the first paper to notice that the price-volume relation in the tail is different from the overall relation. Applying a linear regression to U.S. data from 1885 to 1990, they find that large (in absolute term) minimal returns to show little correlation with trading volume. As Longin and Solnik (1999) and Ang and Chen (2000) point out, it is not reliable to compare directly the estimated correlations conditional on different values of one or two underlying variables, and methods based on a simple linear regression may be misleading. A statistical distribution function has to be specified in order to test for changes in the correlation coefficient based on different exceedance values. Longin (1996) examines the extreme movements of the U.S. stock market over a century of daily observations by fitting a univariate them to extreme value model. Susmel (1999) focuses on the tails of the unconditional distribution of the stock returns of emerging Latin American markets. The tail of stock return is estimated by a univariate extreme value model. Longin and Solnik (1999) use bivariate extreme value theory to study international equity markets correlation. Marsh and Wagner (2000) study the price-volume relation in seven international equity markets using a bivariate extreme model.

Extreme value theory has gone through a rapid development and has recently become a mature and significant branch of probability theory. Representative papers on bivariate extreme theory include Tawn (1988), Ledford and Tawn (1997), and Smith (1993). There are basically two approaches. The first class of models is based on the asymptotic distribution of the unconditional extremes. The second method is based on the asymptotic conditional distribution of exceedance over a high threshold. Marsh and Wagner (2000) apply the first approach, while Longin and Solnik (1999) use the second approach. As one can explicitly control the exceedence level during the estimation, the threshold methods have begun gain in popularity as compared to the classical method based directly on extreme value distribution. So, in this paper, I apply a multivariate threshold model to study the price-volume relation for the extreme observations.

Suppose a $d-$ dimensional random variable $(Y_j; J = 1,...,d)$ has a joint distribution F. Multivariate extreme value theory is concerned with the nondegenerate limiting distribution of the componentwise maxima[3] of observations from F. The statistical methods for estimating the joint tail of F exploit the asymptotic theory which studies the limiting distribution of F. This involves estimating the joint tail from an independent and identically distributed sample of vector observations. The limiting results have two separate aspects, marginal structure and dependence structure.

For the univariate approaches to marginal modelling, I apply the peaks over threshold model of Pickands (1975) and Davison and Smith (1990). Extreme observations are defined in

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[3]The componentwise maxima is defined as:

for random variable

$Y_i = (y_{i,1}\ ,\ y_{i,2,}...,y_{i,d}\};1 \le i \le n$

$\max\limits_{1 \le i \le n} Y_i = (M_{n,1}, M_{n,2}...M_{n,d})$

where $M_{n,k} = \max\limits_{1 \le i \le n}(y_{i,k}) \quad 1 \le k \le d$

terms of exceedance over a threshold υ . The probability of such exceedance is $1-F(\upsilon)$, and the cumulative conditional distribution function is denoted by $F_{\upsilon}(y)$:

$$F_{\upsilon}(y) = \Pr(\upsilon \le Y \le y \mid Y \ge \upsilon) = \tfrac{F(y)-F(\upsilon)}{1-F(\upsilon)} \quad \textit{for} \quad y > \upsilon$$

The extreme value theory states that the asymptotic distribution of $F_{\upsilon}(y)$, when the threshold υ converges to the upper limit of the distribution F , is the Generalized Pareto Distribution (GPD),

$$\inf_{\xi} \quad \lim_{\upsilon \to \omega_F} \sup \mid F_{\upsilon}(y) - G_{\upsilon}(y;\sigma,\xi) \mid = 0$$

$$G_{\upsilon}(y,\sigma,\xi) = 1-(1+\xi\cdot(y-\upsilon)/\sigma)_{+}^{1/\xi}$$

where $\omega_F = \sup\{x \,:\, F(x) < 1\}$ is the right hand endpoint of F, which may be finite and infinite. $\sigma > 0.$ σ is the scale or dispersion parameter . $x_{+} = \max(x,0).$ ξ is any real number, which represents the tail index. The fat-tailed distributions (such as Students- t) correspond to the case $\xi > 0.$ Thin-tailed distributions (such as normal distribution) correspond to the case $\xi = 0.$ $\xi < 0$ is the case of no-tail distribution, as in the case of uniform distribution.

In essence, the extreme value theory states that the limiting distribution of exceedances above the threshold of a univariate random variable constitutes the Generalized Pareto distribution. This result is robust to any kind of Distribution of F. Leadbetter, Lindgren and Rootzén (1983) conclude that this result holds true even when the observations are not i.i.d.

Multivariate extreme value theory is concerned with the joint distribution of extremes of two or more dependent random variables. The first attempt to construct threshold-based methods of statistical inference in the multivariate cases is that of Coles and Tawn (1991) and Joe et al. (1992). Let F denote the joint distribution function of a d-dimensional random variable $(Y_1, Y_2, Y_3, ..., Y_d)$, and let F_j denote the marginal distribution function of Y_j for $j = 1, ..., d$. The vector of thresholds is $\upsilon = (\upsilon_1, \upsilon_2, ... \upsilon_d)$. The results from Ledford and Tawn (1997) and Tawn (1988) state that the limiting distribution for the multivariate exceedances function in terms of original variables is:

$$G(y_1, ... y_d) = \exp[-V\{-1/\log F_1(y_1), ..., -1/\log F_d(y_d)\}]$$

where V is the dependence function and is defined from R^d into R. One feature of multivariate extreme value distributions is that the dependence structure is preserved under transformations of the marginal distributions, so there is no loss of generality in restricting attention to a particular univariate extreme value family. As F_j can be arbitrary marginal distribution, I follow Daison and Smith (1990) in using the Generalized Pareto Distribution to model each marginal distribution above a high threshold. Connecting these marginal distributions to the marginal threshold distributions, we have for probability $0 \le p_j \le 1$,

$$F_j(y_j) = (1 - p_j) + p_j\{1 + \xi_j \cdot (y_j - \upsilon_j) / \sigma_j\}_+^{1/\xi_j} = 1 - p_j\{1 + \xi_j \cdot (y_j - \upsilon_j) / \sigma_j\}_+^{1/\xi_j}$$

where p_j is the small probability that the observation is above the threshold υ_j, the threshold υ_j is taken to be the $1 - p_j$ quantities of the marginal distribution. This means that, for a marginal distribution that fails to exceed the threshold, the only relevant information conveys for our model is that it occurs below the threshold, not its actual value.

Combining the above two equations, we have the joint distribution function for the multivariate threshold model:

$$G(y_1, \ldots y_d) = \exp[-V\{-1/\log[1 - p_1(1 + \xi_1 \cdot (y_1 - \upsilon_1) / \sigma_1)_+^{1/\xi_1}], \ldots,$$

$$-1/\log[1 - p_d(1 + \xi_d \cdot (y_d - \upsilon_d) / \sigma_d)_+^{1/\xi_d}]\}]$$

The dependence function V maps the d-dimension marginal distribution function to a real number. The multivariate extreme theory does not give us any guidance on how to choose the dependence function V. In a specific case in which the marginal variables are independent, then $V(z_1, z_2,..., z_d) = \sum z_j^{-1}$. In this case the model factors into the product of the marginal distribution, since,

$$G(y_1,...y_d) = \exp[\sum_{j=1}^{d} \log\{1 - p_j (1 + \xi_j \cdot (y_j - \upsilon_j) / \sigma_j)_+^{1/\xi_j}\}] = \Pi\{1 - p_j (1 + \xi_j \cdot (y_j - \upsilon_j) / \sigma_j)_+^{1/\xi_j}\}$$

$$= \Pi F_j(y_j)$$

For the general case of the multivariate extreme dependent variable, the form of the dependence function is not known. In the field of engineering, the multivariate logistic dependence structure is commonly used. Following Tawn (1990), the symmetric logistic dependence function is:

$$V(z_1, z_2,..., z_d) = (z_1^{-1/\alpha} + ... + z_d^{-1/\alpha})^{\alpha}$$

where α is the dependence parameter between 0 and 1. The limiting case of $\alpha \to 0$ corresponds to the case in which the random variables are perfectly dependent. As α increases, the dependence weakens. When $\alpha = 1$, the variables are totally independent. The correlation coefficient ρ of extremes is related to the coefficient α via $\rho = 1 - \alpha^2$.

The logistic dependence function is widely used in engineering, hydrology and other fields. The attraction of this specification is its simplicity. The dependent structure is fully characterized by a single parameter α. The systematic property of this function implies that the dependence is strongest under equally large extremes for each variate, and an equal reduction in the magnitude of each extreme yields the same reduction in dependence as measured by α.

6. Estimation Procedure and Empirical Results

6.1. Maximum Likelihood Estimation

There are two major methods to test the multivariate extreme model. One is the maximum likelihood estimator (MLE). MLE is straightforward in nearly all practical cases. The asymptotic properties of MLE are regular whenever the tail index $\xi > -1/2,$ and alternative remedies are available for $\xi < -1/2.$ [4]Another competitor is the probability weighted moments (PWM) method of Hosking and Wallis (1987). However, as PWM is much less flexible than MLE as a general estimation method, I will apply MLE. In developing the likelihood for the model, I consider marginal observations below their respective thresholds as censored data at the thresholds. Thus, the likelihood contribution for a typical observation $(y_1, y_2, ..., y_d)$ in which the components $j_1, \ldots j_m$ exceed their thresholds is given by:

$$\frac{\partial^m F(x_1,...,x_d)}{\partial x_{j_1} ... \partial x_{j_m}} \Big|_{\{x_j = \max X(\upsilon_{j,}\ y_j),\ j=1,...,d\}}$$

In the bivariate case, for a pair of high thresholds υ_1 and υ_2 , the outcome space is divided into four regions:

$$\{R_{kl}; k = I(Y_1 > \upsilon_1), \quad l = I(Y_2 > \quad \upsilon_2)\}$$

[4]See, Smith, R.L.(1985,1994) for detail.

where I is the indicator function, which is equal to 1 if the condition is satisfied. Let the transformed marginal threshold be $r_j = -1/\log(1-p_j)$ and let $z_j = -1/\log\{1-p_j\{1+\xi_j \cdot (y_j - \upsilon_j)/\sigma_j\}_+^{1/\xi_j}$. I denote the likelihood contribution corresponding to a point (y_1, y_2) which falls in region R_{kl} by $L_{kl}(y_1, y_2)$, then we have the following:

$$L_{00}(y_1, y_2) = \exp\{-V(r_1, r_2)\}$$

$$L_{01}(y_1, y_2) = \exp\{-V(r_1, z_2)\}V_2(r_1, z_2)K_2$$

$$L_{10}(y_1, y_2) = \exp\{-V(z_1, r_2)\}V_1(z_1, r_2)K_1$$

$$L_{11}(y_1, y_2) = \exp\{-V(z_1, z_2)\}\{V_1(z_1, z_2)V_2(z_1, z_2) - V_{12}(z_1, z_2)\}K_1K_2$$

where V_i denotes the partial derivative with respect to component i, and V_{ij} is cross derivative with respect to the i component and the j component. K_j is the derivative of z_j with respect to y_j.

The likelihood contribution from a typical point (y_{1i}, y_{2i}) from the logistic model with dependence parameter α and unknown parameters $\Theta = \{\upsilon_j, \sigma_j, \xi_j, p_j \ : \ j = 1, 2\}$ is given by

$$L_i(\alpha, \Theta) = \sum_{k,l \in \{0,1\}} L_{kl}(y_{1i}, y_{2i}) \quad I_{kl}(y_{1i}, y_{2i})$$

where $I_{kl}(y_{1i}, y_{2i})$ is the indicator function of (y_{1i}, y_{2i}) for observations belong to region R_{kl}. The likelihood for a set of n independent points is given by

$$L_n(\alpha, \Theta) = \Pi L_i(\alpha, \Theta)$$

Finally, the BFGS procedure is used to seek the parameters that maximize the above likelihood function.

6.2. Score Test for Independence

Under the bivariate threshold model, when the dependence parameter is $0 < \alpha < 1$, there is some dependence between the two variables. When the variables are independent, that is $\alpha = 1$, α is on a boundary of the parameter space. Following Tawn (1988), I consider the score statistic as independence, defined for a typical pair of observations i by:

$$s_i = \tfrac{\partial}{\partial \alpha} \log L_i(\alpha, \tilde{\Theta})\,|_{\alpha=1}$$

where $\tilde{\Theta}$ is the value of the parameters that jointly maximize the above likelihood function when $\alpha = 1, i.e.$ $L_n(1, \Theta)$. The total score for a set of n observations is defined as

$S_n = s_1 + ... + s_n$. Ledford and Tawn (1996)[5] show that if the variables are independent, then $-S_n / c_n \to N(0,1)$, where $c_n = (n \log n / 2)^{0.5}$ as $n \to \infty$. My score tests are based on this result.

6.3. Threshold Selection

The distribution of observations over a certain threshold converges to the Generalized Pareto Distribution only when the threshold converges to the upper limit of the distribution, which is positive infinite in our case. But, in practice, a finite threshold value has to be used. Threshold selection is a critical issue in extreme value theory. Many theories are rather hard to use in practice because the theoretical results themselves depend on additional parameters that are unknown. Longin and Solnik (1999) use Monte Carlo simulation, which optimizes the trade-off between bias and inefficiency. But their method is computation-intensive and only applies to a positive tail estimator. So I use an alternative approach, that is relatively easy and intuitive. This technique is called the mean residual life plot (Davison and Smith (1990), Smith (1990)). The motivation for this method is quite simple: if the distribution of a random variable is Generalized Pareto Distribution, $Y \sim G(\sigma, \xi)$, with $\mu = 0$, and $\upsilon > 0$ (assuming $\upsilon < -\sigma / \xi$ in the case of $\xi < 0$), the mean residual life is defined as:

$$E\{Y - \upsilon \mid Y > \upsilon\} = \frac{\sigma + \xi\upsilon}{1 - \xi}$$

[5]See their proposition 1.

Therefore, an empirical plot of $E\{Y-\upsilon \mid Y>\upsilon\}$ against υ should be approximately a straight line. I use the sample analogy of the mean residual function for the observations of random variable Y, $(y_1, y_2 ... y_n)$, which is the following:

$$\frac{\sum (y_i-u) I(y_i>u)}{\sum I(y_i>u)} \qquad I(y_i>u) \text{ is one, when } y_i>u, \text{ and zero otherwise}$$

I plot this function against u and look for the smallest u over the region in which this is a straight line. As u increases, the number of observations that exceed u is decreasing. When u is approaching its upper boundary, the plot becomes irregular. So I restrict the number of exceeding observations to those larger than 5 (i.e., $\sum I(y_i>u)>5)$. The smallest u in the picture that makes the mean residual plot a straight line is the optimal threshold level in the model.

6.4. Empirical Results

There are a total of seven unknown parameters: the tail probability $(p_1 and \quad p_2)$, the dispersion parameters (σ_1 and σ_2) , the tail indexes (ξ_1 and ξ_2) and the dependence parameter α. The results of all the unknown parameters for each of the six countries are listed in Table 5. Panels A, B, C, D, E and F correspond to the estimation results of Argentina, Malaysia, Chile, Mexico, Singapore and Thailand, respectively. For each country, Panel 1 shows the estimation of bivariate threshold model based on absolute price change and abnormal trading volume irrespective of the direction of price change. In order to test whether the asymmetric relation between price change and volume exists in the tail, I divide the total sample for each country into positive price changes and negative price changes. The results based on positive price changes, i.e., $corr(\max|r_{i,t}|, \max(vol))$ where $r_{i,t} > 0$, are shown in Panel 2 for each country. The results of negative price changes, i.e., $corr(\max|r_{i,t}|, \max(vol))$ where $r_{i,t} < 0$ are shown in Panel 3. The overall unconditional correlation coefficients of price change and volume dependence are listed in the last row of each table. The score tests for independence are listed in the last column of each table.

Most of the estimated tail indexes are greater than $-1/2$ which guarantees the asymptotic efficiency of MLE [6]. The estimated probability that the observations exceed the threshold is equivalent to the empirical frequency. The tail indexes for absolute return are all positive except in the case of Thailand. The dispersion parameter σ, probability p, and the correlation ρ are all estimated with great precision.

The estimated correlated coefficients change with the chosen thresholds. Let's take a look at the exceedence correlation between absolute return and abnormal trading volume irrespective of the direction of price change. For all six countries, there is strong evidence that a positive relation between price change and volume exists in the tail, as well as overall joint distribution. The score tests strongly reject the hypothesis that the variables are independent. Except for Malaysia, all countries show a decreasing absolute return and volume relation when the threshold

[6] Except for Table A1 and A3 (2.25, 2.25) threshold and Table F3 (2.0, 2.0) threshold.

goes higher. For example, in the results based on the data for Mexico, the correlation estimated based on the observations that exceed their relative means is 0.2686. For threshold at mean plus one standard deviation, the correlation coefficient drops to 0.2175, and mean plus 1.5 standard deviation, correlation goes to 0.1425. From the plot of mean residual life, the optimal threshold for return is at mean plus 1.85 times standard deviation, and for volume it is mean plus 1.3 times standard deviation. At the optimal threshold value, the correlation coefficient is 0.1406. Beyond this, when the threshold is cut at mean plus 2.05 times standard deviation, the correlation coefficient is 0.0898. Compared with the sample correlation between absolute return and trading volume 0.2239, the price -volume relation becomes weaker beyond the optimal threshold value. In finance theory, there are two potential explanations for the decreased correlation between absolute return and trading volume in the tail. First, trading volume is a noisy proxy for the underlying information process. The extent of noisiness of the volume data is more severe during periods of high volume of trading. If the correlation between return and volume is due to the same underlying information process, more noise in the trading volume data in the tail can lead to a decreased correlation between return and volume. Secondly, as argued by Gennotte and Leland (1990), in the absence of significant news, a small amount of hedge trading can cause crashes due to the reduced liquidity of the financial markets. Given the relative illiquidity of emerging markets compared with those of developed countries, the return-volume relation is prone to break down during extreme stock price movements.

Dividing total observations into directions of price change provides some interesting findings about the asymmetric relation between return and volume in the tail. Figure 2 graphically depicts the exceedence correlation and the thresholds used to define this for each of the country. In each figure, the solid line is for the correlation between absolute return and volume irrespective of direction of price change, the dotted line is for the extreme correlation between positive return and volume and the dashed lines for correlation between absolute return and trading volume when the return is negative. Except in the case of Malaysia, all the curves are downward sloping indicating that the estimated value of correlation coefficient ρ is decreasing as the level of the threshold increases. Except for Argentina and Mexico, the extreme correlation between absolute return and abnormal trading volume is higher for positive return than for negative return. In other words, the asymmetric correlation between return and volume is preserved in the tail for all four of other countries. For Argentina and Mexico, there is no clear consistent pattern regarding which direction of price change has a larger return-volume relation. For example, in the case of the Mexican market index, when the threshold is the empirical mean plus half the standard deviation, correlation for absolute return and volume is higher for positive price changes (0.3093) than for negative price changes (0.2031). But when the threshold is mean plus 2.0 and 2.15 times standard deviation, the correlations for positive change (0.0220 and 0.0177 , respectively) are lower than the corresponding negative price changes (0.0801 and 0.0443, respectively). For Chile, the correlation becomes 0 when the threshold is above its empirical mean plus 1.5 times its standard deviation.

The last column of each table is the score for testing the independence between absolute return and trading volume. In most cases, the score tests reject strongly the independence between return and volume. For example, for Chile, the correlation between absolute return and volume when return is negative, the score is 8.77 for observations above their empirical mean plus one half of the standard deviation, and this value is clearly significant at the 1% level, indicating the independence is strongly rejected. As the thresholds go higher, the score becomes 1.29 for the threshold at mean plus 1.5 times the standard deviation and 0.92 for the optimal threshold. These values are less significant, indicating that return and volume dependence is weaker. The values of the score tests verify our empirical results: as the threshold increases, the value of the score decreases and the dependence between absolute value of return and trading volume is smaller for the extreme observations exceeding the threshold.

7. Conclusion

This paper provides empirical evidence about the dependence of daily return and trading volume relations on each other for six emerging markets: Argentina, Chile, Malaysia, Mexico, Singapore and Thailand.

First, simple OLS estimation suggests a finding that absolute return and trading volume are positively correlated, which supports the mixture distribution hypothesis that trading volume and price movement are governed by the same underlying information process. The return and volume relation overall is asymmetric, i.e., the correlation associated with positive return and volume is greater than the correlation between negative return and volume. The relative cost of short position trading and the different behavior of optimist and pessimist traders can provide explanations for this asymmetrical relation. The information contained in the past trading volume does not have much power to predict future price movements.

Secondly, I estimate the GARCH model and find that for all six countries, the autoregressive coefficient of conditional volatility is reduced when contemporary volume data is plugged into the volatility equation. But the persistence of conditional volatility remains about the same.

Thirdly, I use bivariate threshold theory to explicitly model the joint distribution of absolute return and trading volume. I find overall a positive correlation between absolute return and trading volume using all the observations for all six markets. Five out of the six countries have weaker but still significant correlations based on the observations that exceed thresholds beyond the optimal ones. For four out of the six countries, the return-volume asymmetry is preserved in the tail. Previous work has indicated that volume is a noisy measure of the rate of information flow. When trading volume is higher, the degree of noise may be even higher, so the return and volume dependence may be lower during extreme price change and trading volume. If the market is illiquid in the emerging countries, it is important to note that a small amount of price change can trigger a large amount of trading volume, which causes the return-volume dependence to become weaker in the tail.

Overall, my empirical results support the "mixture of distribution hypothesis" for these six emerging markets. Although there are significant institutional differences between mature and emerging financial markets, the old Wall Street adage "it takes volume to move price" generally holds across different markets. But it lacks an unified theory to explain the asymmetric relation between return and trading volume and, more important, to explain the weaker dependence in the tail. Further work should thus pursue this thread to develop a microstructure model consistent with these empirical findings on the return-volume relation.

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Table 1 Summary Statistics

This table gives the summary statistics for return and log trading volume for market Indies for six emerging markets. The second column is the mean. (stock return in percentage) The third column is the standard deviation. The fourth and fifth column give the minium and maximum of the observations. The sixth and seventh column are the excess kurtosis and skewness. Numbers on brackets are the significant level at which H_0 of no excess kurtosis (no skewness) can be rejected.

	mean	*std*	*min*	*max*	*Excess kurtosis*	*skewness*
Argentina R	0.0084	1.9039	−13.3942	11.9649	6.0482 [0.0000]	−0.0784 [0.1587]
Argentina adj_vol	−0.0001	0.4198	−5.1540	1.9556	27.7606 [0.000]	−1.5157 [0.000]
Chile R	0.0531	1.5588	−15.0358	17.5038	17.2238 [0.0000]	0.3498 [0.0000]
Chile adj_vol	−0.0002	0.4112	−1.8165	2.5902	2.2116 [0.0000]	0.3403 [0.0000]
Malaysia R	0.0035	1.9399	−22.2153	24.3267	28.3542 [0.0000]	0.6703 [0.000]
Malaysia adj_vol	−0.0006	0.3041	−1.2494	1.8969	1.8016 [0.0000]	0.4632 [0.0000]
Mexico R	0.0443	1.9379	−21.7500	19.0118	17.7344 [0.0000]	−0.7107 [0.0000]
Mexico adj_vol	−0.0001	0.5106	−2.3898	5.8328	30.7506 [0.0000]	1.5566 [0.0000]
Singapore R	0.0129	1.2826	−8.4648	9.8042	7.4116 [0.0000]	−0.0414 [0.3649]
Singapore adj_vol	0.0000	0.4962	−1.6864	2.0280	2.1056 [0.0000]	0.4576 [0.0000]
Thailand R	−0.0285	2.2708	−13.5225	15.8388	5.4737 [0.0000]	0.4301 [0.0000]
Thailand adj_vol	−0.0005	0.4122	−2.5594	3.4935	3.1625 [0.0000]	0.5555 [0.0000]

Table 2 Correlation between Return and Trading Volume

	$corr(r_m, \ln(V))$	$corr(abs(r_m), \ln(V))$	$corr(r^2, \ln(V))$
Argentina	0.1287	0.2883	0.1914
Chile	0.0865	0.1398	0.0671
Malaysia	0.1780	0.2366	0.1711
Mexico	0.1033	0.2239	0.1026
Singapore	0.0855	0.2782	0.1908
Thailand	0.1002	0.2942	0.1859

Table 3 Results from OLS estimation

$$V_t = \beta_0 + \beta_1 |r_t| + \beta_2 D_t |r_t| + \beta_3 r_{t+1} + \varepsilon_t$$

where V_t is the trading volume at time t. $|r_t|$ is the absolute return at time t. r_{t+1} is the return at time t+1. $t-statistics$ are in the brackets. One, two and three asterisks indicate significant at 10%, 5% and 1% levels respectively.

Panel A:

	β_0	β_1	β_2	β_3	R^2
Argentina	-0.0925^{***} [−8.08]	0.0986^{***} [12.88]	-0.054^{***} [−6.08]	0.0043 [0.99]	0.085
Chile	-0.0435^{***}	0.0636^{***} [8.45]	-0.0385^{***} [−3.94]	-0.0016 [−0.33]	0.025
Malaysia	-0.0523^{***} [−7.35]	0.0750^{***} [16.15]	-0.0564^{***} [−9.31]	-0.0025 [−0.82]	0.084
Mexico	-0.0947^{***} [−8.41]	0.1050^{***} [13.75]	-0.0599^{***} [−6.68]	-0.0036 [−0.81]	0.065
Singapore	-0.0702^{***} [−9.80]	0.1233^{***} [17.53]	-0.0843^{***} [−10.08]	-0.0056 [−1.35]	0.097
Thailand	-0.1947^{***} [−10.74]	0.1579^{***} [16.37]	-0.0563^{***} [−4.66]	-0.0175^{**} [−2.19]	0.095

Table 4 Estimation of GARCH model with and without volume variable

The results are based on the following model:

$$r_t = \mu + \varepsilon_t \quad where \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

without volume: $h_t = p_0 + p_1\varepsilon_{t-1}^2 + p_2 h_{t-1}$

with volume: $h_t = p_0 + p_1\varepsilon_{t-1}^2 + p_2 h_{t-1} + q * vol_t$

Standard errors are given below in parentheses. The likelihood ratio tests the hypothesis that $H_0 : q = 0, H_1 : q \neq 0$. The P-values of likelihood ratio tests are given below in brackets.

	μ	p_0	p_1	p_2	$p_1 + p_2$	q	$\chi^2(1)$
Argentina (*no−volume*)	0.0616 (0.0338)	0.1287 (0.0397)	0.1325 (0.0217)	0.8347 (0.0102)	0.9672		
Argentina (*with−volume*)	−0.0152 (0.0405)	0.3199 (0.1142)	0.2475 (0.0368)	0.5285 (0.0657)	0.7760	3.9133 (1.0452)	3.88 [0..05]
Chile (*no−volume*)	0.0009 (0.0065)	0.0035 (0.0099)	0.0422 (0.0206)	0.9333 (0.0077)	0.9755		
Chile (*with−volume*)	0.0184 (0.0208)	0.0255 (0.0223)	0.1353 (0.0177)	0.8603 (0.0059)	0.9953	0.0451 (0.0271)	45.40 [<0.001]
Malaysia (*no−volume*)	0.0585 (0.0199)	0.0329 (0.0178)	0.1198 (0.0182)	0.8731 (0.0065)	0.9929		
Malaysia (*with−volume*)	0.0597 (0.0201)	0.0000 (0.1205)	0.1415 (0.0173)	0.8434 (0.0053)	0.9849	0.4718 (0.0153)	22.24 [<0.001]
Mexico (*no−volume*)	0.1069 (0.0260)	0.1621 (0.0336)	0.1947 (0.0214)	0.7693 (0.0119)	0.9640		
Mexico (*with−volume*)	0.0934 (0.0281)	0.1878 (0.0606)	0.3068 (0.0279)	0.5895 (0.0309)	0.8963	1.8841 (0.3526)	55.90 [<0.001]
Singapore (*no−volume*)	0.0349 (0.0171)	0.0301 (0.0202)	0.1226 (0.0238)	0.8643 (0.0096)	0.9869		
Singapore (*with−volume*)	0.0062 (0.0172)	0.0758 (0.0408)	0.3149 (0.0305)	0.5424 (0.0366)	0.8573	1.0865 (0.1893)	38.96 [<0.001]
Thailand (*no−volume*)	0.0284 (0.0303)	0.0487 (0.0296)	0.0978 (0.0189)	0.8966 (0.0064)	0.9944		
Thailand (*with−volume*)	0.0288 (0.0309)	0.0220 (0.0667)	0.1328 (0.0328)	0.8476 (0.0171)	0.9804	0.4216 (0.1638)	27.95 [<0.001]

Table 5 Main Results: Estimation of Bivariate Threshold Model

The following model is estimated:

$$G(y_1, y_2) = \exp[-V\{-1/\log[1 - p_1(1+\xi_1 \cdot (y_1 - \upsilon_1)/\sigma_1)_+^{1/\xi_1}],$$

$$-1/\log[1 - p_2(1+\xi_2 \cdot (y_2 - \upsilon_2)/\sigma_2)_+^{1/\xi_2}]\}]$$

$$V(z_1, z_2) = (z_1^{-1/\alpha} + z_2^{-1/\alpha})^{\alpha}$$

where $\upsilon_1 = mean + \theta_1 * std$;

$\upsilon_2 = mean + \theta_2 * std$;

p_1 and p_2 are the probabilities that certain observations exceeding their thresholds. σ_1 and σ_2 are dispersion parameters. ξ_1 and ξ_2 are tail indexes. α is related to the correlation coefficient by $\rho = 1 - a^2$. The corresponding standard deviations are in the parenthesis. * indicates optimal threshold based on the residual life plot. P-values of score tests are given below in brackets.

Panel A1. Argentina: correlation between absolute value of return and trading volume

Threshold (θ_1, θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
(0.5, 0.5)	0.3726 (0.0146)	0.1917 (0.0562)	0.9582 (0.0719)	0.4385 (0.0147)	−0.0167 (0.0412)	0.1820 (0.0111)	0.8292 (0.0174)	0.3124	39.51 [0.000]
(1.0,1.0)	0.2339 (0.0135)	0.2150 (0.0815)	1.0358 (0.1081)	0.1835 (0.0125)	0.0539 (0.0815)	0.1628 (0.0181)	0.8391 (0.0240)	0.2959	26.08 [0.000]
(1.5,1.5)	0.1403 (0.0114)	0.1795 (0.1106)	1.2249 (0.1717)	0.0581 (0.0078)	−0.1120 (0.2660)	0.2184 (0.0639)	0.8547 (0.0355)	0.2694	17.45 [0.000]
(1.75,1.75)	0.1117 (0.0105)	0.1942 (0.1357)	1.2070 (0.2036)	0.0328 (0.0060)	−0.2966 (0.1907)	0.3841 (0.0877)	0.9137 (0.0363)	0.1651	11.45 [0.000]
(2.4,1.46)*	0.0657 (0.0083)	0.2081 (0.1872)	1.3048 (0.2950)	0.0624 (0.0081)	−0.1460 (0.2310)	0.2293 (0.0600)	0.8572 (0.0407)	0.2652	15.56 [0.000]
(2.4, 2.1)	0.0658 (0.0084)	0.1834 (0.1797)	1.2927 (0.2888)	0.0214 (0.0049)	−0.2793 (0.2717)	0.3182 (0.0949)	0.9223 (0.0447)	0.1493	10.03 [0.000]
(2.25, 2.25)	0.0708 (0.0087)	0.0945 (0.1515)	1.4550 (0.2899)	0.0186 (0.0046)	−0.7117 (0.2968)	0.2513 (0.0854)	0.9528 (0.0350)	0.0922	7.43 [0.000]
$corr(\|r\|, v)$								0.2883	

A2 Argentina: correlation between absolute return and trading volume when return is positive

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
(0.5, 0.5)	0.3604 (0.0205)	0.2440 (0.0816)	0.9461 (0.1018)	0.4333 (0.0208)	−0.0119 (0.0592)	0.1886 (0.0162)	0.7825 (0.0259)	0.3877	29.53 [0.000]
(1.0,1.0)	0.2258 (0.0188)	0.2868 (0.1183)	1.0222 (0.1525)	0.2002 (0.0181)	0.3022 (0.1416)	0.1155 (0.0198)	0.7850 (0.0355)	0.3327	20.78 [0.000]
(1.5,1.5)	0.1342 (0.0159)	0.2668 (0.1790)	1.1768 (0.2571)	0.0499 (0.0104)	−0.4195 (0.2172)	0.4216 (0.1082)	0.9152 (0.0428)	0.1624	7.27 [0.000]
(1.75,1.75)	0.1030 (0.0143)	0.2240 (0.2064)	1.3812 (0.3448)	0.0385 (0.0091)	−0.4368 (0.2712)	0.3591 (0.1092)	0.8846 (0.0543)	0.2175	6.96 [0.000]
(2.8,1.5)*	0.0474 (0.0101)	0.4077 (0.4559)	1.3347 (0.6391)	0.0511 (0.0105)	−0.4388 (0.2261)	0.4352 (0.1119)	0.8532 (0.0656)	0.2720	6.97 [0.000]
(2.25, 2, 25	0.0648 (0.0118)	0.0760 (0.2720)	1.7859 (0.5893)	0.0251 (0.0076)	−0.3470 (0.3215)	0.1268 (0.0540)	0.9661 (0.0414)	0.0667	2.55 [0.011]
$corr(\|r\|,v)$								0.3213	

A3 Argentina: correlation between absolute return and trading volume when return is negative

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
(0.5, 0.5)	0.3650 (0.0206)	0.0902 (0.0710)	1.1715 (0.1177)	0.4410 (0.0209)	−0.0284 (0.0530)	0.1685 (0.0139)	0.8725 (0.0231)	0.2387	29.97 [0.000]
(1.0,1.0)	0.2375 (0.0191)	0.1554 (0.1094)	1.1528 (0.1632)	0.1739 (0.0173)	0.0741 (0.1182)	0.1458 (0.0235)	0.8490 (0.0340)	0.2791	20.04 [0.000]
(1.5,1.5)	0.1464 (0.0164)	0.0943 (0.1248)	1.3383 (0.2318)	0.0551 (0.0108)	0.2089 (0.3353)	0.1322 (0.0522)	0.8808 (0.0486)	0.2114	12.74 [0.000]
(1.75,1.75)	0.1224 (0.0154)	0.1644 (0.1581)	1.1576 (0.2403)	0.0267 (0.0078)	−0.4400 (0.3590)	0.3076 (0.1396)	0.9190 (0.0547)	0.1554	11.53 [0.000]
(2.0,1.4)*	0.0997 (0.0141)	0.3260 (0.2280)	0.9780 (0.2623)	0.0766 (0.0126)	0.2993 (0.2601)	0.1071 (0.0333)	0.8810 (0.0469)	0.2238	12.72 [0.000]
(1.85,1.85)	0.1141 (0.0150)	0.2261 (0.1818)	1.0626 (0.2426)	0.0221 (0.0071)	−0.4046 (0.4713)	0.3595 (0.1932)	0.9007 (0.064)	0.1887	11.47 [0.000]
(2.25, 2.25)	0.1004 (0.0400)	0.4075 (01987)	0.8524 (0.2048)	0.0159 (0.0038)	−0.8422 (0.9065)	0.1172 (0.0683)	0.9389 (0.0039)	0.1184	5.61 [0.000]
$corr(\|r\|,v)$								0.1936	

Panel B1 Malaysia: correlation between absolute return and volume

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
$(0.5, 0.5)$	0.2917 (0.0116)	0.3552 (0.0553)	0.8648 (0.0637)	0.4415 (0.0121)	0.0599 (0.0194)	0.1838 (0.0077)	0.8419 (0.0150)	0.2912	60.61 [0.000]
$(1.0,1.0)$	0.1653 (0.0099)	0.3988 (0.0853)	1.0649 (0.1161)	0.2301 (0.0110)	0.1620 (0.0501)	0.1551 (0.0115)	0.8315 (0.0206)	0.3086	43.62 [0.000]
$(1.5,1.5)$	0.0977 (0.0081)	0.3953 (0.1219)	1.3825 (0.2100)	0.0990 (0.0081)	0.2770 (0.0953)	0.1473 (0.0189)	0.8212 (0.0292)	0.3056	34.89 [0.000]
$(2.0, 2.0)$	0.0619 (0.0067)	0.3262 (0.1637)	1.8825 (0.3761)	0.0414 (0.0055)	0.3615 (0.1518)	0.1614 (0.0320)	0.8065 (0.0415)	0.3495	30.59 [0.000]
$(2.45,1.4)^*$	0.0467 (0.0058)	0.3390 (0.2113)	1.9147 (0.4892)	0.1199 (0.0089)	0.2463 (0.0828)	0.1461 (0.0167)	0.8461 (0.0331)	0.2841	30.77 [0.000]
$(2.45,1.75)$	0.0473 (0.0059)	0.3507 (0.2156)	1.9186 (0.4932)	0.0598 (0.0066)	0.2561 (0.1064)	0.1757 (0.0270)	0.8343 (0.0389)	0.3039	28.62 [0.000]
$(2.25, 2.25)$	0.0503 (0.0061)	0.1977 (0.1624)	2.3532 (0.4923)	0.0286 (0.0046)	0.4412 (0.1943)	0.1477 (0.0366)	0.8504 (0.0460)	0.2768	28.69 [0.000]
$corr(\|r\|,v)$								0.2366	

Panel B2 Malaysia: correlation between absolute return and volume when return is positive

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	*score*
$(0.5, 0.5)$	0.2786 (0.0159)	0.4591 (0.0875)	0.8232 (0.0919)	0.4208 (0.0169)	0.1014 (0.0384)	0.1785 (0.0116)	0.8090 (0.0221)	0.3455	44.28 [0.000]
$(1.0,1.0)$	0.1526 (0.0133)	0.4587 (0.1248)	1.1701 (0.1850)	0.2066 (0.0148)	0.2531 (0.0804)	0.1395 (0.0159)	0.7836 (0.0318)	0.3860	34.90 [0.000]
$(1.5,1.5)$	0.0938 (0.0111)	0.4809 (0.1764)	1.4622 (0.3169)	0.0773 (0.0102)	0.3908 (0.1533)	0.1423 (0.0287)	0.7877 (0.0458)	0.3795	27.08 [0.000]
$(1.75,1.75)$	0.0746 (0.0101)	0.4647 (0.2061)	1.6648 (0.4181)	0.0457 (0.0081)	0.4470 (0.1953)	0.1553 (0.0401)	0.7979 (0.0548)	0.3633	24.01 [0.000]
$(2.25,1.45)^*$	0.0514 (0.0084)	0.5325 (0.2933)	1.8854 (0.6312)	0.0843 (0.0106)	0.3695 (0.1443)	0.1487 (0.0282)	0.7761 (0.0536)	0.3977	24.41 [0.000]
$(2.0, 2.0)$	0.0619 (0.0092)	0.5055 (0.2464)	1.7520 (0.5076)	0.0333 (0.0069)	1.0098 (0.4528)	0.0749 (0.0347)	0.7600 (0.0649)	0.4224	24.78 [0.000]
$(2.25, 2.25)$	0.0519 (0.0086)	0.4753 (0.2762)	1.7987 (0.5982)	0.0192 (0.0053)	1.0306 (0.5132)	0.0880 (0.0482)	0.8480 (0.0698)	0.2808	19.28 [0.000]
$corr(\|r\|,v)$								0.2789	

Panel B3 Malaysia: correlation between absolute return and volume when return is negative

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
$(0.5,0.5)$	0.2917 (0.0167)	0.4200 (0.1008)	0.8458 (0.1016)	0.4741 (0.0174)	-0.0253 (0.0404)	0.1837 (0.0118)	0.8716 (0.0208)	0.2403	26.06 (0.000)
$(1.0,1.0)$	0.1592 (0.0141)	0.2269 (0.1135)	1.4435 (0.2153)	0.2860 (0.0168)	0.0772 (0.0606)	0.1447 (0.0141)	0.8990 (0.0248)	0.1918	18.50 (0.000)
$(1.5,1.5)$	0.1076 (0.0121)	0.2333 (0.1462)	1.6322 (0.3064)	0.1233 (0.0128)	0.1632 (0.1323)	0.1463 (0.0254)	0.8791 (0.0347)	0.2272	14.83 (0.000)
$(1.75,1.75)$	0.0903 (0.0113)	0.2397 (0.1631)	1.6376 (0.3449)	0.0799 (0.01808)	0.1368 (0.1754)	0.1618 (0.0367)	0.9095 (0.0354)	0.1728	12.20 (0.000)
$(2.0,2.0)$	0.0720 (0.0103)	0.2000 (0.1753)	1.9082 (0.4372)	0.0544 (0.0091)	0.2249 (0.2752)	0.1559 (0.0501)	0.8870 (0.0445)	0.2132	11.51 (0.000)
$(1.65,1.41)^*$	0.0952 (0.0115)	0.2316 (0.1555)	1.6742 (0.3351)	0.1522 (0.0139)	0.2032 (0.1211)	0.1290 (0.0203)	0.8854 (0.0336)	0.2161	14.8 (0.000)
$(2.25,2.25)$	0.0592 (0.0094)	0.1715 (0.1847)	2.0573 (0.5088)	0.0374 (0.0076)	-0.0428 (0.2928)	0.2280 (0.0814)	0.9054 (0.0476)	0.1802	9.21 (0.000)
$corr(\|r\|,v)$								0.1968	

Panel C1. Chile: correlation between absolute return and trading volume

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	score
$(0.5,0.5)$	0.3158 (0.0119)	0.3564 (0.0637)	0.7704 (0.0586)	0.4425 (0.0122)	0.0683 (0.0349)	0.2530 (0.0127)	0.9284 (0.0135)	0.1380	17.41 [0.000]
$(1.0,1.0)$	0.1838 (0.0103)	0.3149 (0.0870)	1.0004 (0.1047)	0.2404 (0.0112)	0.1327 (0.0566)	0.2336 (0.0180)	0.9525 (0.0153)	0.0927	9.34 [0.000]
$(1.5,1.5)$	0.1176 (0.0088)	0.2755 (0.1031)	1.1957 (0.1528)	0.1198 (0.0089)	0.2137 (0.0911)	0.2196 (0.0261)	0.9630 (0.0174)	0.0726	5.75 [0.000]
$(2.0,2.0)$	0.0796 (0.0075)	0.3325 (0.1303)	1.2179 (0.2040)	0.0558 (0.0064)	0.3293 (0.1534)	0.2134 (0.0401)	0.9691 (0.0206)	0.0608	3.68 [0.000]
$(1.85,1.95)^*$	0.0925 (0.0080)	0.3576 (0.1317)	1.1153 (0.1736)	0.0574 (0.0065)	0.2577 (0.1368)	0.2435 (0.0428)	0.9631 (0.0214)	0.0724	4.29 [0.000]
$(2.25,2.25)$	0.0633 (0.0068)	0.2941 (0.1551)	1.3781 (0.2590)	0.0378 (0.0053)	0.5063 (0.2373)	0.1837 (0.0492)	0.9884 (0.0161)	0.0231	1.93 [0.054]
$corr(\|r\|,v)$								0.1398	

Panel C2. Chile: correlation between absolute return and trading volume when return is positive

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	*score*
(0.5, 0.5)	0.3204 (0.0165)	0.4600 (0.0945)	0.7166 (0.0782)	0.4320 (0.0169)	0.1205 (0.0506)	0.2357 (0.0168)	0.8848 (0.0200)	0.2171	17.99 [0.000]
(1.0,1.0)	0.1749 (0.0141)	0.3231 (0.1260)	1.1479 (0.1735)	0.2222 (0.0153)	0.2062 (0.0851)	0.2191 (0.0248)	0.9233 (0.0239)	0.1475	9.78 [0.000]
(1.5,1.5)	0.1077 (0.0118)	0.2534 (0.1701)	1.5095 (0.3047)	0.1018 (0.0115)	0.3639 (0.1596)	0.2058 (0.0398)	0.9265 (0.0302)	0.1416	6.77 [0.000]
(2.0, 2.0)	0.0723 (0.0100)	0.1020 (0.1589)	2.0687 (0.4351)	0.0443 (0.0080)	0.5321 (0.3206)	0.2309 (0.0808)	0.9264 (0.0400)	0.1416	4.56 [0.000]
(2.15,1.4)*	0.0704 (0.0098)	0.2039 (0.2047)	1.7231 (0.4250)	0.1261 (0.0126)	0.3825 (0.1483)	0.1812 (0.0321)	0.9422 (0.0296)	0.1122	5.41 [0.000]
(2.25, 2.25)	0.0655 (0.0096)	0.1592 (0.1949)	1.8504 (0.4520)	0.0262 (0.0062)	0.2066 (0.3242)	0.4498 (0.1788)	0.9579 (0.0375)	0.0824	2.73 [0.006]
$corr(\lvert r \rvert, v)$								0.1861	

Panel C3. Chile: correlation between absolute return and trading volume when return is negative

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	*score*
(0.5, 0.5)	0.3284 (0.0173)	0.3759 (0.0940)	0.7221 (0.0800)	0.4642 (0.0174)	0.0322 (0.0550)	0.2572 (0.0192)	0.9654 (0.0174)	0.0680	8.77 [0.000]
(1.0,1.0)	0.1794 (0.0148)	0.2300 (0.1066)	1.1456 (0.1576)	0.2577 (0.0164)	0.0162 (0.0770)	0.2647 (0.0281)	0.9779 (0.0209)	0.0437	3.96 [0.000]
(1.25,1, 25)	0.1447 (0.0137)	0.2373 (0.1209)	1.1877 (0.1855)	0.1815 (0.0149)	−0.0182 (0.0843)	0.2825 (0.0347)	0.9929 (0.0209)	0.0141	2.26 [0.024]
(1.5,1.5)	0.1191 (0.0127)	0.2521 (0.1344)	1.2007 (0.2087)	0.1292 (0.0132)	−0.0271 (0.0932)	0.2864 (0.0411)	1.000 (0.0206)	0.0000	1.29 [0.197]
(2.15,1.51)*	0.0701 (0.0102)	0.3704 (0.2101)	1.1716 (0.2959)	0.1292 (0.0132)	−0.0164 (0.0951)	0.2794 (0.0404)	1.000 (0.0226)	0.0000	0.92 [0.358]
$corr(\lvert r \rvert, v)$								0.0811	

Panel D1: Mexico: correlation between absolute return and volume

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	*score*
$(0.5, 0.5)$	0.3492 (0.0119)	0.2937 (0.0516)	0.8883 (0.0574)	0.4516 (0.0121)	0.0595 (0.0341)	0.2385 (0.0117)	0.8552 (0.0143)	0.2686	19.84 [0.000]
$(1.0, 1.0)$	0.2031 (0.0106)	0.3308 (0.0745)	1.0035 (0.0915)	0.2190 (0.0109)	0.2194 (0.0687)	0.1901 (0.0164)	0.8846 (0.0186)	0.2174	14.68 [0.000]
$(1.5, 1.5)$	0.1218 (0.0089)	0.4379 (0.1114)	0.9788 (0.1272)	0.0713 (0.0071)	0.1678 (0.1469)	0.2715 (0.0474)	0.9260 (0.0235)	0.1425	6.88 [0.000]
$(2.0, 2.0)$	0.0656 (0.0069)	0.4456 (0.1652)	1.3010 (0.2458)	0.0314 (0.0049)	−0.0818 (0.1792)	0.4101 (0.0960)	0.9481 (0.0294)	0.1011	3.13 [0.000]
$(1.85, 1.35)^*$	0.0864 (0.0077)	0.6554 (0.1759)	0.8273 (0.1551)	0.1241 (0.0090)	0.4108 (0.1261)	0.1590 (0.0227)	0.9270 (0.0219)	0.1406	6.83 [0.000]
$(2.05, 2.05)$	0.0627 (0.0067)	0.4463 (0.1699)	1.3164 (0.2560)	0.0291 (0.0047)	−0.1108 (0.1800)	0.4257 (0.1018)	0.9540 (0.0289)	0.0898	2.81 [0.005]
$(2.25, 2.25)$	0.0521 (0.0062)	0.4323 (0.1865)	1.4340 (0.3079)	0.0245 (0.0043)	−0.0229 (0.2328)	0.3558 (0.1034)	0.9718 (0.0273)	0.0556	1.68 [0.093]
$corr(\|r\|, v)$								0.2239	

Panel D2: Mexico: correlation between absolute return and volume when return is positive

Threshold (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ζ	*score*
$(0.5, 0.5)$	0.3618 (0.0164)	0.3068 (0.0727)	0.8828 (0.0784)	0.4417 (0.0167)	0.0499 (0.0471)	0.2253 (0.0152)	0.8311 (0.0203)	0.3093	21.65 [0.000]
$(1.0, 1.0)$	0.2187 (0.0150)	0.3546 (0.1097)	0.9178 (0.1202)	0.1928 (0.0145)	0.2600 (0.1061)	0.1578 (0.0208)	0.9219 (0.0230)	0.1501	9.56 [0.000]
$(1.5, 1.5)$	0.1207 (0.0122)	0.2715 (0.1372)	1.2991 (0.2209)	0.0536 (0.0086)	0.1094 (0.2319)	0.2769 (0.0765)	0.9277 (0.0347)	0.1394	4.51 [0.000]
$(1.75, 1.75)$	0.1034 (0.0115)	0.3965 (0.1779)	1.0817 (0.2229)	0.0337 (0.0069)	−0.0143 (0.3030)	0.3334 (0.1198)	0.9485 (0.0359)	0.1003	2.89 [0.004]
$(2.0, 2.0)$	0.0751 (0.0101)	0.4686 (0.2561)	1.2458 (0.2875)	0.0252 (0.0064)	0.4504 (0.9117)	0.2387 (0.1368)	0.9889 (0.0310)	0.0220	0.66 [0.509]
$(2.70, 1.15)^*$	0.0472 (0.0081)	0.7295 (0.3567)	0.8961 (0.3329)	0.1347 (0.0128)	0.3535 (0.1536)	0.1506 (0.0271)	0.9449 (0.0316)	0.1072	4.18 [0.000]
$(2.15, 2.15)$	0.0702 (0.0098)	0.2179 (0.1762)	1.6092 (0.3619)	0.0210 (0.0056)	−0.2401 (0.3751)	0.4187 (0.1901)	0.9911 (0.0296)	0.0177	0.23 [0.818]
$corr(\|r\|, v)$								0.2722	

Panel D3: Mexico: correlation between absolute return and volume when return is negative

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5,0.5)$	0.3437 (0.0174)	0.3538 (0.0813)	0.8262 (0.0826)	0.4514 (0.0177)	0.0835 (0.0524)	0.2478 (0.0182)	0.8927 (0.0197)	0.2031	16.94 [0.000]
$(1.0,1.0)$	0.1890 (0.0151)	0.3814 (0.1208)	1.0129 (0.1468)	0.2268 (0.0160)	0.1433 (0.0907)	0.2451 (0.0293)	0.9111 (0.0253)	0.1699	9.04 [0.000]
$(1.5,1.5)$	0.1084 (0.0124)	0.4553 (0.1851)	1.1455 (0.2420)	0.1086 (0.0124)	0.3179 (0.1885)	0.2164 (0.0468)	0.9240 (0.0317)	0.1462	5.43 [0.000]
$(2.0,2.0)$	0.0636 (0.0098)	0.3399 (0.2080)	1.6737 (0.4241)	0.0430 (0.0082)	−0.0962 (0.2052)	0.4640 (0.1296)	0.9591 (0.0375)	0.0801	1.96 [0.050]
$(2.6,1.45)^*$	0.0454 (0.0084)	0.7454 (0.4034)	1.1382 (0.4589)	0.1215 (0.0130)	0.3743 (0.1864)	0.1962 (0.0408)	0.9146 (0.0422)	0.1635	3.37 [0.000]
$(2.15,2.15)$	0.0572 (0.0049)	0.3641 (0.2265)	1.6431 (0.4493)	0.0384 (0.0078)	−0.0745 (0.2231)	0.4339 (0.1312)	0.9776 (0.0350)	0.0443	1.15 [0.250]
$corr(\|r\|,v)$								0.1794	

Panel E1: Singapore correlation between absolute return and volume

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5,0.5)$	0.3621 (0.0120)	0.2505 (0.0505)	0.6177 (0.0404)	0.3897 (0.0121)	0.0208 (0.0379)	0.2560 (0.0141)	0.8408 (0.0147)	0.2930	45.69 [0.000]
$(1.0,1.0)$	0.2198 (0.0109)	0.2421 (0.0714)	0.7222 (0.0656)	0.1512 (0.0096)	0.0297 (0.0681)	0.2528 (0.0247)	0.8638 (0.0203)	0.2538	32.22 [0.000]
$(1.5,1.5)$	0.1327 (0.0092)	0.1861 (0.0910)	0.8769 (0.1045)	0.0548 (0.0063)	0.1493 (0.1341)	0.2023 (0.0365)	0.8922 (0.0270)	0.2039	24.11 [0.000]
$(2.0,2.0)$	0.0844 (0.0077)	0.1738 (0.1223)	0.9510 (0.1507)	0.0279 (0.0046)	0.1810 (0.2322)	0.2095 (0.0615)	0.9388 (0.0287)	0.1186	19.33 [0.000]
$(2.4,1.55)^*$	0.0641 (0.0068)	0.3199 (0.1866)	0.8384 (0.1834)	0.0502 (0.0061)	0.2234 (0.1568)	0.1840 (0.0368)	0.9270 (0.0324)	0.1406	19.17 [0.000]
$(2.45,1.75)$	0.0585 (0.0065)	0.2347 (0.1856)	0.9358 (0.2099)	0.0280 (0.0046)	0.1875 (0.2331)	0.2094 (0.0614)	0.9367 (0.0308)	0.1226	17.71 [0.000]
$(2.25,2.25)$	0.0674 (0.0069)	0.1698 (0.1455)	1.0311 (0.1889)	0.0516 (0.0061)	0.0024 (0.0859)	0.2107 (0.0313)	0.9402 (0.0282)	0.1160	16.03 [0.000]
$corr(\|r\|,v)$								0.2782	

Panel E2: Singapore correlation between absolute return and volume when return is positive

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5, 0.5)$	0.3643 (0.0166)	0.3277 (0.0737)	0.5368 (0.0502)	0.4545 (0.0168)	-0.0912 (0.0440)	0.2431 (0.0161)	0.8056 (0.0201)	0.3510	45.24 [0.000]
$(1.0,1.0)$	0.1996 (0.0145)	0.2268 (0.0987)	0.8086 (0.1030)	0.2796 (0.0160)	-0.0768 (0.0666)	0.2238 (0.0212)	0.8019 (0.0270)	0.3569	36.95 [0.000]
$(1.5,1.5)$	0.1302 (0.0126)	0.1904 (0.1226)	0.8972 (0.1458)	0.1374 (0.0129)	-0.2056 (0.0890)	0.2550 (0.0343)	0.8500 (0.0333)	0.2775	30.48 [0.000]
$(2.0, 2.0)$	0.0863 (0.0107)	0.2252 (0.1663)	0.9115 (0.1949)	0.0715 (0.0098)	-0.1735 (0.1614)	0.2156 (0.0469)	0.8616 (0.0418)	0.2576	24.32 [0.000]
$(2.30,1.5)^*$	0.0661 (0.0095)	0.2201 (0.1984)	0.9604 (0.2428)	0.1389 (0.0130)	-0.2107 (0.0876)	0.2556 (0.0342)	0.8657 (0.0386)	0.2505	24.01 [0.000]
$(2.25, 2.25)$	0.0761 (0.0101)	0.2573 (0.1882)	0.8970 (0.2118)	0.0622 (0.0092)	0.0084 (0.2389)	0.1603 (0.0464)	0.8661 (0.0440)	0.2498	22.81 [0.000]
$corr(\|r\|,v)$								0.3321	

Panel E3: Singapore correlation between absolute return and volume when return is negative

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5, 0.5)$	0.3506 (0.0173)	0.2200 (0.0749)	0.6873 (0.0665)	0.4463 (0.0175)	0.1255 (0.0564)	0.1684 (0.0130)	0.8889 (0.0192)	0.2098	21.48 [0.000]
$(1.0,1.0)$	0.2262 (0.0159)	0.2589 (0.1063)	0.7200 (0.0950)	0.2466 (0.0163)	0.1987 (0.0940)	0.1639 (0.0197)	0.8910 (0.0241)	0.2061	14.75 [0.000]
$(1.5,1.5)$	0.1422 (0.0136)	0.2531 (0.1403)	0.8189 (0.1405)	0.1254 (0.0130)	0.1727 (0.1375)	0.1961 (0.0338)	0.8865 (0.0317)	0.2141	24.11 [0.000]
$(2.0, 2.0)$	0.0848 (0.0111)	0.2348 (0.2133)	0.9390 (0.2344)	0.0635 (0.0097)	0.0407 (0.1639)	0.2637 (0.0594)	0.9384 (0.0354)	0.1194	5.21 [0.000]
$(2.2,1.85)^*$	0.0741 (0.0104)	0.3848 (0.2852)	0.8209 (0.2535)	0.0829 (0.0109)	0.2047 (0.1985)	0.2004 (0.0470)	0.9066 (0.0392)	0.1780	6.73 [0.000]
$(2.25, 2.25)$	0.0753 (0.0105)	0.2713 (0.2473)	0.9016 (0.2554)	0.0564 (0.0092)	0.0711 (0.1841)	0.2462 (0.0612)	0.9583 (0.0328)	0.0817	3.88 [0.000]
$corr(\|r\|,v)$								0.1810	

Panel F1: Thailand correlation between absolute return and volume

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5, 0.5)$	0.3504 (0.0120)	0.1373 (0.0511)	1.5981 (0.1046)	0.4302 (0.0121)	0.0358 (0.0351)	0.3149 (0.0161)	0.8462 (0.0145)	0.2839	41.94 (0.000)
$(1.0,1.0)$	0.2294 (0.0110)	0.0714 (0.0653)	1.8984 (0.1589)	0.1543 (0.0096)	0.0075 (0.0727)	0.3224 (0.0316)	0.8610 (0.0204)	0.2586	25.95 (0.000)
$(1.5,1.5)$	0.01618 (0.0099)	0.0902 (0.0863)	1.7907 (0.1945)	0.0483 (0.0059)	0.0560 (0.1355)	0.3618 (0.0661)	0.9205 (0.0251)	0.1527	14.86 (0.000)
$(2.0, 2.0)$	0.1031 (0.0084)	0.0026 (0.1035)	2.1042 (0.2827)	0.0178 (0.0037)	0.0881 (0.2352)	0.3561 (0.1108)	0.9392 (0.0329)	0.1179	10.29 (0.000)
$(2.75,1.75)^*$	0.0556 (0.0064)	0.1528 (0.1014)	2.6051 (0.4009)	0.0302 (0.0048)	0.1013 (0.1984)	0.3370 (0.0827)	0.9422 (0.0301)	0.112	9.8 (0.000)
$(1.85,1.85)$	0.0510 (0.0061)	0.1738 (0.1018)	2.6864 (0.4241)	0.0241 (0.0043)	0.0613 (0.1922)	0.3652 (0.0952)	0.9443 (0.0332)	0.1083	9.47 (0.000)
$(2.25,2.25)$	0.0824 (0.0076)	0.1344 (0.0812)	2.5308 (0.3343)	0.0119 (0.0032)	0.1043 (0.2964)	0.3459 (0.1372)	0.9494 (0.0402)	0.0986	5.58 (0.000)
$corr(\|r\|,v)$								0.2942	

Panel F2: Thailand correlation between absolute return and volume when return is positive

$Threshold$ (θ_1,θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	$score$
$(0.5, 0.5)$	0.3508 (0.0168)	0.2726 (0.0783)	1.2324 (0.1186)	0.4490 (0.0172)	0.0521 (0.0536)	0.3235 (0.0237)	0.7589 (0.0216)	0.4240	35.50 [0.000]
$(1.0,1.0)$	0.2220 (0.0155)	0.2186 (0.1150)	1.5037 (0.2049)	0.1572 (0.0137)	0.1070 (0.1296)	0.3006 (0.0477)	0.8101 (0.0309)	0.3437	20.94 [0.000]
$(1.5,1.5)$	0.1383 (0.0133)	−0.0058 (0.1697)	2.0701 (0.4135)	0.0430 (0.0080)	−0.4061 (0.2687)	0.5140 (0.1629)	0.9031 (0.0406)	0.1844	11.84 [0.000]
$(2.0, 2.0)$	0.1142 (0.0231)	−0.0769 (0.2031)	2.2541 (0.2156)	0.0211 (0.0056)	−0.5044 (0.3452)	0.4608 (0.2158)	0.9431 (0.0436)	0.1105	9.26 [0.000]
$(2.55,1.05)^*$	0.0547 (0.0089)	−0.4598 (0.2037)	3.6078 (0.8878)	0.1612 (0.0141)	0.0540 (0.1223)	0.3104 (0.0481)	0.8837 (0.0385)	0.2190	10.88 [0.000]
$(2.25, 2.25)$									
$corr(\|r\|,v)$								0.3424	

Panel F3: Thailand correlation between absolute return and volume when return is negative

Threshold (θ_1, θ_2)	p_r	ξ_r	σ_r	p_v	ξ_v	σ_v	α	ρ	*score*
$(0.5, 0.5)$	0.3780 (0.0170)	0.2420 (0.0805)	1.0327 (0.0997)	0.4089 (0.0171)	0.0493 (0.0465)	0.2840 (0.0199)	0.8745 (0.0199)	0.2352	17.95 [0.000]
$(1.0, 1.0)$	0.2258 (0.0155)	0.0969 (0.0987)	1.3904 (0.1723)	0.1755 (0.0143)	0.1683 (0.0963)	0.2384 (0.0309)	0.9183 (0.0246)	0.1567	8.70 [0.000]
$(1.5, 1.5)$	0.1421 (0.0133)	-0.0215 (0.1113)	1.6785 (0.2518)	0.0602 (0.0093)	0.3151 (0.2104)	0.2230 (0.0576)	0.9747 (0.0265)	0.0499	2.50 [0.012]
$(2.0, 2.0)$	0.0929 (0.0113)	-0.0722 (0.1297)	1.8020 (0.3265)	0.0175 (0.0052)	0.2156 (0.3658)	0.3979 (0.1856)	0.9821 (0.0312)	0.0354	1.28 [0.201]
$(2.5, 1.35)^*$	0.0567 (0.0090)	-0.1813 (0.1495)	2.1786 (0.4751)	0.0842 (0.0108)	0.3122 (0.1831)	0.2118 (0.0466)	0.9546 (0.0332)	0.0887	2.91 [0.004]
$(2.25, 2.25)$	0.0886 (0.0110)	0.0361 (0.1697)	1.4920 (0.3187)	0.0159 (0.0050)	0.5526 (0.5862)	0.2424 (0.1546)	0.9785 (0.0338)	0.0425	1.31 [0.190]
$corr(\|r\|, v)$								0.2222	

Figure 1

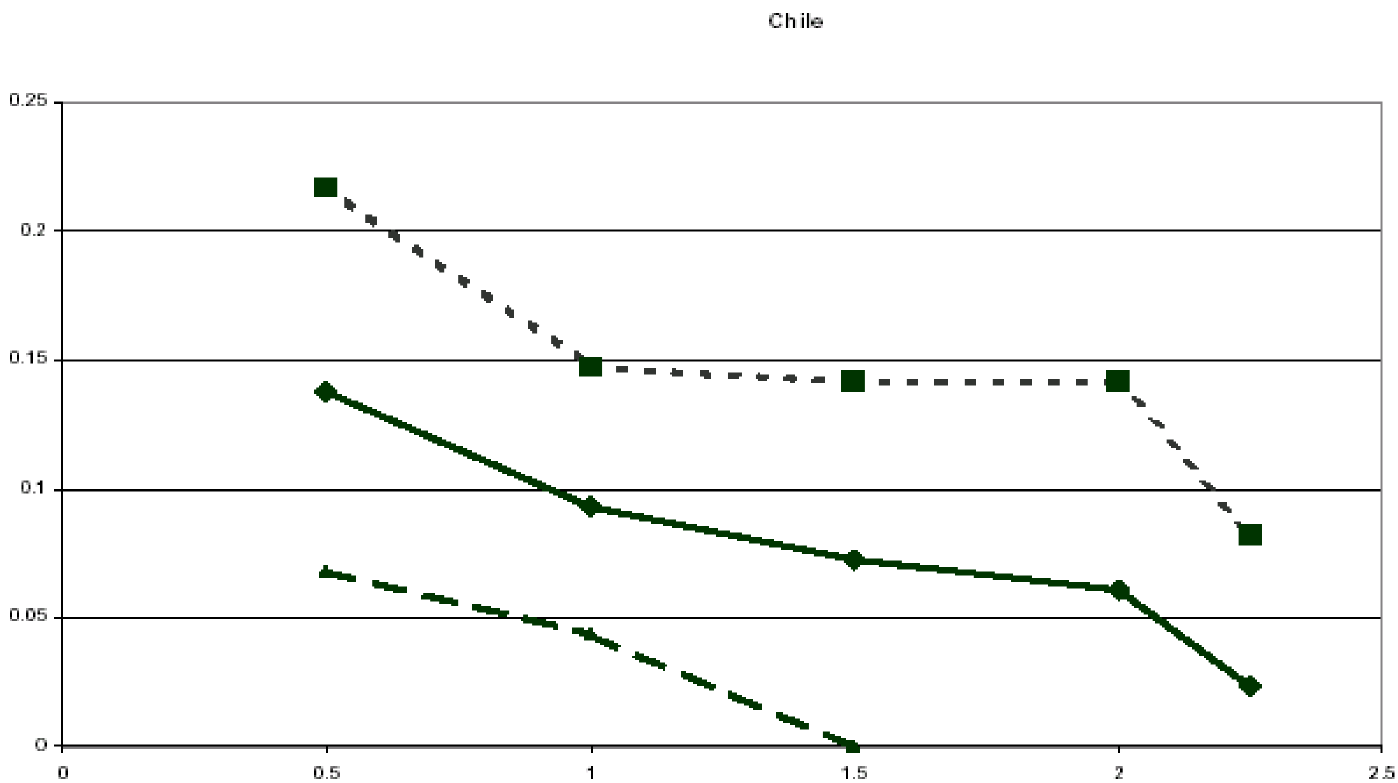
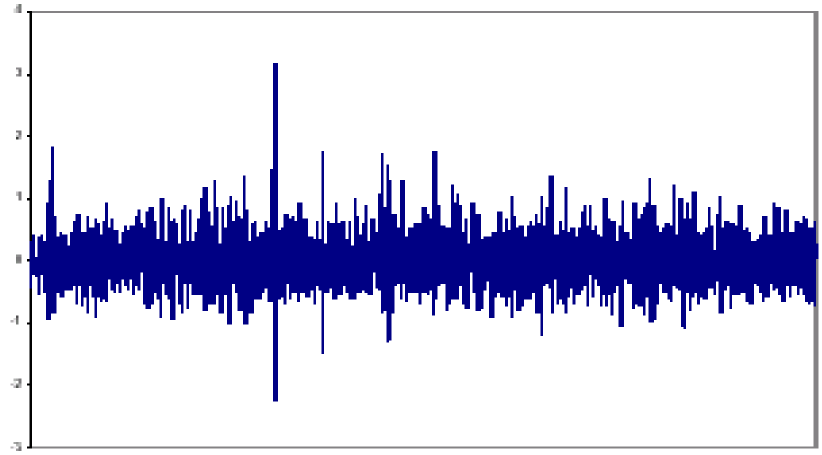
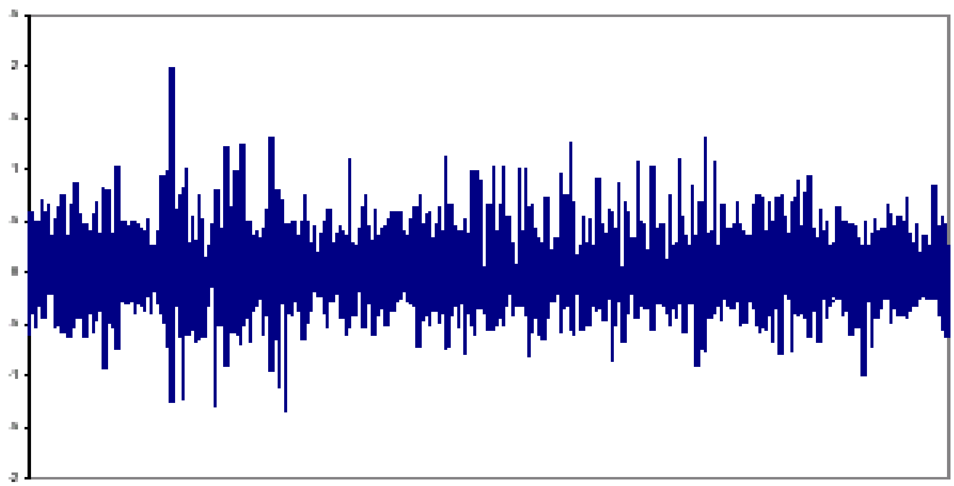


Figure 2



Thailand Adjusted-Volume



Singapore Adjusted Volume

Chapter III

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