Trends in Earnings Volatility, Earnings Quality and Idiosyncratic Return Volatility: Managerial Opportunism or Economic Activity

Abstract

This paper examines the causes for the increasing earnings volatility and the deteriorating earnings quality over the past three decades and the roles of these trends in explaining rising idiosyncratic return volatility. We find that the trend in earnings volatility is primarily caused by increases in cash flow volatility. The key driver for the deteriorating earnings quality embodied in the Dechow and Dichev (2002) accruals quality measure is the less negative contemporaneous correlation between cash flow and accruals. Collectively, the trends in earnings volatility and its components and the trend in earnings quality help explain the documented increasing idiosyncratic stock return volatility. Our results highlight the roles of both operating volatility (economic forces) and financial reporting quality (managerial opportunism) in explaining earnings volatility and idiosyncratic return volatility, with economic forces dominating managerial opportunism.

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Trends in Earnings Volatility, Earnings Quality and Idiosyncratic Return Volatility: Managerial Opportunism or Economic Activity

I. Introduction

There is evidence in the literature suggesting that earnings volatility has increased over time (Wei and Zhang, 2006). Different interpretations have been provided regarding the implications of the upward trend in earnings volatility. Wei and Zhang (2006) find that increasing earnings volatility and decreasing corporate earnings explain the upward trend of idiosyncratic stock return volatility documented in Campbell, Lettau, Malkiel and Xu (2001), a now well-known empirical regularity in the stock market. Others typically use scaled earnings volatility as a measure of income smoothing, where the scalar can be cash flow volatility (Francis, LaFond, Olsson, and Schipper, 2004) or sales variability (Imhoff, 1981 and Albrecht and Richardson, 1990). Holding cash flow volatility or sales volatility constant, increasing earnings volatility indicates decreasing income smoothing.

Interestingly, in a similar vein, Rajgopal and Venkatachalam (2006) find a positive association between deteriorating financial reporting quality and increasing idiosyncratic return volatility. One of their primary measures for financial reporting quality is earnings quality based on Dechow and Dichev (2002, hereafter "DD"). The DD earnings quality measure, or accruals quality as they called it, is the standard deviation of residuals in a regression of change in working capital on multi-period cash flows and captures the degree of mapping between accruals and cash flows. Since accruals are created when there is a difference in timing between actual cash flow and reported earnings, firms with lower earnings quality would book this shift in timing in a less timely manner. As DD put it, “Firms with low accrual quality have more accruals that are unrelated to cash flow realizations, and so have more noise […] in their earnings.”

DD find a strong association between earnings volatility and accrual quality. Indeed, DD report that the correlation between the standard deviation of earnings and their accrual quality measure is as high as 0.82 for their sample period of 1987-1999. Our paper investigates three questions: (1) Do the above-cited earnings volatility and earnings quality trends contain some common elements? (2) If there is only partial commonality in these trends, what other factors also contribute to them? And (3) how do earnings volatility and earnings quality trends together explain the return volatility trend?

DD's evidence on the association between earnings volatility and accrual quality is only cross sectional—that is, unconditionally and across firms. Earnings volatility is negatively correlated with accrual quality through a decomposition of earnings volatility into cash flow volatility and accrual volatility. This cross sectional relation, however, does not necessarily translate into a time-series one: increasing earnings volatility may not imply decreasing earnings quality. The reason is that if the increased variability in earnings is picked up by additional fluctuations in accruals, then the mapping between cash flows and accruals will improve, which by DD's definition, meaning that earnings quality will improve. In other words, the change in earnings volatility could be attenuated by a more extensive use of accruals.

A decomposition of earnings volatility illustrates the above argument:

$$Var(E) = Var(CF + ACC) = Var(CF) + Var(ACC) + 2\rho_{CF,ACC}\sqrt{Var(CF)}\sqrt{Var(ACC)},$$

where $Var(\cdot)$ is the variance of a variable, E is earnings, CF is cash flow, ACC is accruals, and $\rho_{CF,ACC}$ is the correlation between CF and ACC. A change of earnings variance could be caused by a change in any of the three components: cash flow volatility, accrual volatility, or $\rho_{CF,ACC}$. Earnings quality measures the degree of correlation between cash flow and accruals, or captures $\rho_{CF,ACC}$ in the above decomposition. This however, does not preclude the other two variables from contributing to the trend in earnings volatility.

Based on this decomposition, we show that the trend in earnings volatility is strongly associated with changes in cash flow volatility in a large sample of quarterly firm data over the period, 1978 to 2006. We illustrate that the trend in earnings volatility is similar in magnitude to that of cash flow volatility but much stronger than the trend in accrual volatility. Furthermore, both the marginal contribution and overall contribution of the cash flow volatility trend to the earnings volatility trend dominate those of accrual volatility and those of correlation. Our results are robust to controls of firm characteristics such as size and market-to-book and leverage.

We find that the increase in earnings volatility is related to increasing volatility in firm operating activities. With accrual accounting, higher operating volatility forces the firm to report more volatile earnings, as it is infeasible to smooth cash flow fluctuations and shift them to accruals. At the same time, firms respond to increasing operating volatility operating with larger efforts in accrual recognition, which results in a growing accrual volatility. However, the effort devoted to income smoothing through accrual management is not sufficient to offset the volatility in cash flows. As a result, the correlation between accruals and cash flow becomes less negative. Therefore, we argue that management opportunism and operating volatility both lead to increasing earnings volatility. However, temporally, operating volatility dominates managerial opportunism in contributing to the trend in earnings volatility.

We further show that the trend in earnings quality reported by DD relies almost exclusively on the correlation between accruals and cash flow but not on cash flow volatility. We illustrate this by simulating the cash flow and change in working capital series based on the parameters calibrated from empirical data. In regressions of simulated data that vary along three dimensions, namely, increasing cash flow volatility, relatively stable volatility in working capital accruals and decreasing correlation between accruals and cash flow, the DD-measure shows a decreasing trend only when the correlation between accruals and cash flow decreases. We conclude that decreasing earnings quality as measured by DD is neither caused by increasing earnings volatility nor does it serve as a leading factor for increasing earnings volatility. Based on our results, we believe that a correct way to interpret the DD measure is to focus on its original meaning—the correlation between cash flow and accruals. This finding is consistent with Wysocki (2005), where the author also stresses that the DD measure is driven by the negative correlation between accruals and cash flow. Finally, we show that both earnings volatility trend and earnings quality trend coexist in explaining the trend in idiosyncratic return volatility. This suggests that both financial reporting quality and the economic environment affect idiosyncratic volatility.

In sum, this paper contributes to the literature in a number of ways. First, we identify the drivers for the trend in earnings volatility. While a few papers have separately identified the trend either in earnings or cash flow volatilities, this paper brings these strands of literature together. Our main finding is that cash flow volatility is the primary but not the only driver for earnings volatility. We also document the role of management opportunism in contributing to the earnings volatility trend. Second, we find that earnings quality, financial reporting volatility, and cash flow volatility coexist in explaining idiosyncratic stock return volatility. Our results highlight the roles of both operating volatility (economic forces) and financial reporting quality (managerial opportunism) in explaining earnings volatility and idiosyncratic return volatility, with economic forces dominating managerial opportunism.

This study features several novelties in the research methodology. First, we use quarterly data to increase the frequency for volatility estimation. Prior studies typically rely on annual data for volatility estimation, which constrains the number of observations across the time-series. Using quarterly data greatly enlarges the time-series observations and is suitable for our trend studies in volatility. In order to document trends, we match fiscal quarters with calendar time. Second, to address the seasonality problem in the quarterly data, we employ the X11 procedure of the US Census Bureau. The X11 deseasonalization is widely used in economics but has not yet gained much attention in accounting and finance. Finally, we use simulation techniques to examine the drivers contributing to the trend in earnings quality.

The rest of the paper is organized as follows. Section II provides a brief review of the literature and research design. Section III describes our sample and deseasonalization technique. Section IV examines the earnings volatility trend and its determinants. Section V discusses the earnings quality trend and the role of the contemporaneous correlation between cash flow and accruals in deciding the earnings quality trend. Section VI investigates the causes for the idiosyncratic return volatility trend, Section VII presents some robustness results and Section VIII concludes.

II. A Review of the Literature and a Description of the Research Design

Campbell et al. (2001) find that the level of firm-specific stock return volatility has been increasing over the period from 1962 to 1997 in the US. Their findings are confirmed by Morck, Yeung and Yu (2000), who show that the ratio of idiosyncratic return risk to systematic risk has surged over time. These findings indicate that investment portfolios may not always have been fully diversified and that the risk-reward relationship tends to be weakened. In fact, Ang et al. (2006) show that idiosyncratic volatility is negatively correlated with future stock returns, a puzzling result given the traditional wisdom of a positive risk-return tradeoff.

Two recent papers endeavor to uncover the causes for the trend in return volatility. Wei and Zhang (2006) link the rising return volatility to firm fundamentals. They document a positive association between return volatility and earnings volatility, arguing that this is consistent with the notion that stock return volatility is naturally driven by uncertainty about future profits. Moving a step further, Irvine and Pontiff (2005) attribute the Wei and Zhang (2006) results to rising fundamental cash flow shocks from product market competition. A recent paper by Rajgopal and Venkatachalam (2006) provides evidence that the increase in return volatility is related to the deterioration in earnings quality, which is affected by firm's accounting choices.

One primary earnings quality measure employed in Rajgopal and Venkatachalam (2006) is the Dechow and Dichev (2002) accrual quality measure (the DD measure). While, Dechow and Dichev (2002) show that the DD measure is highly correlated with earnings volatility, Wysocki (2005) argues that the DD measure is primarily driven by the contemporaneous correlation between cash flow and accruals. Given the relation between earnings quality and earnings volatility, it is necessary to differentiate the contribution of earnings volatility and earnings quality to return volatility so as to distinguish between the findings of Wei and Zhang (2006) from Rajgopal and Venkatachalam (2006).

In order to make the above distinction, we decompose earnings as the sum of cash flow and accruals:

$$E = CF + ACC,$$

where E is earnings, CF is cash flow, and ACC is accruals. The decomposition of earnings into pre-managed economic earnings and the remaining noneconomic earnings is motivated in part by the previous literature that documents a pervasive use of income smoothing techniques in financial reporting (Subramanyam, 1996, and Graham et al. 2005). Following the prior literature (e.g. Francis et al. 2004, and Irvine and Pontiff, 2005), we use operating cash flow as a proxy for pre-managed economic earnings because it is less prone to management manipulation. Taking the variance of both sides, we have

$$Var(E) = Var(CF) + Var(ACC) + 2\rho_{CF,ACC}\sqrt{Var(CF)}\sqrt{Var(ACC)}.$$

Therefore, there are three components to earnings volatility: earnings volatility, cash flow volatility and the contemporaneous correlation between cash flows and accruals. Following the literature, we use standard deviation to proxy for volatility. Denote $\sqrt{Var(E)}, \sqrt{Var(CF)}, \sqrt{Var(ACC)}$ as EV, CFV and $ACCV$ respectively. If as suggested in Brown (2001), managers have been able to meet earnings targets more frequently in more recent years during 1984 to 1999, earnings volatility will not increase over time unless the volatility of economic earnings has increased to an extent that cannot be offset by the recognition of income-smoothing accruals.

We interpret CFV as operating volatility or economic volatility from firms' economic activities. We interpret $ACCV$ as firms' financial reporting volatility, as higher variability in accruals implies more shifts in timing between earnings and actual cash flows. The interpretation of $\rho_{CF,ACC}$ is a subject of debate. An empirical regularity is that $\rho_{CF,ACC}$ is negative (see, e.g., Dechow, 1994). The negative correlation tends to arise from the smoothing of income. The debate focuses on the motive of income smoothing that causes $\rho_{CF,ACC}$. Dechow (1994) and Dechow, Kothari and Watts (1998) argue that the correlation reflects the smoothing of temporary cash flow components and is indicative of improved earnings quality. On the other hand, the correlation could be due to managerial opportunism in managing accruals and is indicative of deteriorated earnings quality (see, e.g., Myers and Skinner (2002) and Leuz, Nanda and Wysocki (2003)). Regardless of the motive, there is consensus that $\rho_{CF,ACC}$ is a measure for earnings management. We interpret $\rho_{CF,ACC}$ as the degree of earnings management—firms that manage earnings tend to have accruals negatively correlated with cash flow. Together, $ACCV$ and $\rho_{CF,ACC}$ are treated as accounting (or financial reporting volatility) components of earnings volatility. We therefore decompose earnings volatility into economic volatility and financial reporting volatility and investigate the contribution of each component. A larger $ACCV$ or a less negative $\rho_{CF,ACC}$ indicates higher financial reporting volatility.

However the earnings volatility decomposition is not sufficient to differentiate earnings volatility from earnings quality. Since the DD earnings quality is the standard deviation of the residuals from a regression of accruals on past, contemporaneous and future cash flows, we simulate accruals and cash flow series to gauge the link between accrual volatility, cash flow volatility and earnings quality. Wysocki (2005) argues that the DD earnings quality measure is primarily driven by the negative correlation between cash flow and accruals and reflects opportunistic earnings smoothing by the management. We arrive at the similar conclusion—we find that the trend in the DD measure is predominantly driven by the trend in $\rho_{CF,ACC}$ but not the trends in other components of earnings volatility. Thus, despite the close correlation between earnings volatility and the DD measure, the trend in the DD measure is related to the trend in only one component in earnings volatility, but not to the general earnings volatility trend.

Establishing that the DD measure captures the financial reporting uncertainty but not the economic volatility of firms enables us to study the simultaneous impacts of earnings quality and earnings volatility on return volatility. Our central hypothesis in the paper is therefore that the trend in return volatility is collectively caused by the trends in earnings volatility (and some of its components) and in earnings quality. The rest of the paper evolves from this central hypothesis.

III. Sample Description

III.A. Sample Selection and Deseasonalization

Our sample covers nearly three decades of data relating to all NYSE/NASDAQ/AMEX listed firms during the time period between January 1978 and December 2006. All our accounting variables are from the Compustat quarterly tape, and the return variables are from CRSP. The fiscal quarterly accounting variables are converted to calendar time and matched to monthly return observations to create a panel data set at a monthly frequency. Consistent with prior studies, we remove financial firms (SIC 6000-6999) and utility firms (SIC 4900-4949) since these firms are regulated.

Following the literature (e.g., Wei and Zhang, 2006, and Francis et al., 2005), we use the standard deviation of a variable estimated over a rolling window to proxy for its volatility. Specifically, we define earnings volatility (*EV*) as the standard deviation of the ratio of earnings before extraordinary items to assets over the past 12 quarters. The estimation window of 12 quarters is also used in Wei and Zhang (2006).[1] Cash flow volatility (*CF*V), accrual volatility (*ACCV*) and sales volatility (*SALESV*) are defined analogously. These volatility input measures are available for a large number of firms in Compustat from 1978 onwards. Since cash flow reporting is required by the SEC only after 1988 (ten years after the start of our sample period), we do not use this reported measure but calculate cash flow as the sum of earnings, depreciation, and change in working capital, where working capital is defined as per Richardson et al. (2005). Accruals are defined as earnings minus cash flow. We provide the description of these and other variables in Appendix 1.

We use quarterly data to increase the frequency of observations. However, quarterly operating variables such as earnings and cash flow display strong seasonality. We illustrate seasonality in the raw data using earnings as an example. To determine seasonality, we run the regression of current quarter earnings on earnings of the previous four quarters for each firm. In our final sample of 6,074 firms, 2,346 firms, or 38.6% display significantly positive autocorrelation in quarterly earnings at the 5% significance level. In comparison, 70.2% of firms in the Compustat population (23,583 firms) have a significant fourth lag autocorrelation in quarterly earnings. The seasonality in earnings also holds true for the ratio of earnings to assets (ROA). Given the presence of seasonality, estimating standard deviation using non-seasonalized series would produce estimates that are biased upward.

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[1] Our results are robust to estimation windows of 16 and 20 quarters.

We adopt the X11 procedure developed by the U.S. Bureau of Census to deseasonalize the following four operating series for every firm: earnings, cash flow, change in working capital, and sales. Developed in 1953, the X11 procedure has been used extensively in economics as a deseasonalization tool. In accounting, Brochet, Nam and Ronen (2007) also use the X11 procedure to deseasonalize quarterly cash and accruals.[2] After the deseasonalization, the number of firms in our sample with significantly positive fourth-lag autocorrelation reduces to 1,545, or to 25.3% of the sample.

Table I provides a detailed description of our sample selection. The implementation of the X11 procedure requires at least 12 consecutive observations and that observations are non-missing over time. To meet these requirements, we restrict the sample to firms that have consecutive observations in earnings, cash flow, change in working capital, and sales over their lifetime on Compustat and further remove firms that fail to meet the 12 consecutive observations threshold. In order to carry out time-series analysis, we expand the quarterly observations to monthly observations. Our final sample consists of 271,913 firm-month observations.

[Insert Table I about here.]

III.B. Summary Statistics and Correlation

In Panel A, Table II, we report the summary statistics for *EV*, *CFV*, *ACCV*, and $\rho_{CF,ACC}$ – the correlation between cash flow and accruals for all firm-months during the sample period. All volatility measures have been winsorized at the 0.5 and 99.5% percentiles. In Panel B, we report the correlation among *EV*, *CFV* and *ACCV*. The mean

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[2] We use the built-in X11 procedure of the SAS® software. Brochet, Nam and Ronen (2007) provide a brief introduction to the X11 procedure.

of the cash flow volatility and the mean of accruals volatility are greater than that of the earnings volatility. The correlations between *CFV* and *EV*, and between *CFV* and *ACCV* are high, whereas the correlation between *EV* and *ACCV* is much smaller. These correlations suggest that *EV* is more closely related to *CFV* than to *ACCV*.

[Insert Table II about here.]

IV. Trend in Earnings Volatility and Its Determinants

In this section, we show that earnings volatility and its components have been increasing over the past three decades. We then investigate the determinants for earnings volatility and its trend.

IV.A. Graphical Analysis of the Trend

Panel (a) of Figure 1 plots the simple cross sectional mean of *EV, CFV*, and *ACCV* over time, denoted as $\overline{EV}$, $\overline{CFV}$, and $\overline{ACCV}$ respectively. In the remainder of the paper, we use the "bar" notation for mean. We observe a steady increase in these series before 2002, with a short period of decrease in the late 1980s and followed by a decline after 2002. This pattern is comparable to the findings of Brandt et al. (2005) for idiosyncratic return volatility and to the findings of Wei and Zhang (2006) for earnings volatility. Among the three series, $\overline{CFV}$ is always larger than $\overline{EV}$, but their trends match each other almost perfectly. The upward trend in $\overline{ACCV}$ is only modest. As a result, although $\overline{ACCV}$ started out almost as large as $\overline{CFV}$ at the beginning of the sample period, it becomes smaller than $\overline{EV}$ in the early 2000s. The difference in the trends between $\overline{CFV}$ and

$\overline{ACCV}$ suggests that the correlation between cash flow and accruals is trending down. This is indeed the case, as shown in Panel (b), Figure 1, where the time series of the simple cross sectional mean of $\rho_{CF,ACC}$ is plotted. We observe that the trend of $\overline{\rho_{CF,ACC}}$ is almost similar to the trend of $\overline{CFV}$ and $\overline{EV}$: The negative correlation decreases until 2002, with short periods of reversal in the late 1980s and after 2002. Overall, $\overline{\rho_{CF,ACC}}$ decreases from over –0.90 in the early 1980s to –0.76 in 2002.

[Insert Figure 1 about here.]

IV.B. Regression Analysis of the Trend

Figure 1 shows the average trend. To formally establish the trend for the entire sample, we run pooled regressions of earnings volatility and its components on a time trend variable. We run two specifications of regressions, one for the pooled sample, and the other by industry. The regression equations are:

$$Variable_{i,t} = \alpha + \beta \times t + \varepsilon_{i,t}$$

$$Variable_{i,j,t} = \alpha_j + \beta_j \times t + \varepsilon_{i,j,t,} \qquad (1)$$

where *i* indexes the firm, *j* indexes the industry, *t* indexes the time, and ε is the residual. Time, *t* runs from 1978:01, which is recorded as 1, to 2006:12, recorded as 348. We select the five industries defined by Kenneth French, namely consumer products and services, manufacturing, high-tech, health care, and others.[3] We test the trend of the following five variables: *EV*, *CFV*, *ACCV*, $\rho_{CF,ACC}$, and *CWCV*, where *CWCV* is the volatility in change in working capital, defined analogously as CF*V*. By definition, the difference between

[3] The industry definition is available at Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

change in working capital and accruals is depreciation. As such, change in working capital can be treated as operating accruals. Table III reports the results from regressions (1).

[Insert Table III about here.]

Panel A of Table III reports the full sample results. We observe that all these series are significantly upward trending. Since the scalar used to calculate *EV, CFV, ACCV* and *CWCV* is the same (assets), if we assume that over the long term, these series differ only in their mean, their trends are comparable to each other. From Panel A, we observe that the trend in *EV* is the steepest, and it is similar to the *CFV* trend at around 1×10^{-4}. The trends in *ACCV* and *CWCV* are similar and are much smaller than those of *EV* and *CFV*. Notice that the trend in *ACCV* is higher than the trend in *CWCV*, confirming the traditional wisdom that operating accruals are less volatile than total accruals. The trend in $\rho_{CF,ACC}$ is large in magnitude with an estimate of 4.94×10^{-4}. At the beginning of our sample period (1978:01), $\rho_{CF,ACC}$ started at -0.948. The estimated trend in $\rho_{CF,ACC}$ predicts that $\rho_{CF,ACC}$ at the end of the sample period (2006:12) would be -0.776, which is roughly the same as the realized value of -0.788. These trend analyses indicate that over the past three decades, earnings and cash flow became more volatile, and cash flow and accruals became less correlated.

The above patterns extend to the five industries, as shown in Panel B: For each industry, *EV* and *CFV* increase at a rate higher than *ACCV* and *CWCV*, and the correlation between accruals and cash flow becomes less negative. The only exception is the manufacturing sector that has downward trending *ACCV* and *CWCV*. Note that there are significant industry differences. In particular, high-tech and health care industries experience much higher trending in these variables than the other industries.

We next test whether the trend is statistically different across *EV*, *CFV* and *ACCV.* To accomplish this, we run multivariate tests. We test the following three null hypotheses: (1) *EV*, *CF*V and *ACC*V have the same trend; (2) the trend in *E*V is equal to the trend in *CFV*; and (3) the trend in *CFV* is equal to the trend in *ACCV*. For the first test, we run a two-sided test and report the associated F statistics. For hypotheses (2) and (3), we run one-sided tests and report the associated *t*-statistics. The test statistics are reported in the bottom of Panel A, Table III. All three null hypotheses are strongly rejected at the 1% significance level. The one-sided test results suggest that the trend in *EV* is greater than that of *CFV*, which is in turn greater than that of *ACCV*. Results of the tests by industry are similar and are not reported.

IV.C. Determinants for Earnings Volatility

We now explore the determinants of earnings volatility. Earlier we decomposed *EV* into *CFV*, *ACCV* and $\rho_{CF,ACC}$. Instead of relying on the mathematical equivalence that earnings variance equal to the variance of the sum of cash flow and accruals, we are interested in the size of contribution of *CFV*, *ACCV* and $\rho_{CF,ACC}$ to *EV*. To fully understand their contributions, we need to control for other elements that affect earnings volatility. We argue that aside from *CFV*, *ACCV* and $\rho_{CF,ACC}$, other factors that impact earnings variability include sales variability, growth opportunities, degree of leverage, and macro economic conditions. The choice of these variables are based on Wei and

Zhang (2006), where the authors use age, size, book-to-market and leverage as control variables to explain changing return volatility.

The hypothetical sign of each of these control variables on earnings volatility is discussed below. Sales variability can be thought as another proxy for fluctuations in operating activities and is positively associated with earnings volatility. We use age, market capitalization, and market-to-book to proxy for growth opportunities. Pastor and Veronesi (2002) argue that younger firms tend to have more growth potentials and therefore higher future uncertainty in earnings. By the same argument, smaller firms tend to have higher growth opportunities and thus higher earnings volatility. Market to book is another proxy for growth opportunities frequently used in the literature (e.g., Gaver and Gaver, 1993). Higher market-to-book ratio implies more growth opportunities and therefore higher earnings volatility. Leverage increases the equity beta and therefore earnings volatility. We use the real GDP growth rate to capture the macroeconomic condition. French, Schwert and Stambaugh (1987) show that stock return volatility increases in bad markets. We expect earnings volatility responds asymmetrically to GDP growth in a similar manner. Finally, we use industry dummy variables to capture the potential industry differences in volatility trends documented in Table III.

The full model for earnings volatility is therefore:

$$EV_{i,t} = \alpha + \beta_1 CFV_{i,t} + \beta_2 ACCV_{i,t} + \beta_3 \rho_{CF,ACC_{i,t}} + \eta_1 SALESV_{i,t} + \eta_2 AGE_{i,t} + \eta_3 SIZE_{i,t} + \eta_4 MB_{i,t} + \eta_5 LEVERAGE_{i,t} + \eta_6 RGDPG_t + \sum_{j=2}^{5} \gamma_j D_{i,j,t} + \varepsilon_{i,t}, \quad (2)$$

where age (AGE) is measured as the logarithm of the number of months a firm has been in CRSP, size ($SIZE$) as the logarithm of the market value of equity at the beginning of the month, market to book equity (MB) as the beginning of the month market equity to the end of the month book equity, leverage (*LEVERAGE*) as the long-term debt to book value of assets, *RGDPG* is the annual real GDP growth rate, and $D_{i,j,t}$ is a dummy variable that equals 1 if firm *i* is in industry *j* at month *t* and zero otherwise. Table IV presents the results for the following four specifications of the above equation: (1) using only the main variables (*CFV*, *ACCV* and $\rho_{CF,ACC}$) as the independent variables, (2) using both the main and control variables (*SALESV, AGE, SIZE, MB, LEVERAGE, RGDPG*), (3) adding industry dummies to specification (2), and (4) re-estimating specification (3) using the standard cross sectional regression approach first advocated by Fama and MacBeth (1973). Note that in specification (4), *RGDPG* is no longer suitable as an independent variable since it has no monthly variation across firms.

[Insert Table IV about here.]

The most telling result across all of the specifications from Table IV is that *EV* is positively associated with *CFV* and $\rho_{CF,ACC}$, and negatively associated with *ACCV*. Recall that our primary interpretation for *CFV* is operating volatility, for *ACCV* is reporting volatility, and for $\rho_{CF,ACC}$ is earnings management. The coefficient on *CFV* is positive and close to one, which means that a one-unit increase in operating volatility is almost fully reflected in reported earnings volatility. After controlling for operating volatility and the correlation between cash flow and accruals, reported earnings volatility is negatively related to *ACCV*, indicating that earnings volatility is dampened by financial reporting volatility. A higher degree of earnings management means a more negative correlation between cash flows and accruals and leads to less volatile earnings. This relationship is verified by the positive coefficient on $\rho_{CF,ACC}$.

Among the control variables, the coefficients for *SALESV*, *LEVERAGE* and *MB* are positive and the coefficient for *RGDPG* is negative, as expected. We note that the signs for *SIZE* and *AGE* are often positive in these specifications. A further examination reveals that the signs for *SIZE* and *AGE* are indeed negative if the "main" variables are excluded. The results presented in Table IV suggest that the size and age effects are reversed after controlling for the earnings volatility components.

Table IV shows that *CFV*, *ACCV* and $\rho_{CF,ACC}$ all contribute significantly to earnings volatility. However, from the regression results we cannot tell which component is the most significant contributor. In particular, there are two questions. (1), If *ACCV* dampens *EV* while *CFV* increases *EV*, would their combined marginal effects cancel each other? And (2), how do we rank the overall contribution of the three components? To answer question (1), we run an F-test of the null hypothesis that $|\hat{\beta}_1| = |\hat{\beta}_2|$. To answer question (2), we compare the values of $|\hat{\beta}_1 \times \overline{CFV}|$, $|\hat{\beta}_2 \times \overline{ACCV}|$, and $|\hat{\beta}_3 \times \overline{\rho_{CF,ACC}}|$ in one-sided tests, where $\overline{CFV}$ is the sample mean of CFV as shown in Table II, and analogously for $\overline{ACCV}$ and $\overline{\rho_{CF,ACC}}$. $\hat{\beta}_1 \times \overline{CFV}$ can be thought of as the overall contribution of cash flow volatility to earnings volatility, with similar interpretations for $\hat{\beta}_2 \times \overline{ACCV}$ and $\hat{\beta}_3 \times \overline{\rho_{CF,ACC}}$.

We test the above hypotheses within specification (3). Using other specifications would yield the same conclusions. The F-statistics for $|\hat{\beta}_1| = |\hat{\beta}_2|$ is 171,071, strongly reject the null hypothesis that the marginal effect of *ACCV* cancels out the marginal effect of *CFV*. In the horse race of the overall effect, note that since

$\left|\hat{\beta}_1 \times \overline{CFV}\right| > \left|\hat{\beta}_3 \times \overline{\rho_{CF,ACC}}\right| > \left|\hat{\beta}_2 \times \overline{ACCV}\right|$, we need only to do two one-sided tests that $\left|\hat{\beta}_1 \times \overline{CFV}\right| = \left|\hat{\beta}_3 \times \overline{\rho_{CF,ACC}}\right|$ and $\left|\hat{\beta}_3 \times \overline{\rho_{CF,ACC}}\right| = \left|\hat{\beta}_2 \times \overline{ACCV}\right|$. The two one-sided tests have Z-statistics of 65.2 and 133.7 respectively, again strongly rejecting the nulls.[4] We conclude that in ranking the contribution to earnings volatility, *CFV* makes the most significant contribution, followed by $\rho_{CF,ACC}$ and *ACCV* in that order. In sum, our regression results indicate that earnings volatility is primarily driven by firms' operating volatility.

IV.D. Association between the EV Trend and the CFV, ACCV and $\rho_{CF,ACC}$ Trends

We have examined the overall contribution of each component to *EV* and our findings indicate that *CFV* is the most significant source of contribution in the full sample. We now examine whether the trend in *EV* is most significantly affected by the trend in *CFV*. We use two methods to establish the association between the *EV* trend and the trends in its components. In the first method, we examine the time-series of the responsiveness of each *EV* component to the formation of *EV*. In the second method, we adopt a time-series test as in Wei and Zhang (2006). We illustrate both methods in detail below.

We first examine the time-series trend of the coefficients in the cross sectional regression specification of Equation (2) (Specification, 4). We focus on the monthly time series of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$, namely the loadings of *CFV*, *ACCV* and $\rho_{CF,ACC}$ on *EV*

[4] The Z-statistics are from the Wald tests for the corresponding two-sided tests, which have a chi square distribution. Since both the null hypotheses have a degree of freedom of one, the square root of the chi statistics follows a standard normal distribution. The one-sided tests can therefore be based on the square root of the chi statistics, or the Z statistics.

respectively. These time series can be interpreted as the responsiveness of the *EV* components to the formation of *EV* after controlling for the other variables.

Figure 2 plots these monthly series, as well as their fitted trend against the time variable, *t*. We observe the three series all show an increasing trend. Since $\hat{\beta}_1$ and $\hat{\beta}_3$ are increasing in magnitude and $\hat{\beta}_2$ is decreasing in magnitude, these trends imply that over time, *EV* is more responsive to changes in *CFV* and $\rho_{CF,ACC}$ but less sensitive to changes in *ACCV*. Furthermore, compared to the loadings of *ACCV* and $\rho_{CF,ACC}$, the loading of *CFV* increases the most over time: the trend estimate for the *CFV* loading is substantially larger than either the loading of *ACCV* or $\rho_{CF,ACC}$. In untabulated regressions, we test the difference of the trends among these loadings. The test statistics reveals that the trend in the loading of *CFV* is statistically larger than the trend in the loadings of *ACCV* and $\rho_{CF,ACC}$. these results suggest that the trend in *CFV* is the most important factor for the trend in *EV*.

[Insert Figure 2 about here.]

One drawback of the above method is that the differences in values among *CFV*, *EV* and $\rho_{CF,ACC}$ may make the direct comparison of their loadings difficult, since the scale on which these loadings are based is different. We therefore augment the first method by the time-series test in Wei and Zhang (2006). In the time series test, we test the following regression:

$$\overline{EV}_t = \alpha + \beta_o t + \beta_1 \overline{CFV}_t + \beta_2 \overline{ACCV}_t + \beta_3 \overline{\rho_{CF,ACC_t}} + \eta_1 \overline{SALESV}_t + \eta_2 \overline{AGE}_t + \eta_3 \overline{SIZE}_t + \eta_4 \overline{MB}_t + \eta_5 \overline{LEVERAGE}_t + \eta_6 RGDPG_t + \varepsilon_t, \quad (3)$$

where $\overline{EV_t}$ is the cross sectional average of EV at month t, and analogously for other variables. If $\overline{EV_t}$ shows a trend, it should be picked up by t (as shown in Regression (1)). Furthermore, if there exists some other trending variable that explains the $\overline{EV_t}$ trend, the loading of t will be attenuated by this trending variable. If a variable has no trend, then it should not have any explanatory power on $\overline{EV_t}$ and therefore no effect on the coefficient estimate of t.

Table V presents the results. In "Regression 1", we present the raw time trend of $\overline{EV_t}$. Consistent with Table III, $\overline{EV_t}$ is increasing over time. The estimates on t are greatly reduced when we controlled from other trending variables. In "Regression 2", we control for the EV components. We observe that the coefficient estimate on t is reduced from 0.976×10^{-4} in Regression 1 to 0.151×10^{-4}, a reduction of about 85%. At the same time, the adjusted R^2 improves to almost 100%. A further control of other variables renders the estimate on t insignificant, as shown in "Regression 2". These results indicate that the trend in EV can be explained by the contemporaneous trends in its components: *CFV, ACCV*, and $\rho_{CF,ACC}$. Consistent with Table IV, $\overline{CFV_t}$ contributes positively and $\overline{ACCV_t}$ contributes negatively to $\overline{EV_t}$. The rankings of the marginal contribution and overall contribution are similar to those of Table IV. Again, these results suggest that the *CFV* trend is the most important contributor to the *EV* trend.

[Insert Table V about here.]

V. The Trend in Earnings Quality and Earnings Volatility

This section describes the trend in earnings quality and investigates its causes. Our primary focus is on the Dechow and Dichev (2002) earnings quality measure since it is closely related to earnings volatility.

V.A. Trend in the Dechow and Dichev (2002) Earnings Quality Measure

Based on quarterly data, the Dechow and Dichev (2002) measure of accrual quality is the standard deviation of residual from the following regression:

$$CWC_{i,q} = \alpha + \beta_1 CF_{i,a-1} + \beta_2 CF_{i,q} + \beta_3 CF_{i,q+1} + \varepsilon_{i,q} \qquad (3)$$

where q indexes quarter and all variables are deflated by assets and *CWC* is change in working capital. he essence of Equation (3) is to measure the degree of matching between operating accruals and lagged, contemporaneous, and lead cash flows. The greater is the residual noise, the poorer is the matching and hence the earnings quality. Using total accruals (ACC) instead of CWC and annual data in the above equation, Rajgopal and Venkatachalam (2006) show that earnings quality is deteriorating over time. To match Rajgopal and Venkatachalam (2006)'s findings, we first examine the earnings quality trend in our quarterly data. To show the trend of earnings quality, we estimate the standard deviation of $\varepsilon_{i,q}$ for each firm using a rolling window of the past twelve quarters.

We run the above regression in three ways. In the first method, we follow Dechow and Dichev (2002) to run a regression for each firm based on our full sample data. This is Dechow and Dichev's (2002) primary earnings quality measure. We call this earnings quality measure the "DD-Individual" measure. In the second method, we follow

Rajgopal and Venkatachalam (2006) to run a pooled regression for the full sample. We call this earnings quality measure the "DD-Pooled" measure. In both methods, we rely on future information to calculate the rolling residual standard deviation, since the coefficient estimates (and therefore the derived residuals) are based on full sample data. We account for this look-ahead bias in the third method, where we estimate a pooled regression of Equation (3) using only data from a rolling window of past 12 quarters. We call this earnings quality measure the "DD-Rolling" measure. To match the previous decomposition of earnings to cash flow and accruals, we also replace CWC in Equation (3) with ACC and repeat the tests. As in previous sections, in order to show trends, the quarterly earnings quality measures are then expanded into monthly series.

We confirm the earnings quality trend documented in Rajgopal and Venkatachalam (2006). Figure 3 plots the DD measures. Panel (a) shows the trends in the DD measures when CWC is used as the dependent variable and Panel (b) shows the trend in the DD measures when ACC is used as the dependent variable. We observe the upward trends in all of the DD measures. Furthermore, these earnings quality trends are similar to both CFV and EV trends. In untabulated regressions, we also regress these earnings quality measures on time. There is strong upward trend in the DD measures. In a nutshell, the evidence suggests the deterioration of earning quality over time, as measured by the DD earnings quality measure. Since using *ACC* or *CWC* as the dependent variable and the three earnings quality measures yields identical earnings quality trends, to be consistent with previous sections, in the remainder of the paper we focus on the *ACC*-based DD-Pooled measure only.

[Insert Figure 3 about here.]

V.B. Causes for the Deteriorating Earnings Quality

DD shows that EV is highly correlated with earnings quality at 0.82 for their sample period of 1987-1999 using annual data. In our sample of quarterly data during 1978-2006, the correlation between EV and DD-Individual is 0.52. By way of comparison, we find that the correlation between CFV and DD-Individual is much higher at 0.87. This raises the following question: What causes the trend in earnings quality? More specifically, is the trend in CFV responsible for the trend in earnings quality? Answering these questions enables us to differentiate earnings quality from earnings volatility and therefore differentiate Wei and Zhang (2006) and Rajgopal and Venkatachalam (2006).

We address the above questions through simulations. We simulate the trends in *ACCV*, *CFV*, and $\rho_{CF,ACC}$ using the estimated trend parameters shown in Table II. We generate a simulated sample of panel data with 800 firms and 348 months, which is comparable to our regression sample of 271,193 firm-months. In the simulation, *ACC* and *CF* follow a bivariate normal distribution with correlation of $\rho_{CF,ACC}$ and standard deviations of *ACCV* and *CFV* respectively. For simplicity, the bivariate normal distribution is independent across time. Using the simulated data, we run regression for Equation (3) using the monthly frequency data. To investigate the causes for the earnings quality trend, we add the trends in CFV, ACCV, and $\rho_{CF,ACC}$ in a stepwise manner. We study the following four cases: (1) the benchmark case—no trend in CFV, ACCV, and $\rho_{CF,ACC}$; (2) only an increasing trend in CFV; (3) increasing trends in both CFV and *ACCV*, and (4) increasing trends in *CFV* and *ACCV*, and a decreasing trend in $\rho_{CF,ACC}$. Note that case (4) is observed empirically and that the trends in *CFV*, *ACCV*, and $\rho_{CF,ACC}$ are distinct from each other.

Panel A of Table VI presents the regression results of the above four cases. The contemporaneous *CF* is always significant in explaining *ACC*, which is not surprising given the high correlation between the two variables. We notice that when the above volatility trends are added sequentially, the mean DD measure (as measured by DD-Pooled) increases from Case (1) to Case (4). Most notably, there is a significant jump from Case (3) to Case (4), i.e., when the trend of $\rho_{CF,ACC}$ is added. Compared with Case (1), the mean DD measure in Case (4) doubles.

[Insert Table VI about here.]

We show the simulated earnings quality trend of the four cases in Figure 4. We observe that although unconditionally, the mean DD measure increases from Case (1) to Case (4), the increasing trend happens only in Case (4), i.e., only when the trend of $\rho_{CF,ACC}$ is added in the simulation. Economically, this makes sense. Since the DD measure is the goodness of fit between accruals and cash flows, what matters is the correlation between these two variables. If the correlation decreases, the goodness of fit will decrease, resulting in a noisier residual term and hence a larger DD measure.

[Insert Figure 4 about here.]

In order to test for the statistical significance of the trend shown in Figure 4, we break the full simulated data to five sub-periods and run regression of Equation (3) for each subperiod. Panel B of Table VI shows the mean of the DD measure for each subperiod and tests of the difference between the subperiod DD measures across the five subperiods. In terms of magnitude for the DD measure, Case (4) is clearly distinct from the other cases: In each subperiod in Case (4), the DD measure is not only greater than the other cases, but also the upward trend is much greater. The (one-sided) difference tests confirm that the upward trend in Case (4) is stronger than the other cases, in that the t-statistics are much larger. Note that in Cases (1) and (2), there is no statistical trend in the DD measure. In Case (3), there is a statistical trend but the magnitude of upward trending is very small.

In summary, we make the following conclusions from Table VI and Figure 4. First, earnings quality is significantly different from cash flow volatility. Increases in cash flow volatility alone do not cause changes in earnings quality. Second, changes in accrual volatility only contribute marginally to changes in earnings quality. Third, a major contributor to the trend in earnings quality is the trend in correlation between accruals and cash flow. Therefore, to correctly interpret the trend of the DD measure, one should keep in mind the role of $\rho_{CF,ACC}$ .as emphasized by Wysocki (2005).

VI. Why did Individual Stocks Become More Volatile?

This section links our previous findings to stock return volatility. Idiosyncratic stock return volatility has been increasing over the past four decades (e.g., Campbell, Malkiel, Lettau and Xu, 2001, and Morck, Yeung and Yu, 2000). Wei and Zhang (2006) attribute the trend in idiosyncratic return volatility to increasing earnings volatility. In a related paper, Rajgopal and Venkatachalam (2006) relate the trend in return volatility to deteriorating earnings quality. The link between the two arguments however has not been explored. Given the high correlation between earnings quality and earnings volatility documented in Dechow and Dichev (2002), one may wonder whether these two arguments are indeed referring to the same factor. In the previous sections we demonstrate that the main determinants for *EV* is *CFV*, *ACCV*, and $\rho_{CF,ACC}$, and the main driver of the deteriorating earnings quality is decreasing $\rho_{CF,ACC}$. In this section we show that both earnings volatility and earnings quality contribute to idiosyncratic return volatility.

VI.A. Trend in Idiosyncratic Stock Return Volatility

We use two definitions of return volatility: $VRet_{i,t}^{adj}$ ($VRet_{i,t}^{raw}$) is defined as the mean of the past three years' monthly standard deviation of excess (raw) stock returns. Following Campbell et al. (2001) and Wei and Zhang (2006), the monthly standard deviation is measured as the standard deviation of daily stock returns within the month times the square root of trading days within the month. We use the three-year mean to match our horizon for the definition of earnings volatility and its components.

Figure 5 shows the time series of cross sectional mean of idiosyncratic return volatility in our sample firms. We observe that the trend of idiosyncratic return volatility is similar to those documented in these studies. Furthermore, the return volatility trend is by and large similar to *EV*, *CFV* and *DD*: it shows steady increase in the 1980s, a short period of reversal in the late 1980s and early 1990s, and steady decline after 2002. The 1987 market crash introduced a large spike in monthly return volatility but was evened out in the three-year moving average shown in the figure. Observe that the trends in $VRet^{adj}$ and $VRet^{raw}$ are almost identical. In the remainder of the paper we focus only on $VRet^{adj}$.

[Insert Figure 5 about here.]

VI.B. Determinants for Idiosyncratic Return Volatility

We now examine the determinants of idiosyncratic return volatility. We follow Wei and Zhang (2006) in choosing the following control variables: *E* (earnings divided by assets), *Ret* (contemporaneous stock return), *MB* (market to book equity), *AGE*, *SIZE*, and *LEVERAGE*. We run the following regression with the addition of DD-Pooled (*DD*, the earnings quality measure) and earnings volatility or its components to the above regression:

$$V\,Ret_{i,t}^{adj} = \alpha + \eta_1 E_{i,t-1} + \eta_2 Ret_{i,t} + \eta_3 AGE_{i,t} + \eta_4 SIZE_{i,t-1} + \eta_5 MB_{i,t-1} + \eta_6 LEVERAGE_{i,t-1} + \beta_1 DD_{i,t-1} + \beta_2 EV_{i,t-1} + \varepsilon_{i,t}, \qquad (4)$$

In the above equation, when a variable is only available on a quarterly basis (for example, *DD*), the *t-1* subscript refers to the previous quarter instead of previous month.

Wei and Zhang (2006, Table 3) run their primary regression by five subperiods. They show that return volatility is positively associated with return volatility lagged by one period, *Ret,* and negatively associated with *E* across all subperiods. The contemporaneous positive relationship between *Ret* and $V\,Ret^{adj}$ points to a risk-return tradeoff. Their subperiod results on other control variables are not uniform, but generally support a negative association between return volatility and *AGE, SIZE, LEVERAGE*, and a positive association between return volatility and *BM.*

Table VII presents the regression results. In our first specification, we reproduce the Wei and Zhang (2006) results using our sample and pooled OLS regression. In the second specification, we add both *DD* and *EV* to the regression, and find that both earnings volatility and earnings quality are significantly positively related to return volatility. Finally, in the third specification, we split *EV* into its three components, namely

CFV, *ACCV*, and $\rho_{CF,ACC}$ and find that all of the components are significant in explaining return volatility. We also control for industry effects in specification (4), and use the standard cross sectional regression technique in specification (5).

[Insert Table VII about here.]

As before, we interpret *CFV* as firms' operating volatility. The positive loading on *CFV* confirms the point made by Irvine and Pontiff (2005), that the explanatory power of *EV* on return volatility is mainly driven by operating volatilities. We interpret *DD, ACCV,* and $\rho_{CF,ACC}$ as firms' financial reporting choices. DD refers to earnings quality, *ACCV* to income smoothing, and $\rho_{CF,ACC}$ to earnings management. Results in Table VII indicate that firms' financial reporting choice also affect their (idiosyncratic) return volatility. Return volatility is enhanced by poorer earnings quality, and dampened by heavier income smoothing and earnings management. If market participants do not know the true value of economic earnings and rely on reported earnings and cash flows to infer economic earnings, then stock return volatility is related to these financial reporting choices.

A further examination of the results reveals several points that are noteworthy. First, the explanatory power of EV is subsumed by earnings quality. In specification 2, when DD is added, we find that the loading on EV is much smaller (while everything else remains almost the same). Second, when EV is decomposed into CFV, ACCV, and $\rho_{CF,ACC}$, we find that the loading of *DD* is smaller. This is because of the previously discussed relationship between DD and $\rho_{CF,ACC}$, which reduces the explanatory power of DD. Note that although the trend in $\rho_{CF,ACC}$ is responsible for the trend in DD, this is not equivalent to an unconditionally 100% correlation between $\rho_{CF,ACC}$ and DD. In fact, the correlation between DD and $\rho_{CF,ACC}$ is only 24% in our sample. Therefore, in a regression using the pooled sample such as specification 3, we see the effects of DD and $\rho_{CF,ACC}$ side by side.

Finally, we rank the contribution of operating volatility and financial reporting choice elements to idiosyncratic return volatility using the method previously described in Section IV.C. Our ranking is in the order of: DD, CFV, $\rho_{CF,ACC}$ and ACCV.

VI.C. Association of the Trends

As before, we associate the idiosyncratic return volatility trend with both the DD trend and earnings volatility trend in the following regression:

$$\overline{V\mathrm{Re}t_t^{adj}} = \alpha + \beta_0 t + \eta_1 \overline{E_{t-1}} + \eta_2 \overline{\mathrm{Re}t_t} + \eta_3 \overline{AGE_t} + \eta_4 \overline{SIZE_{t-1}} + \eta_5 \overline{BM_{t-1}} + \eta_6 \overline{LEVERAGE_{t-1}} + \beta_1 \overline{DD_{t-1}} + \beta_2 \overline{EV_{t-1}} + \varepsilon_t , \quad (5)$$

where $\overline{V\mathrm{Re}t_t^{adj}}$ is the cross sectional simple average of $VRet^{adj}$ at month t, and similarly for other variables. Table VIII presents the results.

[Insert Table VIII about here.]

The results in Table VIII indicate that the trend in idiosyncratic return volatility is indeed explained by the trend in DD and EV. From "Regression 1", where the only explanatory variable is t, idiosyncratic return volatility is increasing. When DD and EV are added to the regression, most of the trend is explained away, as shown in "Regression 2". Results with EV decomposing to CFV, ACCV and $\rho_{CF,ACC}$ are weaker but still makes the trend less strong (Regressions 3 and 5). Taken as a whole, we find that the idiosyncratic return volatility trend is attributable to both EV and DD trends.

VII. Robustness Tests

VII.A. Decomposition of Earnings into Non-discretionary Earnings and Discretionary Accruals

Our previous results are based on a decomposition of earnings into cash flow and accruals on the basis that cash flow reflects economic operations of the firm. Our cash flow measure is earnings adjusted for accruals. This might raise the question of the degree to which cash flow reflects pre-managed earnings.

Another popular measure for pre-managed earnings is non-discretionary earnings (NDE), that is, earnings adjusted for discretionary accruals (DA). We use the Jones model of Dechow et al. (1995) to calculate DA following the method described in Kothari et al. (2005). In particular, *DA* is the residual from the following regression:

$$ACC_{it} = \beta_0 + \beta_1 \frac{1}{Asset_{i,t-1}} + \beta_2 \Delta(Sales)_{i,t} + \beta_3 PPE_{i,t} + \varepsilon_{it},$$

where *PPE* is property, plants and equipments, and *ACC*, Sales and *PPE* are all scaled by lagged assets. We use quarterly data and run a rolling regression of the past four quarters by industries defined by the first two digits of SIC code to derive *DA*. *NDE* is defined as the difference between earnings and DA. After we calculate DA and NDE, we similarly define $NDEV$ (DAV) as the standard deviation NDE (DA) over the past 12 quarters, and $\rho_{NDE,DA}$ as the contemporaneous correlation between NDE and *DA*.

We note that previous results pertaining to the decomposition of earnings volatility to CFV and ACCV holds. Specifically, (1), the trends the trends in NDEV, DAV, and $\rho_{NDE,DA}$ are almost identical with the trends in CFV, ACCV and $\rho_{CF,ACC}$, (2) the determinants of EV is still primarily driven by NDEV, and (3) DD and NDEV, DAV and

$\rho_{NDE,DA}$ coexist to determine return volatility. To highlight the causes for the trends in earnings and return volatilities, we report the trend analysis results with NDEV in Table IX. The results are highly similar with those in Tables V and VIII.

[Insert Table IX about here.]

VII.B. The Effect of New Listings

Wei and Zhang (2006) argue that the increasing trend in earnings volatility and return volatility are mainly driven by the new listings added to the sample. We find that over our sample period, there has been a steady increase in the number of firms in the entire sample period, suggesting the importance of controlling for new firms effects. There are two possible ways to control for the new firm effects. The first is adopted by Wei and Zhang (2006), who examine incremental volatilities, where a firm's incremental volatility is defined as the volatility over and above the first twelve month average of the firm historical volatility. The advantage of this method is that it keeps the number of observations at a relatively high level. If for the same firm, its volatility increases over time, then the incremental volatility increases as well. However, if the volatility increases previously documented are only due to new firms added to the sample, incremental volatilities will not show similar increases. The second way is to look at a constant sample, where the constant sample is defined as a sample that contains firms covering all or almost all of the sample period. The method has the advantage of being truly free of the new listing effect. The disadvantage is that it may cause a high degree of loss of firms. We choose the first method. However, we can report that our key results are robust to the second method.

Figure 6 shows the trends of cross sectional means of the incremental earnings volatility (IEV), incremental cash flow volatility (ICFV), incremental accruals volatility (IACCV), incremental $\rho_{CF,ACC}$ ($I\rho_{CF,ACC}$), incremental DD-pooled (IDD) measure, and incremental excess return volatility (IVRet).[5] We make several observations. First, the Wei and Zhang (2006) findings are by and large confirmed. We find that although IEV and IVRet are mostly positive throughout our sample period, their trends are much weaker. This suggests that the new firm effect is indeed important in driving the increasing trend of EV. Second, *ICFV, IACCV, IDD* are mostly negative and show a decreasing trend. Finally, and probably the most informative, $I\rho_{CF,ACC}$ is mostly positive until 2004. Recall that $\rho_{CF,ACC}$ is negative. A positive $I\rho_{CF,ACC}$ implies that the correlation between cash flow and accruals declines over time. This explains that IEV remains positive for more than half the time while *ICFV* and *IACCV* are mostly negative. Overall, Figure 6 emphasizes that much of the trends shown previously is due to riskier new listings. After controlling for the new firm effect, Figure 6 suggests that existing firms actually engage in less earnings management, which more than offsets the declines in cash flow volatility and accrual volatility (as evidenced by decreasing ICFV and IACCV) and contributes to a modest increase in earnings volatility.

[Insert Figure 6 about here.]

[5] We choose to present the trends from 1979:01. Note that this does not mean incremental measures are based on the monthly average in 1978. Rather, the benchmark volatility measured as the average of the first twelve months' volatility in the firm's history is subtracted from raw volatility.

In untabulated results, we find that the incremental cash flow volatility and the contemporaneous correlation between incremental cash flow and incremental accruals contribute positively to incremental earnings volatility. Incremental accrual volatility contributes negatively to incremental earnings volatility. The results for idiosyncratic return volatility are similar.

VII.C. Structural Breaks

The visual examination of almost all of our trend figures shows that there is a substantial and persistent decline after 2002. Year 2002 witnesses two major events that could be relevant to this decline: the passage of the Sarbanes-Oxley Act ("SOX") on July 30, 2002 and a significant market drop where the Dow Jones Industrial fell from over 10,000 points in April 2002 to a low of 7,286 on Oct. 8, 2002. To determine the existence of a structural change after 2002, we also separately carry out Chow's structural-break tests for all of our regression analyses. The structural-break results (not reported but available upon request) confirm that a structural break exists in any month between August 2002 and December 2002, generally with August 2002 as the month with the most significant break statistic. This structural break results favor the break point on the SOX adoption date, yet do not rule out the market crash. Proponents of SOX view it as the "the most far-reaching reforms of American business practices since the time of Franklin D. Roosevelt."[6] In a related study, Cohen, Dey, and Lys (2004) argue that there is a substantial drop in both firms' earnings management activities and management opportunism post SOX. In light of this, we break the sample period to the pre- and post-SOX periods. Note that the

[6] Address by President George W. Bush on signing the Sarbanes-Oxley Act, July 30, 2002. The full address is available at http://www.whitehouse.gov/news/releases/2002/07/20020730.html.

post-SOX period includes the post-2002 market crash period. We can report that the trend in *EV* can be explained by the contemporaneous trends in its components: *CFV, ACCV*, and $\rho_{CF,ACC}$ and that the trend in return volatility can be explained by the contemporaneous trends in DD and EV in the pre- and post-SOX periods. Results are available upon request.

VIII. Conclusions

On-going research links rising idiosyncratic return volatility to either firm profit uncertainty or financial reporting uncertainty. For the first approach, Wei and Zhang (2006) find a positive association between idiosyncratic return volatility and earnings volatility, and Irvine and Pontiff (2005) further attribute the Wei and Zhang (2006) findings to cash flow shocks due to economy-wide market competition. For the second approach, Rajgopal and Venkatachalam (2006) relate idiosyncratic return volatility to deteriorating earnings quality. In this paper, we establish a link between earnings volatility and earnings quality, and show that both earnings volatility and earnings quality contribute to the trend in idiosyncratic return volatility.

The motivation to distinguish the Wei and Zhang (2006) approach from the Rajgopal and Venkatachalam (2006) approach comes from Dechow and Dichev (2002) ("DD"), who find a high degree of correlation between their earnings quality measure and earnings volatility. We decompose earnings volatility to three components: cash flow volatility, accruals volatility and the correlation between cash flow and accruals. We show that the trend in the DD earnings quality measure is predominantly driven by the trend in the contemporaneous correlation between cash flow and accruals. The deterioration in earnings quality is consistent with the correlation becoming less negative over time. Thus using the trend in earnings quality to explain the trend in return volatility differs from using the trend in earnings volatility.

We next examine the trend in earnings volatility and its components and find that both cash flow volatility and accruals volatility have been increasing and that the contemporaneous correlation between cash flow and accruals has become less negative. We view cash flow volatility as reflecting the uncertainty in firms' real operating activities, accruals volatility as reflecting firms' absolute financial reporting uncertainty, and the cash flow-accruals correlation as reflecting firms' relative degree of earnings management. The trends in the financial reporting uncertainty and the degree of earnings management, although seemingly at odds with each other, are primarily driven by an under-reaction of accruals to firms' rising operating uncertainties. Higher operating volatility forces firms to respond with greater efforts in accrual recognition to attenuate the volatility of bottom-line earnings. However, the effort devoted to income-smoothing through accrual management is insufficient to fully offset the volatility in cash flow. As a result, the correlation between accruals and cash flow becomes less negative. We view this as a case where economic activities dominate managerial opportunism.

We piece together these elements and find that earnings volatility and earnings quality collectively explain the trend in idiosyncratic return volatility. The trends in cash flow volatility, accruals volatility and earnings quality contribute to the trend in return volatility. The cash flow volatility trend is positively associated with the return volatility trend, reflecting the impacts of firms' economic operations. On the financial reporting side, the return volatility trend is positively associated with the earnings quality trend yet negatively associated with the accrual volatility trend. The deteriorating earnings quality trend comes from a less negative correlation between cash flow and accruals. We view this as firms engage less in opportunistic earnings management. Our results indicate that return volatility is driven by operating volatility and a lower degree of opportunistic earnings management.

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Table I Sample Derivation

Step	Sample Filtering	# of obs.
1	All firm-quarter observations from Compustat (2007 update)	2,216,548
	1.1 Set data36 (cash and short-term investment) and data45 (debt in current liabilities) to zero if missing	
2	Non-missing obs. in earnings and cash flow at the same time	587,499
3	Deseasonalize earnings, cash flow, change in working capital and sales using X11 procedure	217,101
	3.1 Require consecutive observations over the firm lifetime and at least 12 consecutive observations in the above variables	
4	Non-missing obs. in earnings volatility and cash flow volatility at the same time	186,636
	4.1 Require at least 6 observations in estimating earnings and cash flow volatilitie	
5	Remove financials (SIC # 6000-6999) and utilities (SIC # 4900-4949)	155,640
6	Restrict to firms listed in NYSE/AMEX/Nasdaq	104,340
7	Expand to monthly observations & require appearance on CRSP monthly tape	288,717
8	Restrict to calendar time Jan. 1978 to Dec. 2006	271,913
9	Winsorize volatilities of earnings, cash flow and accruals by year at the 0.5 and 99.5 percentiles	271,913

Table II Summary Statistics and Correlations of Earnings Volatility and Its Components

Panel A: Summary Statistics

	N	Mean	Standard deviation	25th percentile	Median	75th percentile
EV	271,913	0.027	0.053	0.005	0.011	0.026
CFV	271,913	0.051	0.061	0.019	0.033	0.057
ACCV	271,913	0.036	0.038	0.016	0.026	0.043
$\rho_{CF,ACC}$	271,883	-0.842	0.251	-0.982	-0.941	-0.821

Panel B: Correlation

	EV	*CFV*	*ACCV*
EV	1		
CFV	0.869***	1	
ACCV	0.440***	0.752***	1

Notes: *EV* = earnings volatility (standard deviation of earnings before extraordinary items/assets over the past 12 quarters), *CFV* = cashflow volatility, *ACCV* = accruals volatility, and $\rho_{CF,ACC}$ = correlation between cash flow and accruals. *EV*, *CFV*, and *ACCV* are winsorized at 0.5% and 99.5% each year. *** indicates significance at the 1% level.

Table III Trend in Earnings Volatility and its Components

Panel A: Full Sample

	EV	*CFV*	*ACCV*	*CWCV*	$\rho_{CF,ACC}$
Intercept	0.005	0.031	0.033	0.033	-0.962
	(17.68)***	(103.41)***	(175.78)***	(183.25)***	(-975.77)***
t/10,000	1.016	0.903	0.163	0.113	4.937
	(93.85)***	(71.54)***	(20.84)***	(14.95)***	(119.08)***
N	271,883	271,883	271,883	271,883	271,883
Adj. R^2	3.1%	1.8%	0.2%	0.1%	5.0%

Tests:	
1. Test that t estimate on CFV, EV, and ACCV is the same (F-stat.)	(4109.26)***
2. Test that t estimate on EV and CFV is the same, one-sided test (T-stat.)	(17.97)***
3. Test that t estimate on CFV and ACCV is the same, one-sided test (T-stat.)	(87.41)***

Panel B: Five Industries

		EV	*CFV*	*ACCV*	*CWCV*	$\rho_{CF,ACC}$
Consumer	Intercept	0.007	0.036	0.034	0.034	-0.971
		(33.81)***	(99.73)***	(118.76)***	(119.29)***	(-817.96)***
	t/10,000	0.305	0.248	0.015	0.006	2.180
		(31.36)***	(15.73)***	(1.16)	(0.49)	(41.56)***
Manufacturing	Intercept	0.011	0.035	0.031	0.031	-0.919
		(46.48)***	(110.93)***	(125.13)***	(124.89)***	(-533.41)***
	t/10,000	0.303	0.124	-0.049	-0.074	2.803
		(27.53)***	(8.59)***	(-4.27)***	(-6.59)***	(35.78)***
High-Tech	Intercept	0.000	0.032	0.038	0.039	-1.011
		(0.28)	(34.04)***	(73.21)***	(80.93)***	(-400.22)***
	t/10,000	1.714	1.476	0.188	0.076	8.092
		(50.99)***	(39.77)***	(9.24)***	(4.07)***	(82.02)***
Health Care	Intercept	0.012	0.042	0.041	0.041	-0.969
		(8.33)***	(26.14)***	(44.19)***	(44.89)***	(-205.16)***
	t/10,000	1.591	1.331	0.101	0.050	8.579
		(28.88)***	(21.54)***	(2.83)***	(1.42)	(46.69)***
Others	Intercept	0.007	0.030	0.030	0.030	-0.917
		(12.48)***	(43.21)***	(62.59)***	(64.51)***	(-367.10)***
	t/10,000	0.600	0.560	0.106	0.079	2.478
		(25.84)***	(19.46)***	(5.18)***	(4.05)***	(23.52)***

Notes: The regression equations for Panels A and B are

$$Variable_{i,t} = \alpha + \beta \times t + \varepsilon_{i,t}, \text{ and } Variable_{i,j,t} = \alpha_j + \beta_j \times t + \varepsilon_{i,j,t},$$

respectively, where *i* indexes firm, *j* indexes industry, *t* indexes time at the monthly frequency, and ε is the residual. *t* runs from 1978:01, which is recorded as 1, to 2006:12, recorded as 348. The independent variables are those in the first row of each panel. *t* or F-statistics are in parenthesis. ***, **, and * ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table IV Determinants of Earnings Volatility

	1	2	3	4
Intercept	0.037	0.031	0.029	0.032
	(286.6)***	(129.9)***	(113.5)***	(78.0)***
CFV	0.952	0.951	0.950	0.886
	(1080.2)***	(1074.6)***	(1065.9)***	(170.6)***
ACCV	-0.535	-0.542	-0.542	-0.562
	(-386.8)***	(-380.8)***	(-380.9)***	(-82.93)***
$\rho_{CF,ACC}$	0.046	0.046	0.046	0.043
	(327.1)***	(327.8)***	(320.8)***	(90.73)***
SALESV		0.032	0.034	0.031
		(40.64)***	(42.60)***	(19.11)***
AGE		0.001	0.001	0.001
		(22.80)***	(23.43)***	(19.82)***
SIZE		0.0003	0.0003	-0.0001
		(14.99)***	(14.43)***	(-4.10)***
LEVERAGE		0.001	0.001	0.001
		(7.19)***	(6.93)***	(4.97)***
MB		0.0000003	0.0000003	0.0002
		(14.22)***	(14.07)***	(10.85)***
RGDPG		-0.014	-0.014	
		(-6.35)***	(-6.54)***	
5-Industry Dummies	No	No	Yes	Yes
N	268,127	268,127	268,127	348 months
Regression Method	Pooled OLS	Pooled OLS	Pooled OLS	Cross-sectional
(Average) Adj. R^2	89.9%	90.0%	90.0%	83.0%

Notes: The regression equation is:

$$EV_{i,t} = \alpha + \beta_1 CFV_{i,t} + \beta_2 ACCV_{i,t} + \beta_3 \rho_{CF,ACC_{i,t}} + \eta_1 SALESV_{i,t} + \eta_2 AGE_{i,t} + \eta_3 SIZE_{i,t} + \eta_4 MB_{i,t}$$

$$+ \eta_5 LEVERAGE_{i,t} + \eta_6 RGDPG_t + \sum_{j=2}^{5} \gamma_j D_{i,j,t} + \varepsilon_{i,t},$$

where *SALESV* = the standard deviation of (sales/assets) over the past 12 quarters, *AGE* = the logarithm of the number of months a firm has been in CRSP, *SIZE* = the logarithm of the market value of equity at the beginning of the month, market to book equity (*MB*) = the beginning of the month market equity to the end of the month book equity, *LEVERAGE* = the long-term debt to book value of assets, *RGDPG* is the annual real GDP growth rate, and $D_{i,j,t}$ is a dummy variable that equals 1 if firm *i* is in industry *j* at month *t* and zero otherwise. *t* statistics are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table V Time-Series Regression of Earnings Volatility on Its Determinants

	1	2	3
Intercept	0.005	-0.020	0.010
	(8.67)***	(-3.89)***	(1.90)**
t/10,000	0.976	0.151	0.011
	(36.15)***	(9.46)***	(0.55)
CFV		1.268	1.061
		(51.06)***	(47.93)***
ACCV		-1.036	-0.893
		(-33.80)***	(-36.60)***
$\rho_{CF,ACC}$		-0.019	0.022
		(-3.59)***	(4.46)***
SALESV			0.180
			(11.26)***
AGE			-0.001
			(-2.25)**
SIZE			0.002
			(9.34)***
LEVERAGE			0.013
			(7.96)***
MB			-0.001
			(-8.35)***
RGDPG			-0.013
			(-8.17)***
N	348	348	348
Adj. R^2	79.0%	99.7%	99.9%

Notes: The regression equation is:

$$\overline{EV}_t = \alpha + \beta_o t + \beta_1 \overline{CFV}_t + \beta_2 \overline{ACCV}_t + \beta_3 \overline{\rho_{CF,ACC_t}} + \eta_1 \overline{SALESV}_t + \eta_2 \overline{AGE}_t + \eta_3 \overline{SIZE}_t + \eta_4 \overline{MB}_t + \eta_5 \overline{LEVERAGE}_t + \eta_6 RGDPG_t + \varepsilon_t ,$$

where $\overline{EV_t}$ is the cross sectional average of *EV* at month *t*, and analogously for other variables. *t* is a time variable ranging from 1978:01 (*t* = 1) to 2006:12 (*t* = 348). *t* statistics are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table VI Estimates and Trends in the Dechow and Dichev (2002) Earnings Quality Measure Using the Simulated Data

Panel A. Parameter estimates from the full sample				
	Case 1	Case 2	Case 3	Case 4
Intercept	0.071	0.058	0.061	0.058
	(1947.1)***	(1798.3)***	(1836.5)***	(1040.8)***
Lagged *CF*	0.000	0.000	0.000	0.001
	(0.53)	(0.81)	(0.78)	(0.78)
CF	-1.013	-0.648	-0.711	-0.638
	(-1856.1)***	(-1513.6)***	(-1635.1)***	(-866.9)***
Lead *CF*	-0.001	0.000	-0.001	-0.001
	(-2.06)**	(-1.00)	(-1.16)	(-1.16)
Mean *DD*	0.009	0.011	0.011	0.018
N	276,798	276,798	276,798	276,798
Adj. R^2	0.926	0.892	0.906	0.731

Panel B. Mean DD value of the five even subperiods				
Subperiod				
Subperiod 1: *DD1*	0.009	0.009	0.009	0.011
2: *DD2*	0.009	0.009	0.009	0.014
3: *DD3*	0.009	0.009	0.010	0.017
4: *DD4*	0.009	0.009	0.010	0.020
5: *DD5*	0.009	0.009	0.010	0.022
T-statistics of the tests, one-sided:				
DD1 = DD2	(0.14)	(1.12)	(-6.93)***	(-58.90)***
DD2 = DD3	(0.06)	(1.00)	(-6.55)***	(-40.85)***
DD3 = DD4	(0.32)	(0.47)	(-6.80)***	(-32.62)***
DD4 = DD5	(-1.11)	(-0.75)	(-8.26)***	(-29.76)***

Notes: We simulate a panel data of 800 firms × 348 periods of two variables: accruals (*ACC*) and cash flow (*CF*). In the simulation, these two variables are jointly normal distributed, with their means being those estimated in Table II, and their standard deviations (*CFV* and *ACCV*), correlation ($\rho_{CF,ACC}$) and time-trends being those estimated in Table III. In case (1), there is no trend in *CFV, ACCV*, and $\rho_{CF,ACC}$. In case (2), only *CFV* has an increasing trend. In case (3), *CFV* and *ACCV* are increasing over time. And in case (4), *CFV* and *ACCV* are increasing over time, and $\rho_{CF,ACC}$ is decreasing over time. To calculate the Dechow and Dichev (2002) earnings quality measure (*DD*), we first estimate the following equation using the full sample (or in Panel B, the sample within a subperiod): $ACC_{i,t} = \alpha + \beta_1 CF_{i,t-1} + \beta_2 CF_{i,t} + \beta_3 CF_{i,t+1} + \varepsilon_{i,t}$. For each firm-period, the *DD* measure is calculated as the rolling standard deviation of the residual for the above regression over the past three years (36 periods in the simulation). *t* statistics are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table VII Determinants of Idiosyncratic Return Volatility

	1	2	3	4
Intercept	0.226	0.211	0.214	0.282
	(254.8)***	(234.7)***	(210.9)***	(33.41)***
E	1.004	0.941	0.910	-0.143
	(116.8)***	(110.2)***	(110.9)***	(-3.85)***
Ret	0.331	0.297	0.285	0.282
	(78.86)***	(71.13)***	(70.8)***	(17.32)***
AGE	-0.017	-0.017	-0.012	-0.007
	(-126)	(-126)	(-93.2)***	(-30.63)***
SIZE	-0.018	-0.017	-0.018	-0.018
	(-298)***	(-274)***	(-294)***	(-55.05)***
LEVERAGE	-0.020	-0.013	0.001	0.002
	(-24.2)***	(-16.5)***	(1.558)	(1.12)
MB	0.096	0.097	0.094	-0.034
	(86.37)***	(87.61)***	(88.46)***	(-0.98)
DD		0.720	0.561	0.367
		(75.07)***	(52.84)***	(15.66)***
EV	0.416	0.315		
	(190.4)***	(124)***		
CFV			0.240	0.446
			(81.63)***	(21.81)***
ACCV			-0.114	-0.291
			(-23.7)***	(-16.37)***
$\rho_{CF,ACC}$			0.034	0.029
			(70.21)***	(44.76)***
5-Industry Dummies	No	No	Yes	Yes
N	251,681	251,681	251,681	345 months
Regression Method	Pooled OLS	Pooled OLS	Pooled OLS	Cross-Sectional
(Average) Adj. R^2	49.8%	50.9%	54.6%	56.1%

Notes: The regression equation is:

$$V\,\mathrm{Re}t_{i,t}^{adj} = \alpha + \eta_1 E_{i,t-1} + \eta_2 \mathrm{Re}t_{i,t} + \eta_3 AGE_{i,t} + \eta_4 SIZE_{i,t-1} + \eta_5 MB_{i,t-1} + \eta_6 LEVERAGE_{i,t-1}$$
$$+ \beta_1 DD_{i,t-1} + \beta_2 EV_{i,t-1} + \varepsilon_{i,t},$$

where $V\,\mathrm{Re}t_{i,t}^{adj}$ = mean of the past three years' monthly standard deviation of excess stock returns. The monthly standard deviation is measured as the standard deviation of daily stock returns within the month times the square root of trading days within the month. *E* = earnings/assets, *Ret* = the average monthly stock return during the past three years, and *DD* = the Dechow and Dichev (2002) earnings quality measure estimated as the rolling standard deviation of the residuals over the past 12-quarter from the following regression using the full-sample data: $ACC_{i,q} = \alpha + \beta_1 CF_{i,a-1} + \beta_2 CF_{i,q} + \beta_3 CF_{i,q+1} + \varepsilon_{i,q}$. When a data item is available at the monthly frequency, its lagged value refers to the previous month value; otherwise the lagged value refers to the previous quarter value. *t* statistics are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table VIII Time-series Regressions of Return Volatility on its Determinants

	1	2	3	4	5
Intercept	0.100	-0.016	-0.724	0.130	-0.729
	(45.49)***	(-1.58)	(-7.30)***	(3.70)***	(-7.4)***
t/10,000	2.374	0.121	2.338	-0.530	1.780
	(21.93)***	(0.76)	(7.46)***	(-1.81)*	(4.89)***
E				1.844	1.885
				(15.91)***	(17.57)***
Ret				-0.095	0.092
				(-0.88)	(0.95)
AGE				-0.026	0.000
				(-4.37)***	(0.048)
SIZE				0.002	-0.001
				(0.668)	(-0.36)
LEVERAGE				0.086	-0.238
				(1.045)	(-2.70)***
MB				0.081	0.153
				(4.641)***	(8.82)***
DD		8.028	6.161	-1.006	1.728
		(10.63)***	(5.27)***	(-1.20)	(1.73)*
EV		0.896		1.012	
		(4.24)***		(5.33)***	
CFV			4.306		3.882
			(8.00)***		(10.17)***
ACCV			-3.958		-4.073
			(-6.33)***		(-9.22)***
$\rho_{CF,ACC}$			-0.760		-0.772
			(-7.14)***		(-10.40)***
N	345	345	345	345	345
Adj. R^2	58.2%	81.3%	83.4%	92.7%	94.1%

Notes: The regression equation is:

$$\overline{V\,\mathrm{Ret}_t^{adj}} = \alpha + \beta_0 t + \eta_1 \overline{E_{t-1}} + \eta_2 \overline{\mathrm{Ret}_t} + \eta_3 \overline{AGE_t} + \eta_4 \overline{SIZE_{t-1}} + \eta_5 \overline{BM_{t-1}} + \eta_6 \overline{LEVERAGE_{t-1}}$$
$$+ \beta_1 \overline{DD_{t-1}} + \beta_2 \overline{EV_{t-1}} + \varepsilon_t ,$$

where $\overline{V\,\mathrm{Ret}_t^{adj}}$ is the cross sectional average of $V\,\mathrm{Ret}_t^{adj}$ at month *t*, and analogously for other variables. *t* is a time variable ranging from 1978:01 (*t* = 1) to 2006:12 (*t* = 348). When a data item is available at the monthly frequency, its lagged value refers to the previous month value; otherwise the lagged value refers to the previous quarter value. The sample consists of 345 months, from April 1978 to Dec. 2006. *t* statistics are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table IX Time-Series Regressions of Earnings Volatility and Idiosyncratic Return Volatility on Non-Discretionary Earnings Volatility

Panel A: Time-Series Regression of Earnings Volatility on Its Determinants

	1	2	3
Intercept	0.004	0.002	0.000
	(9.44)***	(0.601)	(-0.08)
$t/10{,}000$	0.822	0.125	0.165
	(35.34)***	(11.15)***	(7.83)***
NDEV		1.089	1.050
		(67.74)***	(83.71)***
DAV		-0.855	-0.905
		(-37.9)***	(-45.3)***
$\rho_{NDE,DA}$		0.003	0.009
		(0.899)	(3.20)***
SALESV			0.108
			(9.12)***
AGE			0.000
			(0.60)
SIZE			0.000
			(1.10)
LEVERAGE			0.021
			(10.48)***
MB			0.000
			(-2.13)**
RGDPG			-0.00759
			(-4.43)***
N	336	336	336
Adj. Rsq.	78.8%	99.6%	99.8%

Cont'd on next page

Panel B Time-series Regressions Return Volatility on Non-discretionary Earnings Volatility

	1	2	3	4	5
Intercept	0.0971	-0.054	-0.631	-0.038	-0.848
	(44.0)***	(-5.82)***	(-8.84)***	(-0.55)	(-6.58)***
t/10,000	2.285	0.682	2.221	0.776	2.623
	(21.32)***	(4.18)***	(9.63)***	(2.25)**	(6.38)***
ROE				1.778	1.528
				(16.1)***	(13.54)***
Ret				-0.062	-0.045
				(-0.69)	(-0.51)
AGE				0.001	0.058
				(0.043)	(4.35)***
SIZE				-0.001	-0.001
				(-0.33)	(-0.21)
LEVERAGE				0.634	0.249
				(5.63)***	(2.06)**
MB				0.038	0.122
				(2.21)**	(5.11)***
DD		10.925	9.404	-3.732	5.417
		(15.55)***	(7.90)***	(-3.22)***	(2.80)***
EV		-0.209		1.047	
		(-0.87)		(4.59)***	
NDEV			2.071		1.397
			(5.15)***		(4.62)***
DAV			-1.858		-2.585
			(-3.74)***		(-5.97)***
$\rho_{NDE,DA}$			-0.619		-0.486
			(-8.09)***		(-7.12)***
N	333	333	333	333	333
Adj. Rsq.	57.7%	81.4%	84.6%	93.1%	93.7%

Notes: *NDEV* (*DAV*) = Standard deviation of non-discretionary accruals, or *NDE*, (discretionary accruals, or *DA*) to lagged assets over the past 12 quarters, $\rho_{NDE,DA}$ = correlation between NDE and *DA*. *DA* is derived with the Jones model of Dechow et al. (1995) following the method described in Kothari et al. (2005).

The regression equations for Panel A is:

$$\overline{EV}_t = \alpha + \beta_o t + \beta_1 \overline{NDEV}_t + \beta_2 \overline{DAV}_t + \beta_3 \overline{\rho_{NDE,DA_t}} + \eta_1 \overline{SALESV}_t + \eta_2 \overline{AGE}_t + \eta_3 \overline{SIZE}_t + \eta_4 \overline{MB}_t + \eta_5 \overline{LEVERAGE}_t + \eta_6 RGDPG_t + \varepsilon_t,$$

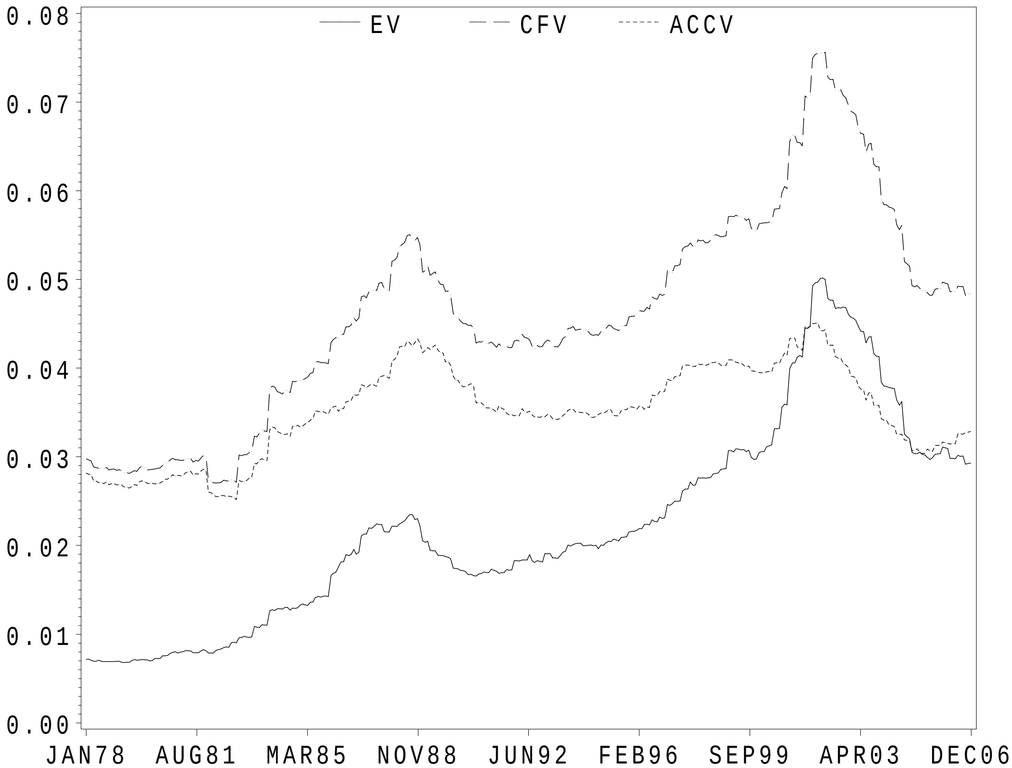
where *t* runs from 1979:01 to 2006:12. The regression equation for Panel B is:

$$\overline{V\,\mathrm{Re}\,t_t^{adj}} = \alpha + \beta_0 t + \eta_1 \overline{E_{t-1}} + \eta_2 \overline{\mathrm{Re}\,t_t} + \eta_3 \overline{AGE_t} + \eta_4 \overline{SIZE_{t-1}} + \eta_5 \overline{BM_{t-1}} + \eta_6 \overline{LEVERAGE_{t-1}} + \beta_1 \overline{DD_{t-1}} + \beta_2 \overline{EV_{t-1}} + \varepsilon_t,$$

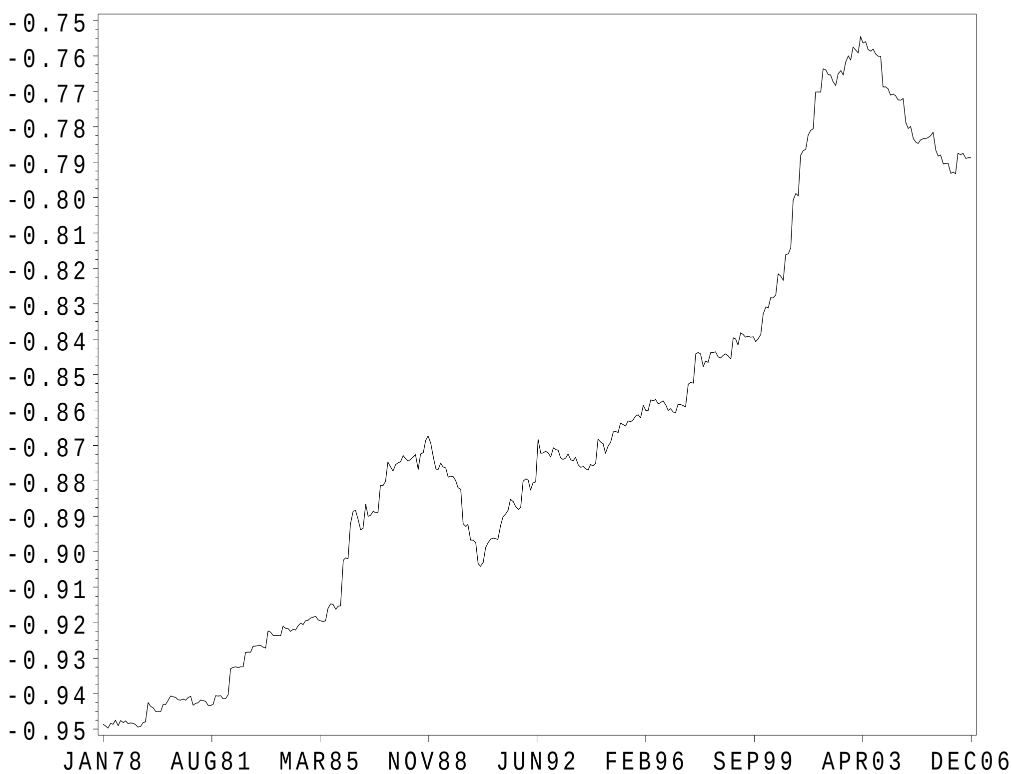
where t runs from 1979:04 to 2006:12. The benchmark time is 1978:01 (*t* = 1).

Appendix 1: Variable Definitions

Variable Name	Definition
E	Earnings before extraordinary items (Compustat quarterly data8). X11 deseasonalized.
CWC	Deseasonalized quarterly change in working capital. Working capital is defined the difference between current assets and cash and short-term investments minus the difference between current liabilities and debt in current liabilities (Compustat quarterly (data40-data36) – (data49-data45)).
CF	Cashflow from operatons: E + CWC + Depreciation (Compustat data5). X11 deasonalized.
ACC	Total accruals: *E* – *CF*.
EV	Earnings volatility: Standard deviation of E/assets (Compustat quarterly data44) over the past 12 quarters.
CWCV	Change in working capital volatility: Standard deviation of *CWC*/assets over the past 12 quarters.
CFV	Cash flow volatility: Standard deviation of *CF*/assets over the past 12 quarters.
ACCV	Accruals volatility: Standard deviation of *ACC*/assets over the past 12 quarters.
$\rho_{CF,ACC}$	Correlation between cash flow/assets and accruals/assets over the past 12 quarters.
SALESV	Sales volatility: Standard deviation of sales (Compustat quarterly data2)/assets over the past 12 quarters.
AGE	Logarithm of the number of months a firm has appeared on the monthly CRSP data tape.
SIZE	Logarithm of the beginning-of-the-month market equity of a firm.
LEVERAGE	Long-term debt (Compustat Quarterly data51) /assets.
BM	Book to market equity: Book equity (Compustat data59) of the current quarter over the beginning-of-the-month market equity (size).
MB	Market to book equity: Inverse of BM.
RDGPG	Real GDP growth rate.
DD-Pooled	The Dechow and Dichev (2002) earnings quality measure based on a pooled regression.
DD-Individual	The Dechow and Dichev (2002) earnings quality measure based on firm-specific regressions.
DD-Rolling	The Dechow and Dichev (2002) earnings quality measure based on rolloing regressions.
Ret	Average monthly stock return of the past three years.
$VRet^{raw}$	Mean monthly raw return volatility of the past three years. Raw return volatility is the square root of the product of the variance of daily stock return during the month times the number of the trading days during the month.
$VRet^{adj}$	Mean monthly adjusted return volatility of the past three years. Adjusted return volatility is the square root of the product of the variance of daily excess stock return during the month times the number of the trading days during the month.
Incremental Measures	The value of a variable minus the first twelve-month mean value of the variable after the firm's listing. For example, *IEV* = *EV* – First 12-month average.
Industries	1 = consumer, 2 = manufacturing, 3 = hi-tech, 4 = health care, 5 = others.

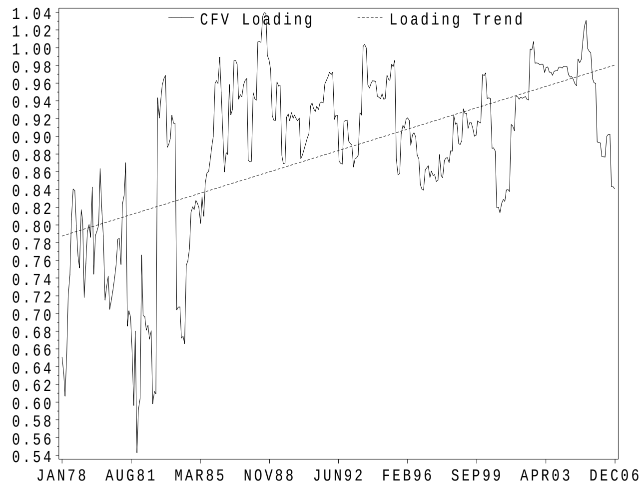


(a) EV, CFV and $ACCV$

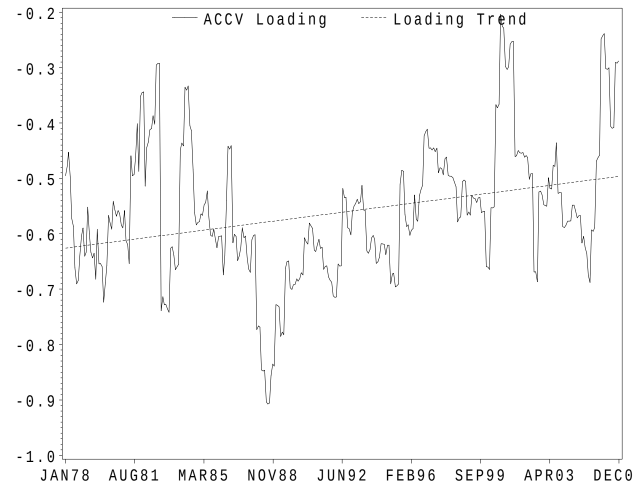


(b) $\rho_{CF,ACC}$

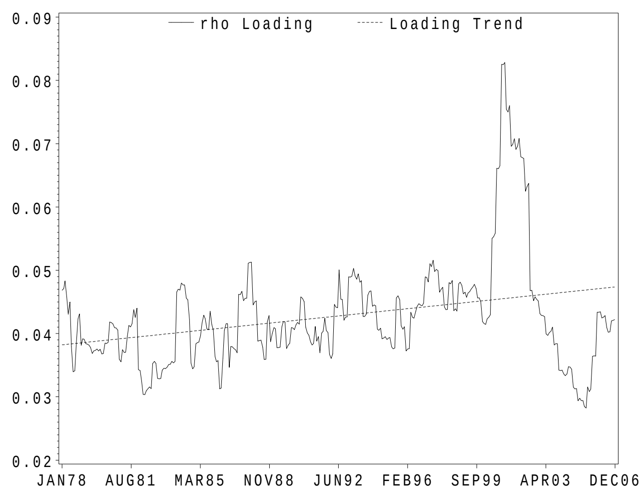
Figure 1: **Trends in earnings volatility and its components: 1978–2006.** This figure plots the time-series of cross-sectional means of EV, CFV, $ACCV$ and $\rho_{CF,ACC}$.



(a) CFV loading over time. Fitted loading: $\widehat{\beta_1} = 0.79 + (6 \times 10^{-4})t$

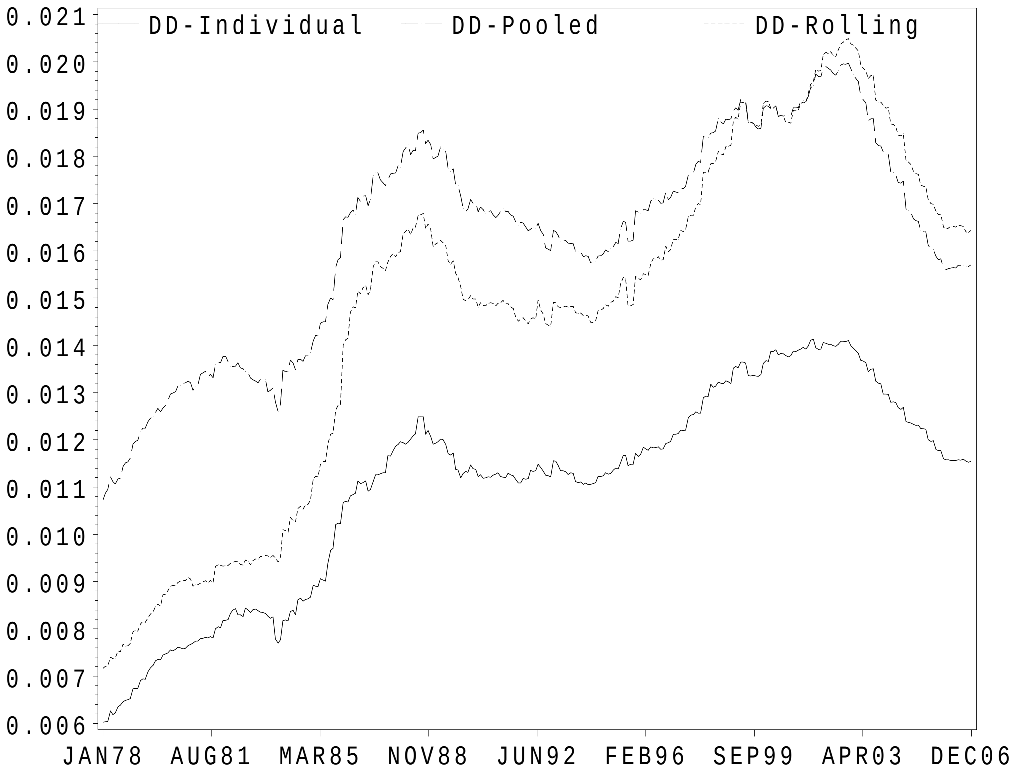


(b) $ACCV$ loading over time. Fitted loading: $\widehat{\beta_2} = -0.63 + (4 \times 10^{-4})t$

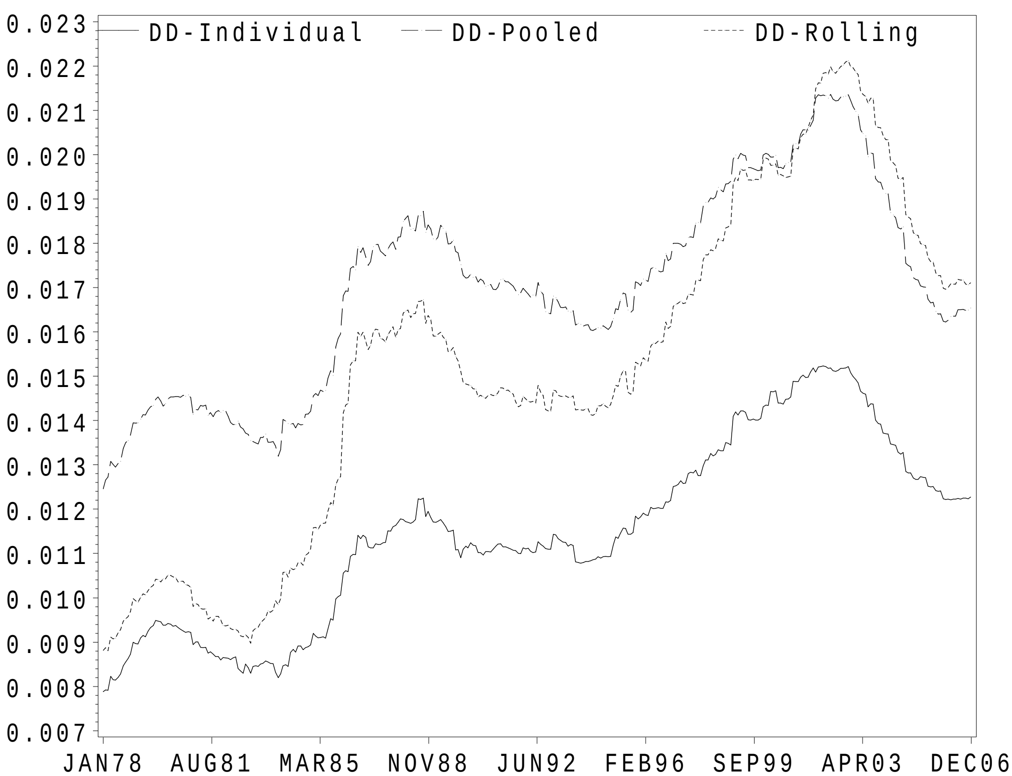


(c) $\rho_{CF,ACC}$ loading over time. Fitted loading: $\widehat{\beta_3} = 0.04 + (0.3 \times 10^{-4})t$

Figure 2: **Trends in the loading of EV components on the formation of EV over time.** This figure plots the time-series of the coefficients of monthly cross-sectional regressions of EV on CFV, $ACCV$, $\rho_{CF,ACC}$ and other control variables in Equation (2).



(a) *CWC* as the dependent variable in Equation (3)



(b) *ACC* as the dependent variable in Equation (3)

Figure 3: **Trends in earnings quality.** This figure plots the time-series of cross-sectional means of the Dechow and Dichev (2002) earnings quality measures.

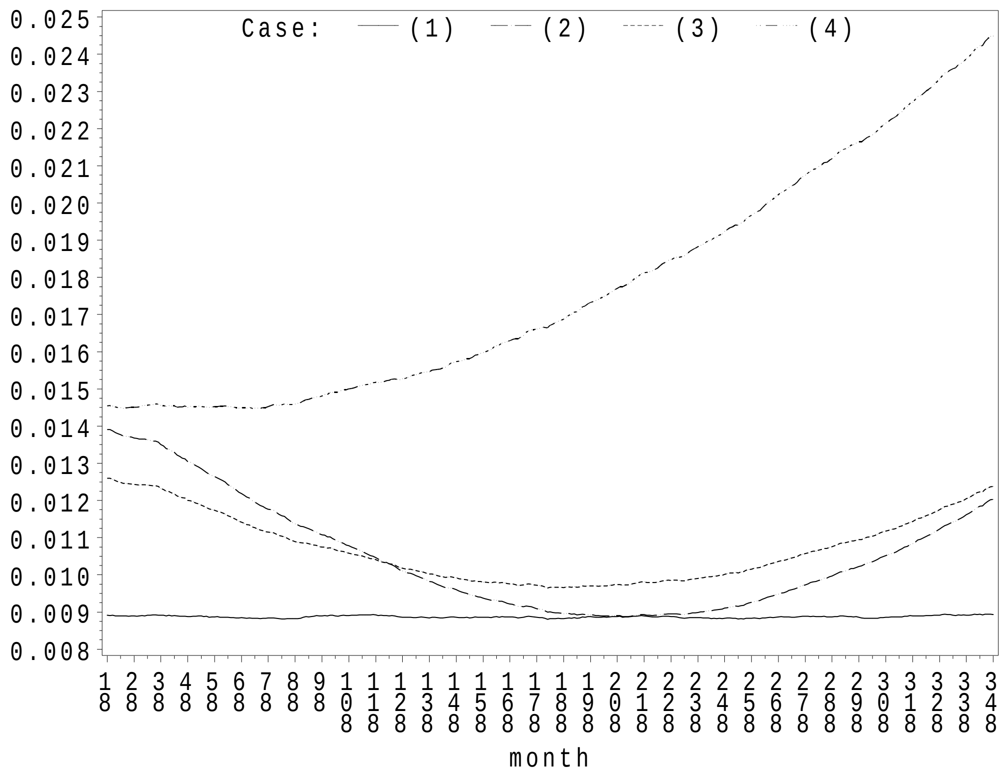


Figure 4: **Simulated trends in earnings quality.** The regression equation is Equation (3) with ACC as the dependent variable. In the simulation, ACC and CF follow a bivariate normal distribution with correlation of $\rho_{ACC,CF}$ and standard deviations of $ACCV$ and CFV respectively. In case (1), there is no time trend in $ACCV$, CFV and $\rho_{ACC,CF}$. In case (2), only CFV has an increasing trend. In case (3), both CFV and $ACCV$ have increasing trends. And in case (4), CFV and $ACCV$ have increasing trends while $\rho_{ACC,CF}$ has a decreasing trend.

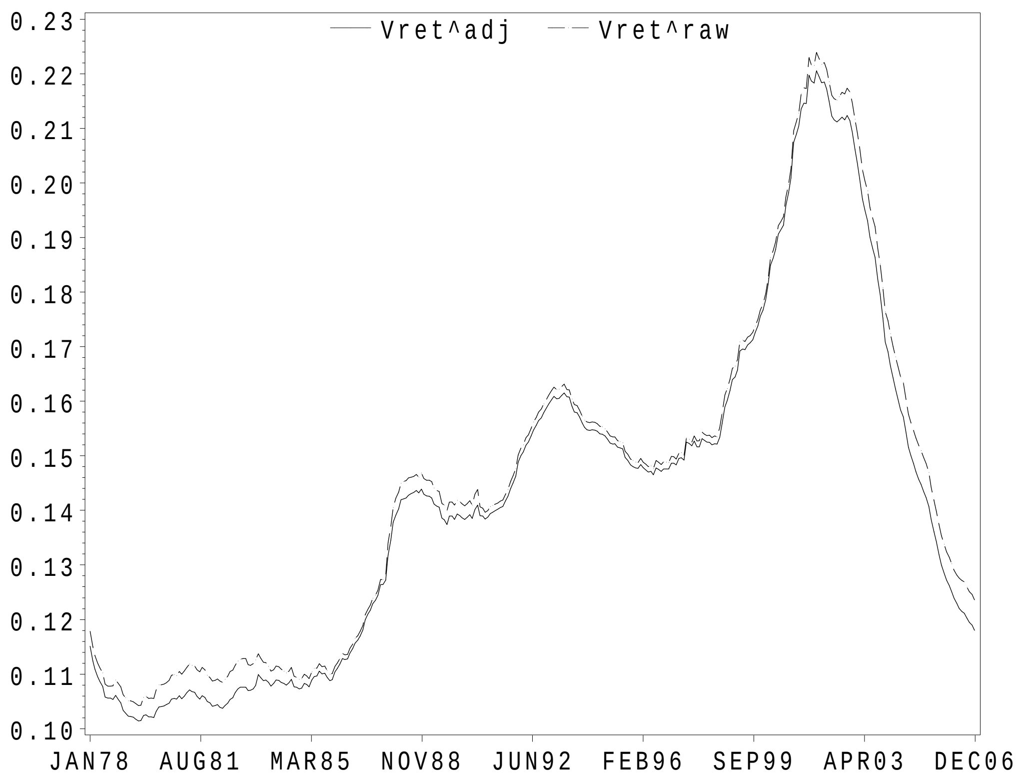
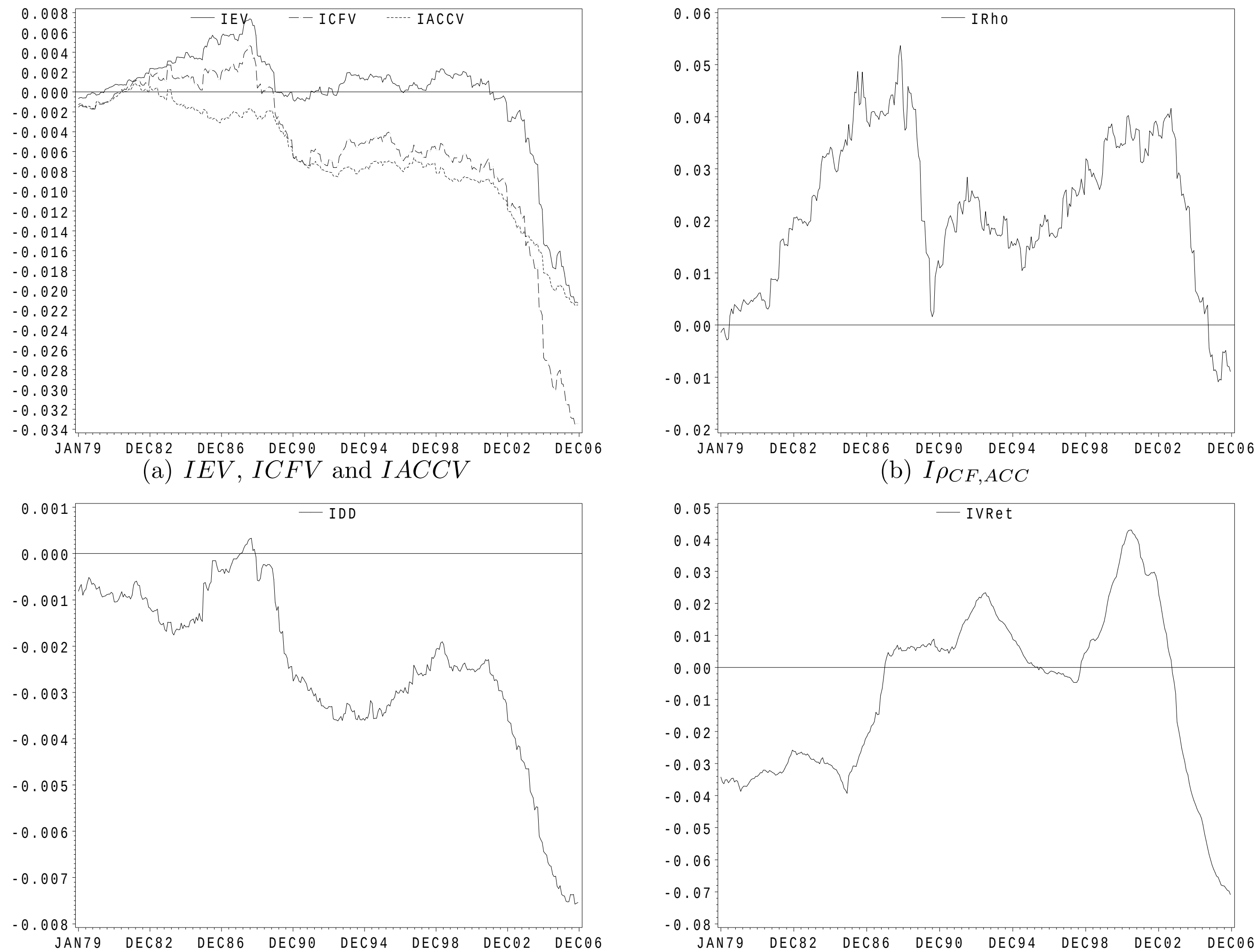


Figure 5: **Trends in idiosyncratic return volatility.** $VRet^{adj}$ ($VRet^{raw}$) is the mean of the past three years' monthly standard deviation of excess (raw) daily returns. The monthly standard deviation is the standard deviation of daily stock returns within the month times the square root of trading days within the month.



(a) IEV, $ICFV$ and $IACCV$ (b) $I\rho_{CF,ACC}$

(c) IDD (d) $IVRet$

Figure 6: **Trends in incremental measures.** This figure plots the time-series of the cross-sectional means of IEV, $ICFV$, $IACCV$, $I\rho_{CF,ACC}$,IDD and $IVRet$. For each firm, $IEV = EV -$ First 12-month average of EV. Other variables are defined analogously.