

2015

# Idiosyncratic Risk and Earnings Noncommonality

Kenneth Yung

Old Dominion University, kyung@odu.edu

Qian Sun

Hamid Rahman

Follow this and additional works at: [https://digitalcommons.odu.edu/finance\\_facpubs](https://digitalcommons.odu.edu/finance_facpubs)

 Part of the [Finance and Financial Management Commons](#)

---

## Repository Citation

Yung, Kenneth; Sun, Qian; and Rahman, Hamid, "Idiosyncratic Risk and Earnings Noncommonality" (2015). *Finance Faculty Publications*. 8.

[https://digitalcommons.odu.edu/finance\\_facpubs/8](https://digitalcommons.odu.edu/finance_facpubs/8)

## Original Publication Citation

Yung, K., Sun, Q., & Rahman, H. (2015). Idiosyncratic risk and earnings noncommonality. *The International Journal of Business and Finance Research*, 9(1), 1-17.

# INDIOSYNCRATIC RISK AND EARNINGS NONCOMMONALITY

Kenneth Yung, Old Dominion University

Qian Sun, Kutztown University

Hamid Rahman, Alliant International University

## ABSTRACT

*The seminal Campbell et al. (2001) paper showing that idiosyncratic risk has increased considerably in recent years has spawned a large number of articles to explain the phenomenon. In this paper, we propose growing earnings noncommonality as a possible source of the increasing idiosyncratic volatility. The empirical results of this research validate this proposition. Our conclusions stand the test of several robustness checks which show that market power and innovativeness previously considered in literature as sources of increased idiosyncratic volatility are not significant in the presence of earnings noncommonality. The findings of this research will be useful for analysts and investors involved in asset pricing.*

**JEL:** G32, G35

**KEYWORDS:** Idiosyncratic Risk, Earnings Noncommonality

## INTRODUCTION

For over a decade now, financial researchers have been pursuing an asset pricing puzzle. The puzzle has its origin in a seminal paper by Campbell et al. (2001) in which the authors analyze the contributing factors of stock return volatility by its three sources - market, industry and firm, and report that the firm-specific or idiosyncratic component of the risk has increased dramatically in the sample period 1963 to 1997. In and of itself, this finding would not have generated much excitement because portfolio theory, and its extension the CAPM, assume that investors hold the market portfolio or are well diversified, and therefore idiosyncratic risk is not priced. However, Levy (1978), Merton (1987), and Malkiel and Xu (2002) show theoretically that idiosyncratic risk is priced if investors are not well diversified. Goetzman and Kumar (2004) find that only ten percent of the investors hold more than ten stocks in their portfolio, while according to Campbell et al. about 50 randomly picked stocks are required for a well-diversified portfolio. Brockman et al. (2009) verify the existence of a positive risk premium for idiosyncratic volatility internationally for 44 markets, and state that the average investor in these markets is not well diversified. Recent findings of Goyal and Santa Clara (2003) and Ang et al. (2006) also suggest that idiosyncratic risk is a priced risk factor. Because investors require compensation for bearing idiosyncratic risk, the apparent rise in idiosyncratic volatility reported by Campbell et al. has “become one of the most actively researched asset pricing puzzles,” (Brandt et al. (2010)).

In this paper, we study the relation between idiosyncratic risk and earnings noncommonality. Specifically, we argue that earnings noncommonality is an important determinant of idiosyncratic return volatility. Earnings noncommonality is defined as the extent to which a firm’s earnings performance is determined by firm-specific factors versus market and industry factors (Brown and Kimbrough (2011)). If firm level earnings are more (less) dependent on firm specific factors, then this is likely to result in higher (lower) levels of earnings noncommonality. The accounting literature indicates a firm’s internal resources and its unique capabilities as factors that influence the noncommonality of earnings between firms (Piotroski and Roulstone (2004) and Elgers et al. (2004)). Palepu et al. (2007) consider intangible investments that form the core of the firm’s competitive differentiation strategy as a major factor in creating earnings noncommonality. These intangible investments consist of moneys spent to create brand image, provide

superior customer service, develop and improve products through R&D, and control systems that result in innovation and creativity. Despite these assertions, empirical evidence regarding the determinants of earnings noncommonality between firms is sparse.

Our basic premise is that earnings noncommonality has increased over time as firms try to improve their market position through differentiation in the marketplace. The natural consequence of this differentiation is that firms become differentially susceptible to common market and industry influences. The structure of the US economy has also been changing as a result of a shift from manufacturing to a service based economy that is perhaps not that susceptible to common risk factors. Further within the manufacturing sector there has been a shift from traditional physical resource intensive manufacturing to high tech human resource based manufacturing that may further reduce the impact of common economic factors. Another reason for the increase in earnings noncommonality is globalization of raw material sources and production. As production has moved to various off-shore locations, firms are less susceptible to local market and industry influences as compared to the former situation when production cycle was mostly domestic. These factors imply that earnings noncommonality has increased concurrently with idiosyncratic volatility and may in fact be an important contributor for this phenomenon.

Consistent with this premise, the empirical analysis in this paper examines whether idiosyncratic volatility is related to earnings noncommonality. We show the existence of a significant positive relationship between idiosyncratic volatility and earnings noncommonality. In addition, low earnings noncommonality reduces idiosyncratic volatility. Several robustness tests performed validate these findings. We also rule out that earnings noncommonality is an indicator of market power or innovativeness. Prior studies suggest that idiosyncratic volatility increases because of more active retail investors, low-priced stocks, and the listing of riskier firms. Our results remain robust after considering the effects of retail investors' influences, institutional ownership, and firm riskiness. Our paper contributes to the literature by suggesting another possible explanation for the recent increase in idiosyncratic volatility as pointed out by Campbell et al. (2001), and aids in a better understanding of the asset pricing puzzle that has intrigued the researchers of late. The robustness tests we conduct show that market power and innovativeness previously suggested in the literature as possible causes of the increased idiosyncratic volatility are not significant in explaining idiosyncratic volatility in the presence of earnings noncommonality as an explanatory variable. On the practical front, the paper identifies an important determinant of idiosyncratic volatility which has important ramifications for portfolio diversification, arbitrageurs, and pricing of employee stock options.

We formulate six models, in two sets of three models each, to test various aspects of the relationship between idiosyncratic volatility and earnings noncommonality. The first set of three models uses cross-sectional regressions of idiosyncratic volatility on earnings noncommonality. The second set of three models uses pooled cross-sectional time-series regressions of idiosyncratic volatility on earnings noncommonality. The second set captures the time-series association between idiosyncratic volatility and earnings noncommonality, whereas the first examines the existence of a cross-sectional relation between idiosyncratic return volatility and earnings noncommonality (Rajgopal and Venkatachalam (2011)). Both are important and would be expected to show convergent findings. We use two specifications of earnings noncommonality – a scalar specification where earnings noncommonality is based on  $1-R^2$  from a Fama French Model regression, and a dummy variable specification where earnings noncommonality is one if below the scalar specification median of the year and zero otherwise. We use one model from each set to show the cross product relationship of low earnings noncommonality with stock turnover and institutional relationship. Consistent with our premise, all the models show a significant positive relationship between idiosyncratic volatility and earnings noncommonality. However, when earnings noncommonality is crossed with time, the relationship fails to achieve significance in one of the models. We subject the positive relationship between idiosyncratic volatility and earnings noncommonality to several robustness tests and the relationship holds through all the tests.

The rest of the paper is organized as follows: In Section 2, we review the literature and develop the hypothesis; Section 3 describes the variables and their computation, the models are formulated in Section 4, Section 5 describes the sample and provides the descriptive statistics, Section 6 discusses the findings, Section 7 describes the robustness tests and Section 8 concludes.

## LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The pursuit of an explanation for the puzzle of increasing idiosyncratic volatility has spawned a plethora of articles. Bennett et al. (2003) and Xu and Malkiel (2003) suggest that the rise in idiosyncratic volatility of individual stocks is associated with the increasing institutional ownership of shares. Thus, the higher the institutional ownership, the higher is the idiosyncratic volatility. Brandt et al. argue the opposite, i.e. low priced stocks are dominated by retail traders and are volatile precisely because they are not held widely by institutions. Jiang et al. (2009) too find that the anomaly is stronger among stocks with a less sophisticated base. Wei and Zhang (2006) investigate why individual stocks have become more volatile and conclude that it is because firm fundamentals have become more volatile. They find that the upward trend in average stock return volatility is fully accounted for by the downward trend in the return-on-equity and the upward trend in the volatility of the return-on-equity. Rajgopal and Venkatachalam (2011) find evidence indicating that the increase in idiosyncratic return volatility is associated with deteriorating earnings quality. Jiang et al.'s (2009) findings supports this view in that corporate selective disclosure is a driver of idiosyncratic volatility. Fink et al. (2010) present evidence that the market-wide decline in maturity of the typical public firm can explain most of the fivefold increase in idiosyncratic volatility during the Internet boom while Brown and Kapadia (2007) show that the observed increase in idiosyncratic volatility is due solely to new listings by riskier companies.

Mazzucato and Tancioni (2008) find a clear relationship between firm-level R&D intensity and idiosyncratic risk. They hypothesize that this is because investment in innovation has uncertain outcomes. Gaspar and Massa (2006) and Irvine and Pontiff (2008) argue that the increase in idiosyncratic volatility is attributable to an increase in product market competition. Their contention is that consumers' ability to direct business to different firms can produce a more competitive environment resulting in more frequent introduction of substitutes with consequent greater price and earnings volatility. In this paper, we present yet another approach to understanding the puzzle of increasing idiosyncratic volatility – the increasing earnings noncommonality between firms.

The current findings in the literature suggest two possible but conflicting relationships between earnings noncommonality and idiosyncratic return volatility. First, the essence of competition is substitutability and commonality, i.e. a large number of firms producing identical goods at identical prices. Thus, the higher the competition, the less is the earnings noncommonality. Irvine and Pontiff (2008) suggest that the recent upward trend in idiosyncratic volatility is related to an increasingly competitive environment in which the firms have less market power. They argue that when the success of one firm in an industry comes at the expense of another firm in that industry, competition contributes to negative covariance in firm performance. Thus in a highly competitive industry, the earnings noncommonality will be low and this will result in greater uncertainty regarding the cash flow and average profitability. The likely outcome is higher levels of idiosyncratic risk. Gaspar and Massa (2006) also reach the same conclusion. They observe that firms enjoying high market power, or established in monopolistic industries, have lower idiosyncratic volatility because market power smoothes idiosyncratic fluctuations and lowers information uncertainty for investors and therefore return volatility. These findings form the basis for our first hypothesis:

*Hypothesis 1:* Firms with higher (lower) levels of earnings noncommonality are associated with lower (higher) levels of idiosyncratic return volatility

Other results suggest the opposite relationship between idiosyncratic risk and earnings noncommonality. Brown and Kimbrough (2011) find that earnings noncommonality is positively associated with intangible asset intensity. Mazzucato and Tancioni (2008) establish that firms with the highest R&D intensity have the highest idiosyncratic risk. These findings suggest a positive relationship between earnings noncommonality and idiosyncratic risk. In addition, higher earnings noncommonality implies from an asymmetric viewpoint that less information is available to investors and consequently higher volatility may occur due to the market friction. This is another reason to expect a positive relationship between earnings noncommonality and idiosyncratic volatility. These findings form the basis of our second competing hypothesis:

*Hypothesis 2:* Firms with higher (lower) levels of earnings noncommonality are associated with higher (lower) levels of idiosyncratic return volatility. These conflicting views suggest a third possibility, that the relation between earnings noncommonality and idiosyncratic return volatility is not straightforward. For example, that the effect of earnings noncommonality and idiosyncratic return volatility may be nonlinear. An empirical investigation is therefore required to test the true nature of the relationship between earnings noncommonality and idiosyncratic volatility.

### Variable Computation and Description

#### Measurement of Earnings Noncommonality

Earnings noncommonality is the portion of return unexplained by market and industry factors. In the literature, earnings noncommonality is measured as the log of 1 minus the  $R^2$  from firm-specific regressions of quarterly return on assets (ROA) on market-and industry-level ROA indices (Morck et al. (2000) and Piotroski and Roulstone (2004)). The  $R^2$  of the regression is return synchronicity and  $1-R^2$  is earnings noncommonality. Following Brown and Kimbrough (2011), the following firm-specific regression is estimated for each quarter over the 20 calendar quarters (requiring a minimum 10 observations) preceding and including quarter  $t$ :

$$ROA_{i,t} = \alpha_0 + \alpha_1 MKTROA_{i,t} + \alpha_2 INDROA_{i,t} + \varepsilon_{i,t} \quad (1)$$

where all variables are defined as in Brown and Kimbrough (2011):

$ROA_{i,t}$  = return on assets for firm  $i$  during calendar quarter  $t$ , measured as reported income before extraordinary items (Compustat data item IBQ) plus quarterly R&D expense (data item XRDQ) less the estimated quarterly R&D amortization expense, scaled by the sum of total recognized assets (ASSETS, data item ATQ) and estimated R&D capital (RDCAP) as of the beginning of calendar quarter  $t$ .  $MKTROA_{i,t}$  = the weighted average ROA (adjusted for R&D capitalization) for all Compustat firms excluding those in the same two-digit SIC code as firm  $i$  during calendar quarter  $t$ , measured as the sum of adjusted income before extraordinary items for all Compustat firms excluding those in the same two-digit SIC code as firm  $i$  scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter  $t$  for all Compustat firms excluding those in the same two-digit SIC code as firm  $i$ .  $INDROA_{i,t}$  = the weighted average ROA (adjusted for R&D capitalization) for all Compustat firms excluding firm  $i$  in the same two-digit SIC code, measured as the sum of adjusted income before extraordinary items for all Compustat firms in the same two-digit SIC code excluding firm  $i$  scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter  $t$  for all Compustat firms in the same two-digit SIC code excluding firm  $i$ .

Return on assets (ROA)—modified for R&D capitalization—is used as the measure of firm-level earnings. R&D capital (RDCAP) is estimated each year as the unamortized cost of R&D investment using current and past R&D expenditures amortized at an annual rate of 20% (assuming a 5-year useful life and

straight-line depreciation). In calculating ROA, quarterly R&D expense are added back to quarterly earnings and then subtracted from the estimated quarterly R&D amortization expense. Next, beginning-of-quarter assets (ASSETS) are adjusted for the implicit capitalization of R&D by adding the estimated amount of R&D capital as of the beginning of quarter t. R&D capital as of the beginning of each quarter is calculated by updating the prior year's R&D capital estimate for subsequent quarterly R&D expenditures and quarterly R&D amortization. The weighted average ROA for the market (MKTROA) is calculated using all firm-quarters with available data in the Compustat database and beginning-of-quarter assets as the weight. Similarly, the weighted average ROA for each industry (INDROA) is calculated using all other firms within the same two-digit SIC code as firm i. We then define earnings noncommonality as the unexplained portion of the firm's ROA (UNEXPLAINED), which is 1 minus the R<sup>2</sup> from each firm-specific regression of Eq.1. Lastly, an unbounded continuous variable for each firm-quarter is created using the log transformation of UNEXPLAINED as defined below:

$$\text{NONCOMMON}_{i,t} = \log(\text{UNEXPLAINED}_{i,t}/1 - \text{UNEXPLAINED}_{i,t}) \quad (2)$$

Higher values of NONCOMMON indicate those quarters in which the firm's ROA varies strongly with firm-specific factors as opposed to market-wide and industry-level factors. LOWNONCOM is a (0,1) dummy variable with a value of 1 if NONCOMMON is below the median of the year. This variable is used in some specifications of the basic model to single out the effect of low earnings noncommonality. An expected negative coefficient on this variable will suggest that idiosyncratic volatility is reduced when firms have lower levels of earnings noncommonality.

#### Measurement of Idiosyncratic Risk

Idiosyncratic risk is measured as the average monthly variance of excess returns adjusted for the three-factor expected returns of Fama and French (1993) model. Excess return is measured as the residual from a regression of a firm's daily stock returns on SMB, HML and market beta factors.

$$R_{i,t} = R_f + \beta_i(R_{m,t} - R_f) + b_s \cdot \text{SMB} + b_v \cdot \text{HML} + \xi_{i,t} \quad (3)$$

Here R<sub>it</sub> is firm i's stock return on day t, R<sub>f</sub> is the risk-free return rate, and R<sub>mt</sub> is the return of the whole stock market on day t. SMB stands for "small (market capitalization) minus big" and measures the historic excess return of small cap over big cap ranked size portfolios. HML stands for "high (book-to-market ratio) minus low" and measures the historic excess return of value stock over growth stock portfolios formed after ranking the stocks by their book to market ratios. The average monthly variance of excess returns VARff is computed as:

$$\text{VARff} = \frac{\sum_{i=1}^n (\xi_{it} - \bar{\xi}_i)^2}{n-1} \quad (4)$$

$\bar{\xi}_i$  is the mean monthly excess return, and n is the number of observations in the month.

$$\text{IDIORISK} = \text{Ln}(\text{VARff}) \quad (5)$$

#### Additional Control Variables

Following Rajgopal and Venkatachalam (2011) and Brown and Kimbrough (2011), the variables used to control for other possible sources of idiosyncratic volatility are: Operating cash flows normalized by assets (CFO/TA) to control for the reported negative association between operating performance and stock return volatility (Hanlon et al. (2004)). The variance of annual operating cash flows normalized by

average total assets over the past five years (CFO<sub>δ</sub>) to control for the positive association between variance of cash flows and idiosyncratic return volatility (Vuolteenaho (2002)).

The ratio of book value of equity to market value of equity (BTM) to control for the expected negative relation between book-to-market and idiosyncratic return volatility caused by the greater stock return volatility of growth firms. Buy and hold returns (BHRET) are used to control for the observed negative relationship between stock return performances and return volatility. The natural log of market capitalization (SIZE) is used to control for the higher return volatility of small firms (Pastor and Veronesi (2003)). The ratio of long-term debt to book value of total assets (LEV) is used to control for the expected positive relationship with leverage because of the greater financial distress probability of levered firms.

The average monthly trading volume of a security divided by the outstanding shares of the security (TURNOVER) is used to control for the expected positive relationship with turnover. TIME is a trend variable that takes on the values from 1 to 27 for each of the sample years 1980 to 2007. It controls for the expected positive temporal link between time and idiosyncratic risk. INST\_OWN is the percentage of shares held by institutional investors. The variable controls for the possible impact of increasing investor sophistication on idiosyncratic risk.

### Model Specifications

#### Cross-Sectional Tests

Base Model (A1) The Base Model to test the effect of earnings noncommonality on idiosyncratic risk takes the following form:

$$\begin{aligned} \text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{NONCOMMON}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\ & + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} + \lambda_8 \text{INST\_OWN}_{i,t-1} \\ & + \lambda_9 \text{BHRET}_{i,t-1} + \varepsilon_{i,t-1} \end{aligned}$$

A positive  $\lambda_1$  would indicate a positive relationship between idiosyncratic risk and volatility after controlling for other confounding variables.

Model (A2) Model (A2) essentially differs from the Base Model (A1) in substituting LOWNONCOM in place of NONCOMMON. LOWNONCOM is a (0,1) dummy variable with a value of 1 if NONCOMMON is below the median of the year. It singles out the effect of low earnings noncommonality on idiosyncratic volatility. Model (A2) takes the following specification:

$$\begin{aligned} \text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{LOWNONCOM}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\ & + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} + \lambda_8 \text{INST\_OWN}_{i,t-1} \\ & + \lambda_9 \text{BHRET}_{i,t-1} + \varepsilon_{i,t-1} \end{aligned}$$

A negative  $\lambda_1$  would indicate that as commonality increases, idiosyncratic risk declines.

Model (A3) Model (A3) differs from Model (A2) in that LOWNONCOM is made to interact with TURNOVER and INST\_OWN. A significant coefficient of the interaction term indicates that the level of one variable influences the slope, i.e. the effect or importance of the other variable.

$$\begin{aligned} \text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{LOWNONCOM}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\ & + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} * \text{LOWNONCOM}_{i,t-1} \\ & + \lambda_8 \text{INST\_OWN}_{i,t-1} * \text{LOWNONCOM}_{i,t-1} + \lambda_9 \text{BHRET}_{i,t-1} + \varepsilon_{i,t-1} \end{aligned}$$

A significant positive  $\lambda_9$  would indicate higher turnover associated with earnings noncommonality increases idiosyncratic risk, and a significant positive  $\lambda_{10}$  would indicate institutional ownership associated with earnings noncommonality increases idiosyncratic risk. commonality increases institutional ownership.

#### Pooled Cross-Section and Time-Series Tests

Model (B1) The seminal Campbell et al. (2001) finding is that idiosyncratic volatility has increased over time. This implies a positive coefficient for TIME in the following regression:

$$\text{IDIORISK}_{i,t} = \eta_0 + \eta_1 \text{TIME}_{i,t} + \varepsilon_{i,t} \quad (6)$$

The hypothesis in this research is that idiosyncratic volatility is associated with earnings noncommonality. It then follows that:

$$\eta_1 = \omega_0 + \omega_1 \text{NONCOMMON}_{i,t} + \psi_{it} \quad (7)$$

Substituting (7) into (6) provides the following specification:

$$\text{IDIORISK}_{i,t} = \lambda_0 + \lambda_1 \text{TIME}_{i,t} + \lambda_2 \text{TIME}_{i,t} * \text{NONCOMMON}_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

Equation 8 and the Basic Model (A1) are then merged by adding the variables of the Basic Model to Equation 8 in their standalone form and crossed with the TIME variable to yield the following specification for Model (B1):

$$\begin{aligned} \text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{NONCOMON}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\ & + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} + \lambda_8 \text{INST\_OWN}_{i,t-1} \\ & + \lambda_9 \text{TIME}_{i,t} + \lambda_{10} \text{TIME}_{i,t} * \text{NONCOMON}_{i,t-1} + \lambda_{11} \text{TIME}_{i,t} * \text{INST\_OWN}_{i,t-1} \\ & + \lambda_{12} \text{TIME}_{i,t} * \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} \\ & + \lambda_{13} \text{TIME}_{i,t} * \text{CFO}_{\delta i,t-1} + \lambda_{14} \text{TIME}_{i,t} * \text{TURNOVER}_{i,t-1} + \lambda_{15} \text{BHRET}_{i,t-1} \\ & + \varepsilon_{i,t-1} \end{aligned}$$

The coefficient of TIME, consistent with prior research, is expected to be positive and if there is a positive association between earnings noncommonality and idiosyncratic volatility then the expected coefficient for TIME \* NONCOMMON should also be positive after controlling for the other interaction terms with TIME. TIME\*Turnover controls for changing investor sentiment over time. TIME\*INST\_OWN controls for changing investor sophistication over time. The coefficients of TIME\*CFO/TA and TIME<sub>it</sub> \* CFO<sub>δ</sub> show how idiosyncratic risk is affected by CFO/TA and CFO<sub>δ</sub> respectively over time. Model (B2) Model (B2) replicates Model (A2) but with the added time dimension as in Model (B1). The Model thus takes the following specification:

$$\begin{aligned}
\text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{LOWNONCOM}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\
& + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} + \lambda_8 \text{INST\_OWN}_{i,t-1} \\
& + \lambda_9 \text{TIME}_{i,t} + \lambda_{10} \text{TIME}_{i,t} * \text{NONCOMMON}_{i,t-1} + \lambda_{11} \text{TIME}_{i,t} * \text{INST\_OWN}_{i,t-1} \\
& + \lambda_{12} \text{TIME}_{i,t} * \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} \\
& + \lambda_{13} \text{TIME}_{i,t} * \text{CFO}_{\delta i,t-1} + \lambda_{14} \text{TIME}_{i,t} * \text{TURNOVER}_{i,t-1} + \lambda_{15} \text{BHRET}_{i,t-1} \\
& + \varepsilon_{i,t-1}
\end{aligned}$$

The coefficient for LOWNONCOM is expected to be negative signifying that firms with low commonality have high idiosyncratic risk. The coefficient for TIME \* NONCOMMON should be positive after controlling for the other interaction terms with TIME.

Model (B3) Model (B3) replicates Model (A3) but with the added time dimension as in Model (B1). The Model thus takes the following specification:

$$\begin{aligned}
\text{IDIORISK}_{i,t} = & \lambda_0 + \lambda_1 \text{LOWNONCOM}_{i,t-1} + \lambda_2 \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} + \lambda_3 \text{CFO}_{\delta i,t-1} + \lambda_4 \text{BTM}_{i,t-1} \\
& + \lambda_5 \text{SIZE}_{i,t-1} + \lambda_6 \text{LEV}_{i,t-1} + \lambda_7 \text{TURNOVER}_{i,t-1} * \text{LOWNONCOM}_{i,t-1} \\
& + \lambda_8 \text{INST\_OWN}_{i,t-1} * \text{LOWNONCOM}_{i,t-1} \\
& + \lambda_9 \text{TIME}_{i,t} + \lambda_{10} \text{TIME}_{i,t} * \text{NONCOMMON}_{i,t-1} + \lambda_{11} \text{TIME}_{i,t} * \text{INST\_OWN}_{i,t-1} \\
& + \lambda_{12} \text{TIME}_{i,t} * \frac{\text{CFO}_{i,t-1}}{\text{TA}_{i,t-1}} \\
& + \lambda_{13} \text{TIME}_{i,t} * \text{CFO}_{\delta i,t-1} + \lambda_{14} \text{TIME}_{i,t} * \text{TURNOVER}_{i,t-1} + \lambda_{15} \text{BHRET}_{i,t-1} \\
& + \varepsilon_{i,t-1}
\end{aligned}$$

This model provides new information with respect to how the relationship between turnover and institutional ownership changes with changing commonality over time.

### Sample Selection and Descriptive Statistics

The data for this research is obtained from COMPSTAT, CRSP, Thomson Financial and Bloomberg. Our sample period is from 1980 to 2007. The data excludes utilities, financials and SIC 99 firms (Non-Operating Establishments). Each firm year is required to have non-missing Research and Development (R&D) data for at least 5 years to estimate quarterly R&D amortization expense and R&D capital. If the quarterly R&D is missing, the quarterly R&D expenditure is assumed to be one quarter of the annual expenditure. Following Brown and Kimbrough (2011), an annual straight line depreciation of 20% is assumed for R&D. Another requirement is that each firm quarter should have non-missing firm, industry and market ROA (return on assets) data for at least 10 calendar quarters preceding quarter t. This provides a 20 quarters moving window for calculating earnings noncommonality with at least 10 observations in each regression. To avoid serial correlation in the base regression model, only the fourth quarter earnings noncommonality data are used in the regression analysis. Another requirement is that there should be no missing data for the regression variables that are downloaded from COMPSTAT, CRSP, Thomson Financial and Bloomberg data bases. Consistent with the literature, financial statement data are winsorized to the 1 and 99 percentiles to eliminate outliers. All the regression variables are calculated based on Brown and Kimbrough (2011) and Rajgopal and Venkatachalam (2011) papers.

The variables needed for the computation of earnings noncommonality resulted in 45,163 observations, but when merged with variables obtained from CRSP, the useful observations are reduced to 37,093.

When finally merged with variables obtained from Thomson Financials, the useful observations are further reduced to 26,622. This constitutes our final sample. Table 1 provides the descriptive statistics for the variables in the models. NONCOMMON has a mean of 1.47, a median of 1.40 and a standard deviation of 1.59. This is consistent with the ENC calculated in Brown and Kimbrough (2011) paper. IDIORISK has a mean of -7.21, a median of -7.20 and a standard deviation of 1.39. Since IDIORISK is the normal log of monthly variance, the raw annualized standard deviation ( $(e^{\text{idiorisk}} * 12)^{0.5}$ ) mean and median are 0.09 and 0.09 respectively. These values are consistent with the normal range reported in the existing literature. The means, medians and standard deviations of the control variables are also given in Table 1 and their values are generally close to values reported by other researchers, for example Rajgopal and Venkatachalam (2011)

Table 1: Descriptive Statistics of the Sample

Variable	Mean	Median	Standard Deviation
IDIORISK	-7.209	-7.203	1.393
NONCOMMON	1.465	1.399	1.593
CFO/AT	0.039	0.066	0.233
CFO $\delta$	13.362	8.168	11.591
BTM	0.616	0.475	0.622
SIZE	5.288	5.146	2.193
LEV	0.177	0.141	0.178
INST_OWN	0.575	0.404	7.170
TURNOVER	0.111	0.065	0.156

Table 1 shows the descriptive statistics of our sample. IDIORISK is defined as the Log of the average monthly variance of returns adjusted for Fama and French three factor model. NONCOMMON refers to the log of 1 minus the R2 from firm-specific regressions of quarterly return on assets (ROA) on market-and industry-level ROA indices. CFO/AT is operating cash flows scaled by average total assets. CFO  $\delta$  is variance of operating cash flows scaled by average total assets over the trailing five years. BTM is the book to market ratio. SIZE is natural log of market value of equity. LEV is financial leverage computed as the ratio of long term debt to total assets. BHRET is annual buy-and-hold return. INST\_OWN is percentage of shares owned by institutional investors. TURNOVER is the average monthly trading volume of a security divided by the outstanding shares of the security.

Table 2: Distribution of Earnings Noncommonality (Median Values Of NONCOMMON) By 1-Digit SIC and Year

YEAR	SIC=0	SIC=1	SIC=2	SIC=3	SIC=5	SIC=6	SIC=7	SIC=8	SIC=9
1980		1.4923	1.0277	1.6501	1.5137	1.0487	1.2793	-0.4506	1.4445
1981		1.0561	1.3200	1.7988	1.5398	1.6202	1.8045	-0.8249	3.1964
1982	0.2672	0.9143	1.0421	1.7313	1.5320	0.8897	1.4067	3.8822	2.2965
1983	-2.6314	0.5281	0.8793	1.5296	1.3198	1.0978	1.4100	1.9001	1.9006
1984	-0.1775	0.2843	0.7256	1.5633	1.2332	1.8458	1.1395	2.2099	1.7116
1985	1.0118	0.1983	0.8965	1.6046	1.3829	1.0630	1.6379	1.8529	1.6556
1986	0.3691	1.1609	0.9771	1.5144	1.1953	0.8850	1.7147	2.3423	2.3820
1987	0.8334	1.6066	1.0934	1.3203	1.0187	2.2604	1.9166	2.8381	1.8117
1988	0.6278	1.0588	1.1554	1.3549	1.0124	0.7966	2.2173	2.6409	0.8271
1989	0.7994	1.4705	1.5057	1.3765	1.1269	0.7430	1.9365	1.1725	0.3775
1990	0.1969	0.2407	1.2669	1.3467	1.1355	0.6441	2.0621	1.7308	1.0485
1991	0.3139	0.8589	1.5406	1.1473	0.9355	1.2767	1.7671	1.7368	1.1325
1992	-0.2472	1.0438	1.4313	1.3037	1.3641	1.2643	1.6734	2.3567	2.1535
1993	-0.3446	1.2619	1.6285	1.5728	1.0002	0.9203	1.6011	1.1435	1.4787
1994	-0.5864	1.5997	1.8764	1.5402	0.9044	0.5585	1.3166	1.8536	2.7778
1995	-0.2009	1.4203	1.5110	1.3020	1.0083	1.7321	1.4608	1.8235	2.2383
1996	0.34261	1.1249	1.3891	1.3186	0.9053	1.4447	1.5488	2.2578	1.2509
1997	0.4844	1.1666	1.4182	1.2664	0.8804	1.1588	1.6362	1.4658	1.0527
1998	0.9401	1.2976	1.3467	1.3868	1.0415	0.8400	1.2076	1.4595	1.5821
1999	1.1071	1.5886	1.3733	1.3719	1.1246	2.9176	0.9886	1.2526	1.4565
2000	1.9343	1.5448	1.5206	1.4054	0.9645	1.5815	1.1677	1.3607	0.944
2001	-0.5481	1.3456	1.4475	1.2361	1.2373	0.7742	1.8116	1.1715	2.4650
2002	-0.5283	1.3533	1.8286	1.3202	1.2518	1.4018	1.6189	1.6347	1.9033
2003	-6.3012	1.8642	1.8429	1.7043	1.3493	2.2440	1.1207	1.5906	2.5887
2004	-6.5355	1.6021	1.8919	1.6105	1.2914	1.8694	1.5654	2.0199	1.8954
2005	0.0523	1.7666	1.6433	1.3766	1.4917	1.7234	1.3722	1.4289	1.3770
2006	-2.4181	2.3467	1.8561	1.2615	1.0605	1.4337	1.1817	1.0606	2.2272
2007	1.8317	1.1269	1.5906	1.2912	0.8547	2.1051	1.2834	1.4578	1.2849

Table 2 provides the distribution of earnings noncommonality (median values of NONCOMMON) by 1 digit SIC code. The highest and lowest earnings noncommonality values show some variation across SIC

codes from year to year but generally the highest earnings noncommonality is clustered in SIC 7 and 8 (Services) and 9 (International Affairs and Non- Operating Establishments). The lowest values are most often found in SIC 0 (Agriculture, Fishing, Forestry).

## EMPIRICAL RESULTS AND ANALYSIS

First of all, the sample period 1980-2007 is divided into seven-four year periods in order to study the time trends in IDIORISK and NONCOMMON. Table 3 shows the result of a simple regression of NONCOMMON on IDIORISK. There is a significant positive relationship between NONCOMMON and IDIORISK in the periods 80-83, 88-91, 92-95 and 96-99. The relationship in the period 00-03 though highly significant is negative and then turns nonsignificant in the 04-07 periods. These results give further credence to the findings of Brandt et al. (2010) that the positive surge in idiosyncratic volatility up to the late 1990s underwent a reversal in the 2000s and by 2003 volatility had fallen back to the pre 1990 level. Our findings are therefore consistent with those of Brandt et al. in that we find that the positive relationship between NONCOMMON and IDIORISK reversed in the 2000-03 period. The  $R^2$  of the relationships are consistently high in all the periods, ranging from 0.43 to 0.68, and indicate that NONCOMMON explains a good portion of IDIORISK changes.

Table 3: Regression of Idiosyncratic Risk on Earnings Noncommonality for Every 4 Years

Variables	80-83	84-87	88-91	92-95	96-99	00-03	04-07
NONCO- MMON	0.02** (2.65)	0.001 (0.13)	0.02* (2.02)	0.02** (2.85)	0.01* (2.17)	-0.02*** (-3.46)	0.001 (0.08)
R-square	0.46	0.43	0.52	0.68	0.58	0.52	0.63
N	2162	3120	3728	3944	4859	5200	3609

*The sample period 1980-2007 is divided into seven-four year periods in order to study the time trends in IDIORISK and NONCOMMON. This table shows the result of a simple regression on the relation between Ln(IDIORISK) and NONCOMMON. IDIORISK is defined as the Log of the average monthly variance of returns adjusted for Fama and French three factor model. NONCOMMON refers to the log of 1 minus the R2 from firm-specific regressions of quarterly return on assets (ROA) on market-and industry-level ROA indices.*

Table 4 presents the estimation results of the six models described in Section III which form the core of this research. NONCOMMON in the Basic Model (A1) and its extension with the TIME trend Model (B1) is positive and significant. Thus our findings support the positive relationship implied by the findings of Mazzucato and Tancioni (2008) and Brown and Kimbrough (2011). In Models (A2), (A3), (B2) and (B3), the primary variable of interest is LOWNONCOM which is a (0,1) dummy variable that takes on the value of 1 if LOWNONCOM is below the median value for the year and zero otherwise. The coefficient for LOWNONCOM in all of the four models is negative and highly significant. Since low earnings noncommonality implies high commonality, the negative association means that firms with high commonality have low idiosyncratic volatility. This relationship is consistent with the findings for Model (A1) and (B1) above. We find a positive and highly significant relationship between buy and hold return and IDIORISK. However, this relationship is positive and not negative as was expected given the findings of Duffie (1995). The positive sign is consistent with the normal risk and return relationship which postulates a positive association between risk and return.

Our results show a negative and highly significant negative relationship between CFO/TA and IDIORISK for all models except Model (A3) which shows a negative relationship but is not significant. This finding is consistent with the findings of Hanlon et al. (2004) who find that operating performance is negatively associated with stock return volatility. In line with expectations, the coefficient for cash flow volatility (CFO\_δ) is significant and positive for all models except Model (A3) where it is significant but negative. Vuolteenaho (2002) shows that idiosyncratic return volatility is positively related to the variance of cash flows. Our results are therefore generally consistent with the findings of Vuolteenaho.

Table 4: Regression Results of Earnings Noncommonality and Idiosyncratic Risk for the Six Models

Model	A1	A2	A3	B1	B2	B3
Intercept	-5.9218***	-5.8266***	-5.0978***	949.50***	948.63***	940.44***
NONCOMMON	0.0088***			0.0106*		
LOWNONCOM		-0.0344***	-0.2165***		-0.0506***	-0.0953***
BHRET	0.1174***	0.1173***	0.1279***	0.1228***	0.1228***	0.1372***
CFO/AT	-0.6798***	-0.6970***	-0.6940	-0.6908***	-0.6787***	-0.7084***
CFO $\delta$	0.3704***	0.3770***	-0.3955***	0.9545***	0.9538***	1.3999***
BTM	-0.0752***	-0.0728***	-0.0852***	-0.0106***	-0.0106***	-0.0499***
SIZE	-0.3135***	-0.3183***	-0.3069***	-0.3205***	-0.3206***	-0.3115***
LEV	-0.2598***	-0.2600***	-0.3688***	-0.1091***	-0.1090***	-0.2378***
TURNOVER	1.4696***	1.4705***		7.1485***	7.1848***	
TURNOVER*			1.5379***			0.0008
LOWNONCOM						
INST_OWN	-0.0005	-0.0005		0.0427***	0.0429***	
INST_OWN*			-0.0005			0.9409***
LOWNONCOM						
TIME				0.5368***	0.5345***	0.5144***
TIME*				0.0005	0.0025**	0.0023*
NONCOMMON						
TIME*INST_OWN				-0.0002***	-0.0002***	0.0000
TIME*CFO/AT				-0.0003	-0.0004	-0.0017
TIME*CFO $\delta$				-0.0395***	-0.0339***	-0.0612***
TIME*TURNOVER				-0.2525***	-0.2528***	-0.0394***
Adj. R <sup>2</sup>	0.49	0.49	0.47	0.53	0.53	0.49

\*\*\*, \*\* and \* denote significance at the 1%, 5%, and 10% levels, respectively this table examines the relation between earnings noncommonality and idiosyncratic risk. dependent variable is ln(idiosyncratic risk). lownoncom is a (01) dummy with a value of 1 if earnings noncommonality is below the median of the year. idiorisk is defined as the log of the average monthly variance of returns adjusted for fama and french three factor model. noncommon refers to the log of 1 minus the r2 from firm-specific regressions of quarterly return on assets (roa) on market-and industry-level roa indices. cfo/at is operating cash flows scaled by average total assets. cfo  $\delta$  is variance of operating cash flows scaled by average total assets over the trailing five years. btm is the book to market ratio. size is natural log of market value of equity. lev is financial leverage computed as the ratio of long term debt to total assets. bhret is annual buy-and-hold return. inst\_ own is percentage of shares owned by institutional investors. turnover is the average monthly trading volume of a security divided by the outstanding shares of the security.

The relationship between BTM and IDIORISK is negative and significant for all models in line with expectations based on the reasoning that firms with greater growth opportunities are likely to experience greater stock return volatility. SIZE is negatively and significantly associated with IDIORISK in all models. Small firms experience higher return volatility (Pastor and Veronesi (2003)) and hence as size increases, volatility decreases producing a negative relationship. LEV also has a negative and significant relationship with IDIORISK in all models. This relationship is contrary to expectations because levered firms are more likely to experience financial distress. This unexpected relationship may be because the sample period covers one of the longest expansions in US economic history and financial distress was not a major factor in forming expectations. A high turnover is often speculative and enhances volatility. The positive and significant signs for TURNOVER coefficients in Models (A1), (A2), (B1) and (B2) are therefore entirely in line with expectations. When TURNOVER is crossed with LOWNONCOM in Models (A3) and (B3), the coefficients are positive in both models.

This indicates that low earnings noncommonality further enhances the relationship of TURNOVER with IDIORISK. Neither INST\_OWN nor INST\_OWN crossed with LOWNONCOM is significant in Models (A1), (A2) and (A3) but once the time dimension is introduced, these variables become significant in Models (B1), (B2) and (B3). Thus, increase in institutional ownership increases IDIORISK, and more so for firms with LOWNONCOM. The time variable is highly significant and this is consistent with the basic premise that IDIORISK has increased over time. If an increase in NONCOMMON explains the increasing trend in idiosyncratic volatility, then TIME \* NONCOMMON should have a positive coefficient after controlling for the other interaction terms with TIME. The coefficients are indeed positive for all of the B class of Models but significant only for Models (B2) and (B3). The lack of significance for Model (B1) may be because the trend between idiosyncratic volatility and earnings noncommonality appears to be reversing in the later part of the sample period and this fact may be rendering the relationship for the whole period insignificant. TIME \* INST\_OWN controls for increasing investor sophistication over time and the coefficient for this variable is negative and significant for Models (B1) and (B2) indicating that increasing investor sophistication reduces IDIORISK. The interaction of TIME with CFO/TA and CFO  $\delta$  controls for the competing explanation that time-trend in cash flow performance and variability is responsible for increasing return volatility. The coefficients for

both these variables are negative in all B class Models but only the TIME \* CFO\_δ coefficients are significant. The significant negative coefficient for TIME \* CFO\_δ is somewhat surprising because it indicates that cash flow volatility is decreasing over time. Since the idiosyncratic volatility has been increasing, this paradoxical result can only be possible if the systemic volatility has been decreasing at an even faster rate. This would be consistent with the premise that synchronicity is decreasing and earnings noncommonality is increasing in stocks. The coefficient for TIME\*TURNOVER is significant and negative. This cross product term controls for an increase in IDIORISK because of turnover. The adjusted R<sup>2</sup> of the models vary in the range of 0.47 to 0.53. In summary, the core models of this research support hypotheses 2 and suggest rejection of hypotheses 1. Thus, higher (lower) levels of earnings noncommonality are associated with higher (lower) levels of idiosyncratic return volatility even after the other confounding influences on idiosyncratic volatility have been controlled.

Additional Checks

Product Market Competition

Several researchers have posited that the increase in idiosyncratic volatility is attributable to an increase in product market competition (Gaspar and Massa 2006; Irvine and Pontiff 2008). To establish the validity of our findings, it is essential to rule out the notion that earnings noncommonality is merely an indicator of market competitiveness. One proxy for market power used in previous literature is excess price-cost margin (EPCM) defined as the difference between a firm’s operating margin and the average operating margin of its industry. We run our six core models with EPCM added as an independent variable. The results of these analyses are provided in Table 5. The focus in table 5 analysis is to see whether after adding EPCM, the coefficients on NonCOMMON and LowNonCOMMON remain unchanged. In addition, a non-significant EPCM would imply that earnings noncommonality supersedes the effect of market power/competitiveness. As can be seen in table 5, the coefficients on NonCOMMON and LowNonCOMMON remain unchanged after EPCM has been added to the independent variables. This rules out any possibility that earnings noncommonality is merely an indicator of market competitiveness. In addition, the coefficient on EPCM is insignificant in all the six models, thereby showing that it has little explanatory power in the presence of earnings noncommonality.

Table 5: Regression Results of Earnings Noncommonality and Idiosyncratic Risk with Presence of EPMC

Model	A1	A2	A3	B1	B2	B3
intercept	-5.6910***	-5.9257***	-5.3788***	982.45***	981.66***	972.22***
noncommon	0.0089***					
lownoncom		-0.0350***	-0.2133***			
epcm	0.0005	0.0005	0.0007	0.0027	0.0026	0.0030
bhret	0.1136***	0.1162***	0.1227***	0.1166***	0.1165***	0.1238***
cfo/at	-0.6929***	-0.6922***	0.7019***	-0.6073***	-0.6046***	-0.6286***
cfo_δ	0.3992***	0.3984***	0.4099***	1.0027***	1.0019***	1.4727***
btm	-0.0654***	-0.0756***	-0.0777***	-0.0016***	-0.0015***	-0.0344***
size	-0.3112***	-0.3115***	-0.3045***	-0.3192***	-0.3192***	-0.3122***
lev	-0.2536***	-0.2538***	-0.3124***	-0.0928***	-0.0928***	-0.2254***
turnover	1.4644***	1.4675***		7.1786***	7.1971***	
turnover*			1.5666***			0.9555***
lownoncom						
inst_own	-0.0005	-0.0005		0.0032	0.0034	
inst_own*			-0.0005			0.0006
lownoncom						
time				0.5535***	0.5511***	0.5351***
time*noncommon				-0.0005	0.0023*	-0.0005*
time*inst_own				-0.0017**	-0.0017**	-0.0000
time*cfo/at				-0.0050	-0.0051	-0.0068
time*cfo_δ				-0.0464***	-0.2539***	-0.0638***
adj. r <sup>2</sup>	0.48	0.48	0.47	0.53	0.53	0.48

\*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively. EPCM (excess price-cost margin, which is a proxy of a firm’s market competitiveness) is added as an independent variable. Dependent variable is ln (idiosyncratic risk). EPCM is defined as the firm’s PCM minus the industry value-weighted average PCM where PCM is price-cost margin which is calculated as operating profit over sales.

Innovativeness

Hsu (2009) shows that technological innovations predict market returns and premiums, and Mazzucato (2008) finds evidence at the firm level that higher R&D intensity leads to higher idiosyncratic return volatility because of greater uncertainty about expected profits. It is therefore necessary to exclude the possibility that earnings noncommonality is just a measure of a firm’s innovativeness. The measure of innovativeness we use is industry adjusted R&D divided by sales (IND\_ADJ R&D). We introduce IND\_ADJ R&D as an independent variable in our six core models and re-estimate the models. The result of these estimations is given in Table 6. Similar to EPCM in table 5, the focus in table 6 analysis is on whether adding IND-ADJ R&D, the coefficients on NonCOMMON and LowNonCOMMON remain unchanged. In addition, a non-significant IND-ADJ R&D would verify that earnings noncommonality supersedes the effect of innovativeness. Table 6 shows that the coefficients on NonCOMMON and LowNonCOMMON remain unchanged after IND-ADJ R&D has been added to the independent variables. This rules out any possibility that earnings noncommonality is merely an indicator of firm innovativeness. In addition, the coefficient on IND\_ADJ R&D is insignificant in all the models. This shows that IND\_ADJ R&D provides little explanatory power in the presence of earnings noncommonality.

Table 6: Regression Results of Earnings Noncommonality and Idiosyncratic Risk with Presence of Innovation Risk

Model	A1	A2	A3	B1	B2	B3
intercept	-88.53***	-88.53***	-95.42***	702.70***	718.75***	653.72***
noncommon	0.0112***			0.0000		
lownoncom		-0.0271**	-0.1915***		-0.0361***	-0.0811***
ind_adj r&d	-0.0000	-0.0000	-0.000	-0.0009	-0.0000	-0.0000
bhret	0.1250***	0.1290***	0.1376***	0.1284***	0.1286***	0.1406***
cfo/at	-0.7230***	-0.7232***	-0.7366***	-0.6873***	-0.6788***	-0.7116***
cfo_δ	0.3598***	0.3146***	0.3144***	0.8883***	0.8850***	1.2617***
btm	-0.0113	-0.0255**	-0.3575***	-0.0074	-0.0079	-0.0412***
size	-0.3119***	-0.3143***	-0.3160***	-0.3192***	-0.3199***	-0.3117***
lev	-0.1131***	-0.1597***	-0.2099***	-0.0693**	-0.0713**	-0.0511***
turnover	1.6277***	1.5781***	1.6545***	6.4777***	6.4858***	
turnover*						1.6389***
lownoncom						
inst_own	0.0002	0.0001	0.0001	0.0148	0.0159	
inst_own*						0.0006
lownoncom						
time				0.4241***	0.4235***	0.3858***
time*				0.0006	0.0012	-0.0038**
noncommon						
time*inst_				-0.0007	-0.0008	-0.0000
own						
time*cfo/at				0.0009	0.0003	0.0001
time*cfo_δ				-0.0343***	-0.0341***	-0.0555***
time*				-0.2229***	-0.2297***	-0.0344***
turnover						
adj. r <sup>2</sup>	0.5114	0.5173	0.5016	0.5446	0.5465	0.5097

\*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively The model now includes a measure of innovation (= industry adjusted R&D/sales) in addition to our base models.

Other Robustness Tests

Brown and Kapadia (2007) suggest that the increase in the listing of riskier firms has contributed to the increase in stock volatility. Brandt et al. (2010) show that low priced stocks that have a high level of retail trades are responsible for the trend of higher idiosyncratic risk. To control for these factors, we introduce two new variables. RISKYFIRMS is a (01) dummy variable that takes on the value of 1 if the firm year observation belongs to the high technology SIC codes, and zero otherwise. This variable controls for the risky firm factor. The second variable, LOWPRC\_HIGHRETAIL, is also a dummy that takes on the value of 1 if the firm-year observation has a share price in the bottom 30% and the INST\_OWN in the

bottom 30%. The Basic Model (A1) is augmented by EPCM, RISKYFIRMS, and LOWPRC\_HIGHRETAIL variables to give Model (C1) and additionally by the variable, IND\_ADJR&D to produce Model (C2). The results are presented in Table 7. The coefficient of RISKYFIRMS is negative and significant in both Models (C1) and (C2). The coefficients for LOWPRC\_HIGHRETAIL are positive and significant in both Models (C1) and (C2) consistent with the findings of Brav et al. (2010). IND\_ADJR&D in Model (C2) continues to be insignificant as in the earlier robustness test, but EPCM becomes significant in Model (D2). However, the coefficient of EPCM is positive and this is contrary to the market power thesis of Gaspar and Massa (2006) and Irvine and Pontiff (2008). The coefficients for NONCOMMON stay positive and significant, implying that the positive association between earnings noncommonality and idiosyncratic risk is robust even in the presence of the newly introduced variables.

Table 7: Regression Results of Base Models Augmented By EPCM, RISKYFIRMS, and LOWPRC\_HIGHRETAIL Variables

	Model C1	Model C2
intercept	-6.5995***	-71.268***
noncommon	0.0098***	0.0133***
epcm	-0.0001	0.3419***
ind_adj. r&d		-0.0000
bhret	0.0581***	0.0587***
cfo/at	-0.5764***	-0.4298***
cfo_δ	0.3375***	0.2046***
btm	-0.0837***	-0.0396***
size	-0.2344***	-0.2275***
lev	-0.2895***	-0.1472***
turnover	1.1795***	1.8419***
inst_own	-0.0004	0.0002
highrisk (01) dummy	-0.3641***	-0.2948**
lowprc_highretail	0.5955***	0.6359***

\*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively RISKYFIRMS is a (01) dummy variable that takes on the value of 1 if the firm year observation belongs to the high technology SIC codes, and zero otherwise. This variable controls for the risky firm factor. The second variable, LOWPRC\_HIGHRETAIL, is also a dummy that takes on the value of 1 if the firm-year observation has a share price in the bottom 30% and the INST\_OWN in the bottom 30%. The Basic Model (A1) is augmented by EPCM, RISKYFIRMS, and LOWPRC\_HIGHRETAIL variables to give Model (C1) and additionally by the variable, IND\_ADJR&D to produce Model (C2).

## CONCLUSION

The seminal article of Campbell et al. (2001) reported that idiosyncratic volatility greatly increased in stock returns during the period 1963-97. A separate strand of literature came to the conclusion that average investors are not well diversified and therefore idiosyncratic risk is priced. Together these findings set off a spate of research to determine the factors responsible for the increase in the idiosyncratic volatility of stock returns. In this paper we suggest earnings noncommonality as a possible source for the increase in idiosyncratic risk. The extant literature on the sources for the increased volatility did not provide a clear cut direction for a possible relationship between earnings noncommonality and idiosyncratic volatility. The product market competition hypothesis suggests a negative relationship while asymmetric information and innovativeness suggests a positive relationship. Our results indicate a significant positive relationship between earnings noncommonality and idiosyncratic volatility after controlling for other influences on volatility. Firms with higher earnings noncommonality experience higher idiosyncratic volatility. The introduction of the TIME variable in the models shows that volatility and earnings noncommonality has generally increased over the sample period. However, in line with recent research indicating that the increase in idiosyncratic volatility changes over time (Brandt et al. (2010), our findings indicate that the relationship between earnings noncommonality and idiosyncratic volatility also exhibits similar changes.

Financial analysts and investors are extremely interested in knowing the factors that determine asset prices. It is generally appreciated that the simple Capital Asset Pricing Model (CAPM) is not sufficient to

provide reliable information about asset returns. If idiosyncratic risk is priced as recent research suggests, then it is important for investors and financial analysts to be knowledgeable about the determinants of idiosyncratic risk. In addition, as pointed out by Rajgopal and Venkatachalam (2011), idiosyncratic volatility has ramifications for portfolio diversification, arbitrageurs, who require substitutes for mispriced stocks with lower idiosyncratic risk, and for pricing of employee stock options. This paper on the relationship between earnings noncommonality and idiosyncratic risk volatility will be particularly useful for practitioners in these areas. One limitation of the study is that it is not prescriptive. It explains the relationship between idiosyncratic risk and noncommonality for the sample period. But noncommonality is not a static concept and its nature and effect changes as the economy evolves. Another limitation is that the sample period covers one of the longest stretch of economic expansion in the U.S. economy and so may not be representative of periods with business cycles. Future research on the subject should apply the models developed in this paper to other periods.

## BIOGRAPHY

Ang A., R. Hodrick, Y. Xing and X. Zhang (2006) “The Cross-Section of Volatility and Expected Returns,” *Journal of Finance*, vol. 61, p. 259-299.

Bennett, J. A., R. W. Sias, and L. T. Starks (2003) “Greener Pastures and the Impact of Dynamic Institutional Preferences,” *Review of Financial Studies* vol. 16 p.1203–38.

Brandt, M. W., A Brav, J.R. Graham and A. Kumar (2010) “The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episode?” *The Review of Financial Studies* vol. 23(2), p. 863-99.

Brockman, P., M.G. Schutte, and W. Yu (2009) “Is Idiosyncratic Risk Priced? The International Evidence,” Available at SSRN: <http://dx.doi.org/10.2139/ssrn.1364530>

Brown, G., and N. Kapadia (2007) “Firm-Specific Risk and Equity Market Development,” *Journal of Financial Economics* vol. 84, p. 358–88.

Brown, N.C. and M.D. Kimbrough (2011) “Intangible investment and the importance of firm-specific factors in determination of earnings,” *Review of Accounting Studies* vol. 16(3), p. 539-573.

Campbell, J., M. Lettau, B. Malkiel, and Y. Xu (2001) “Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk,” *Journal of Finance* vol. 56, p. 1–43.

Duffie, G. (1995) “Stock returns and volatility: a firm-level analysis,” *Journal of Financial Economics* vol. 37, p. 399–420.

Elgers, P., S. Porter, and L. Xu (2004) “Birds of a feather: Do co-movements in accounting fundamentals help to explain commonalities in securities returns?” Working paper, University of Massachusetts, Amherst.

Fama, E., and K. French (1993) “Common risk factors in the returns on stocks and bonds,” *Journal of Financial Economics* vol. 33 p. 3–56.

Fink J., K. E. Fink, G. Grullon and J. P. Weston (2010) “What Drove the Increase in Idiosyncratic Volatility during the Internet Boom?” *Journal of Financial and Quantitative Analysis* vol. 45, p. 1253-1278.

Gaspar, J.M. and M. Massa (2006) “Idiosyncratic Volatility and Product Market Competition,” *Journal of Business* vol. 79(6) p. 3125- 52.

Goetzmann, W. and A. Kumar, (2004) “Why do individual investors hold under-diversified portfolios?” Unpublished working paper, Yale University.

Goyal, A. and P. Santa-Clara (2003) “Idiosyncratic Risk Matters!” *The Journal of Finance* vol. 58 p. 975–1008.

Hanlon, M., S. Rajgopal and T. Shevlin (2004) “Large sample evidence on the relation between stock options and risk taking,” Working Paper, University of Washington.

Hsu, P.H. (2009) “Technological innovations and aggregate risk premiums,” *Journal of Financial Economics* vol. 94 p. 264-279.

Irvine, P. J. and J. Pontiff (2008) “Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition,” *Review of Financial Studies* vol. 22 p.1149–77.

Jiang, G.J., D. Xu and T. Yao (2009) “The Information Content of Idiosyncratic Volatility,” *Journal of Financial and Quantitative Analysis* vol. 44(1) p. 1-28.

Levy, H. (1978) “Equilibrium in an imperfect market: a constraint on the number of securities in the portfolio,” *American Economic Review* vol. 68 p. 643–658.

Malkiel, B. and Y. Xu (2002) “Idiosyncratic risk and security returns,” Unpublished working paper, University of Texas at Dallas.

Mazzucato M. and M. Tancioni (2008) “Innovation and idiosyncratic risk: an industry and firm-level analysis,” *Industrial and Corporate Change* vol. 17(4) p. 779-811.

Merton, R. (1987) “A simple model of capital market equilibrium with incomplete information,” *Journal of Finance* vol. 42 p. 483–510.

Morck, R., B. Yeung, W. Yu (2000) “The information content of stock markets: why do emerging markets have synchronous price movements?” *Journal of Financial Economics* vol. 58 p. 215-260.

Palepu, K., P. Healy, and V. Bernard (2007) “Business analysis and valuation: Using financial statements,” (4th Edition), Mason: Thomson South-Western.

Pastor, L. P. Veronesi (2003) “Stock valuation and learning about profitability,” *Journal of Finance* vol. 58 p. 1749–1789.

Piotroski, J. and D. Roulstone (2004) “The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices,” *The Accounting Review* vol. 79(4) p. 1119–1151.

Rajgopal, S. and M. Venkatachalam (2011) “Financial Reporting Quality and Idiosyncratic Return Volatility,” *Journal of Accounting Economics* vol. 51 p. 1-20.

Vuolteenaho, T. (2002) “What drives firm-level stock returns?” *Journal of Finance* vol. 57 p. 233–264.

Wei, S. X. and C. Zhang (2006) “Why Did Individual Stocks Become More Volatile?” *Journal of Business* vol. 79 p. 259–92.

Xu, Y. and B.G. Malkiel (2003) “Investigating the Behavior of Idiosyncratic Volatility,” *Journal of Business* vol. 76 p. 613-44.

### **AUTHORS’ BIOGRAPHIES**

Kenneth Yung is Professor of Finance in the Old Dominion University’s College of Business and Public Administration. He has published in the *Journal of Financial Economics*, *Journal of Futures Markets*, *Quarterly Review of Economics and Finance*, *Journal of Real Estate Finance and Economic*, *Journal of Real Estate Research*, *Review of Quantitative Finance and Accounting*, *Journal of Business Finance and Accounting*, *International Review of Economics and Finance*, etc. Kenneth Yung College of Business and Public Administration Old Dominion University Norfolk, VA 23529 Email: kyung@odu.edu

Qian Sun, PhD is an Associate Professor of Finance at Kutztown University of Pennsylvania. Her publications have appeared in the *Journal of Business Finance and Accounting*, *Accounting and Finance*, *Managerial Finance*, *Asia Pacific Journal of Management*, among others. She has reviewed for articles submitted to *Financial Management*, the *Quarterly Review of Economics and Finance*, the *Financial Review*, *Journal of Economics and Finance*, *Journal of Real Estate Portfolio Management*, among others. Qian Sun, PhD College of Business Kutztown University of Pennsylvania 15200 Kutztown Rd. Kutztown, PA 19530 sun@kutztown.edu

Hamid Rahman, PhD is Professor of Finance in the Alliant International University’s School of Management. He has published widely on financial issues in Journals such as the *Journal of the Futures Markets*, *Journal of Managerial Finance*, *Journal of Multinational Finance*, *Journal of Global Finance*, *Financial Services Review* etc. He has also been a reviewer for articles submitted to *The Quarterly Review of Economics and Finance*, *Journal of Real Estate Finance and Economic*, *Journal of Technological Forecasting and Social Change*. Hamid Rahman, School of Management Alliant International University 10455 Pomerado Road San Diego, CA 92131 Email: hrahman@alliant.edu