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The Information Content of Idiosyncratic Volatility

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Abstract

Ang, Hodrick, Xing, and Zhang (2006a) show that stocks with high idiosyncratic return volatility tend to have low future returns. This paper further documents that idiosyncratic volatility is inversely related to future earning shocks, and more importantly, that the return-predictive power of idiosyncratic volatility is induced by its information content about future earnings. We examine various explanations of the triangular relation among idiosyncratic volatility, future earning shocks, and future stock returns. Our results show that the idiosyncratic volatility anomaly is not a simple manifestation of previously documented market anomalies related to excessive extrapolation on firm growth, over-investment tendency, accounting accruals, or investor underreaction to earnings news. On the other hand, there is evidence that the idiosyncratic volatility anomaly is related to corporate selective disclosure, and the anomaly is stronger among stocks with a less sophisticated investor base.

I. Introduction

In a recent study, Ang, Hodrick, Xing, and Zhang (2006a) document an intriguing anomaly that stocks with higher idiosyncratic return volatility, on average, have lower future returns. In particular, they find that stocks in the bottom quintile of idiosyncratic volatility (IVOL) outperform stocks in the top quintile by 1.06% per month, and the results are robust to the effects of size, value, momentum, liquidity, trading volume, and dispersion of analyst forecasts. Further

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evidence in Ang et al. (2006b) show that this anomaly cannot be explained by trading frictions, higher moments of returns such as skewness, or asymmetric information among investors.

This paper documents that idiosyncratic return volatility is also inversely predictive of future earnings and earning shocks. For example, when stocks are sorted on IVOL at the end of each quarter, the average differences of return on equity (ROE) between stocks in the bottom and top deciles are 2.19% in the following quarter and 5.87% in the following year. The standardized unexpected earnings (SUE), a measure of earning shocks, are significantly higher for stocks in the bottom decile than for stocks in the top decile in the following quarter and the following year. Using analyst consensus earnings forecasts to measure expected earnings, we find a similar pattern in earning shocks. Such differences in future earnings and earning shocks are not only statistically and economically significant but also robust to the size, book-to-market, momentum, and industry effects.

Since corporate earnings are an important determinant of stock returns, a natural and interesting question is whether the return-predictive power of IVOL is induced by its information content about future earnings. We find that this is indeed the case. Once we control for future earning shocks, there is no longer a significantly negative relation between IVOL and future stock returns. In contrast, the return-predictive power of size, book-to-market ratio, and momentum is not subsumed by earning shocks. This suggests that the IVOL anomaly documented in Ang et al. (2006a) is distinct from classical asset pricing anomalies in the literature.

The finding that stock return differences across idiosyncratic volatility deciles are largely driven by news about firms' future earnings sheds new light on the IVOL anomaly. In particular, it provides an important perspective for assessing potential explanations of the inverse relation between IVOL and stock returns. Several existing asset pricing theories imply a possible inverse relation between IVOL and expected stock returns. For instance, Constantinides (1984) points out that there is a tax-timing option associated with stock return volatility. Since stocks with higher IVOL offer a higher tax-timing option value, investors may require lower expected returns to hold them. The model by Johnson (2004) suggests that equity is valued as an option on the underlying assets of levered firms. Firms with higher IVOL may have higher current equity value but lower expected equity return given the fixed terminal value of the firm. These theories, however, relate idiosyncratic volatility to expected returns but not to firms' future cash flows. Finally, Miller (1977) points out that stock prices reflect optimism in the presence of short-sale constraints. When investors' beliefs are diverse (as proxied by high idiosyncratic volatility) and investors with pessimistic views are kept out of the market, stocks tend to be overvalued and a future price reversal is likely.[1] Similarly, this behavioral hypothesis fails to link cross-sectional differences in IVOL with firms' future realized cash flows.

[1]Boehme, Danielsen, Kumar, and Sorescu (2005) empirically examine short-sale constraints as a possible explanation for IVOL anomaly.

The key question, then, is what causes the inverse relation between idiosyncratic stock return volatility and future corporate earnings. In this study, we examine whether the idiosyncratic volatility anomaly is linked to previously documented market anomalies in the literature. We consider four such anomalies, which are related to excess extrapolation on firm growth (Lakonishok, Shleifer, and Vishny (1994)), tendencies of managers to overinvest (Titman, Wei, and Xie (2004)), investor misreaction to information in accounting accruals (ACC) (Sloan (1996)), and investor underreaction to earnings news (Ball and Brown (1968), Bernard and Thomas (1989), (1990)). These anomalies suggest that firms' future earnings and returns can be predicted by a number of firm-specific variables, including firms' past sales growth (SG), analyst forecasts of firms' long-term growth, firms' capital investments and R&D expenditures, ACCs, past earnings surprises, and analysts' earnings forecast revision.

We first examine the relation between idiosyncratic return volatility and the above firm-specific variables based on sorted portfolios. We find that idiosyncratic return volatility is positively related to SG and the intensity of R&D, and negatively related to past earnings surprises, but has a U-shaped relation with the other variables. The lack of a simple monotonic mapping of IVOL to most of these variables casts doubt on a simple link between the IVOL anomaly and some of the anomalies previously documented in the literature.

We next examine whether the above firm-specific variables can explain the relation of IVOL with future earnings and future returns. Based on Fama-MacBeth regressions, we find that while all these variables have significant power to predict future earnings, they do not subsume the predictive power of IVOL on future earnings. That is, the earnings information contained in IVOL is not simply induced by excess extrapolation on firm growth, firm investment activities, ACCs, or investor underreaction to earnings news. Furthermore, idiosyncratic volatility continues to significantly predict stock returns even after controlling for firm-specific variables associated with the above market anomalies. Consistent with existing literature, we find that investors tend to underreact to earnings news. However, investor underreaction to earnings news does not fully account for the return-predictive power of IVOL.

In addition to the hypotheses related to previously documented market anomalies, we also explore a potential link between the IVOL anomaly and strategic corporate behavior in information disclosure. Theoretical models on voluntary corporate information disclosure (e.g., Verrecchia (1983), Dye (1986), and Shin (2003)) show that under certain conditions management may have incentive to release good news in a timely manner but withhold negative information about future earnings. Less information disclosure generally leads to more heterogeneous investor beliefs and higher stock return volatility. Thus, stocks with high IVOL are more likely to be those with negative earning shocks in the future.

We use the AIMR (Association for Investment and Management Research, now the CFA Institute) corporate disclosure score as a measure of firms' quality of information disclosure. The AIMR disclosure score is based on analysts' ranking of the extent and quality of a firm's financial information disclosure. Our results show that firms with high IVOL tend to have poor disclosure quality, and the negative relation is monotonic. In addition, the disclosure score negatively predicts future earnings. More importantly, controlling for corporate information disclosure significantly reduces the predictive power of IVOL on future earnings. Finally, the disclosure score is negatively related to future stock returns and to a large extent explains the return-predictive power of IVOL.

A direct implication of the above finding is that marginal investors in the stock market are not sophisticated enough to fully understand selective disclosure of corporate information. Thus, the information of IVOL is not fully incorporated into the current valuation of stocks. Consistent with the effect of corporate selective disclosure, we find that mispricing of earnings information occurs mainly for firms with high IVOL (those with a poor prospect of future earnings). To further explore this implication, we construct several measures of investor sophistication and show that the IVOL anomaly is stronger among stocks with a less sophisticated investor base.

To summarize, our results suggest that the idiosyncratic volatility anomaly documented in Ang et al. (2006a) is not a simple manifestation of market anomalies previously documented in the literature. Although there is evidence that the idiosyncratic volatility anomaly is related to investor underreaction to earnings news, investor underreaction cannot fully explain the predictive power of IVOL on future earnings and stock returns. On the other hand, our analysis presents promising evidence linking the IVOL anomaly to corporate selective disclosure. We acknowledge, however, that the empirical evidence presented in our study is limited in scope due to the lack of a direct measure of corporate disclosure quality. Selective corporate disclosure behavior is not directly observable and is difficult to quantify. In addition, the AIMR disclosure score data used in our study are only available over a limited time period for firms that are mostly of large and medium size with an extensive analyst following. Clearly, further extensive research on the effect of selective disclosure requires a more direct measure of corporate disclosure on future earnings information and a sample that covers more firms over an extended time period.

The remainder of the paper is structured as follows. Section II confirms the empirical findings of Ang et al. (2006a) on the idiosyncratic volatility and return relation and presents evidence that IVOL contains information about future earnings. In Section III, we empirically examine various potential explanations of the IVOL anomaly. Section IV examines the effect of investor sophistication on the mispricing of IVOL. Section V concludes.

II. The Idiosyncratic Volatility Anomaly

Ang et al. (2006a) report a significantly negative cross-sectional relation between IVOL and future returns. In this section, we further document an inverse relation between IVOL and future earnings and provide evidence that the stock return anomaly may be induced by earnings information in IVOL.

A. Data and Idiosyncratic Volatility Measure

Data on stock returns, prices, shares outstanding, and trading volume are obtained from CRSP. Analysts' earnings forecasts are from IBES. Book value of equity and net income are from Compustat. In each quarter, we select stocks with the following criteria. First, to ensure an accurate measure of IVOL, a stock must have at least 44 daily return observations in CRSP during a quarter, which is equivalent to a two-month trading period. Second, to avoid market microstructure-related issues, at the end of each portfolio-formation quarter the stock price must be no less than \$5. Third, following Fama and French (1993), we exclude firms with negative book values. Fourth, a firm's fiscal quarter must end in March, June, September, or December. This is to ensure that calender-quarter returns can be matched with fiscal-quarter earnings.[2] The sample period in our study is from January 1974 through December 2002.

Similar to Ang et al. (2006a), we estimate a stock's IVOL in each quarter from daily CRSP data using the Fama and French (1993) three-factor model. To control for the effect of nonsynchronous trading, we include three leads and three lags of market returns as regressors. To be specific, IVOL is the standard deviation of the residuals (ϵ_t) from the following regression:

$$r_t = \alpha + \beta_1 \mathrm{HML}_t + \beta_2 \mathrm{SMB}_t + \sum_{i=-3}^{3} \gamma_i r_{m,t-i} + \epsilon_t, \tag{1}$$

where r_t is the daily stock return, $r_{m,t}$ is the daily CRSP value-weighted index return (the market return), and HML_t and SMB_t are the daily Fama-French book-to-market and size factors. The daily and monthly Fama and French factors used in our analysis are obtained from Ken French's Web site. As robustness checks, we also consider model (1) with no lead or lag for all variables, and one and three leads and lags for each variable, and confirm that the empirical results are consistent. In all cases, only information before the end of the quarter is used in the model estimation.

Table 1 reports summary statistics of IVOL and characteristics of the sample stocks during various subperiods from 1974 to 2002. In our analysis, log market capitalization (ln(SIZE)) is based on stock prices in the last month of each quarter. The book value of equity in the log book-to-market ratio (ln(B/M)) is from the most recently reported fiscal year, assuming a four-month reporting lag. Momentum (PrRet) is the average monthly return during the past 12 months before the last month of the current quarter. Leverage (LEV) is the ratio of the book value of debt to book value of assets from the most recently reported fiscal year. All statistics in Table 1 are calculated first cross-sectionally each quarter and then averaged over time. The results in Panel A suggest that the average IVOL clearly trends up during our sample period, consistent with the pattern documented by Campbell, Lettau, Malkiel, and Xu (2001). Both the average number of firms and

[2]There are 434,326 firm-quarter observations in our data set with the requirements of i) at least 44 daily return observations during a quarter, ii) quarter-end stock price no less than \$5, and iii) non-negative book value. Further restricting firms to have their fiscal quarter matching their calender quarter reduces the firm-quarter observations to 358,199, or 82.5% of the total observations. In untabulated analysis, we confirm that the fiscal-quarter matching restriction is not critical for the negative relation of IVOL with future earnings and stock returns. However, the \$5 minimum stock price restriction is important for the robustness of the inverse relation between IVOL and future returns, possibly due to the noise in measuring the returns of low-price stocks.

TABLE 1

Summary Statistics of Idiosyncratic Volatility and Firm Characteristics

Table 1, Panel A, reports the summary statistics of idiosyncratic volatility (IVOL) and characteristics of sample stocks during subperiods from 1974 to 2002. *N* is the average number of firms in each quarter during the subperiod. IVOL is estimated using daily stock returns during each quarter from the Fama-French three-factor model with three leads and three lags of market returns. ln(SIZE) is the log market capitalization in millions of dollars. ln(B/M) is the log of book value of equity for the current fiscal year divided by market capitalization. Momentum (PrRet) is the average monthly returns during the past 12 months, expressed in percentage points. Leverage (LEV) is the ratio of total assets to the book value of equity. Panel B reports the time series average of the cross-sectional correlations among IVOL, ln(SIZE), ln(B/M), PrRet, and LEV during all subperiods.

Panel A. Descriptive Statistics

		IVOL		ln(SIZE)		ln(B/M)		PrRet		LEV	
Period	*N*	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1974–1979	2,078	1.84	1.65	4.28	4.13	−0.07	0.03	1.75	1.06	3.71	2.19
1980–1984	2,497	1.89	1.72	4.61	4.45	−0.39	−0.22	2.53	1.54	3.93	2.25
1985–1989	2,856	2.07	1.85	4.95	4.68	−0.64	−0.51	1.46	1.00	4.35	2.36
1990–1994	2,986	2.49	2.25	5.18	4.94	−0.75	−0.62	2.26	1.37	4.41	2.38
1995–1999	4,304	2.72	2.42	5.55	5.32	−0.94	−0.80	2.04	1.11	4.35	2.37
2000–2002	4,519	2.87	2.53	5.83	5.72	−0.76	−0.63	2.11	0.70	4.44	2.30

Panel B. Correlation of Variables

	IVOL	ln(SIZE)	ln(B/M)	PrRet	LEV
IVOL	1.00				
ln(SIZE)	−0.37	1.00			
ln(B/M)	−0.07	−0.24	1.00		
PrRet	0.04	0.02	−0.28	1.00	
LEV	−0.07	0.03	0.05	−0.01	1.00

the average market capitalization of stocks in our sample increases steadily in the sample period, while the average book-to-market ratio is relatively stable. The correlations in Panel B suggest that stocks with higher IVOL tend to be smaller in size, and have lower book-to-market ratios and higher past returns.

B. Idiosyncratic Volatility and Stock Returns

We examine stock returns for a holding period of three months after the IVOL is measured. At the end of each quarter in our sample period, we rank stocks based on IVOL to form equal-weighted decile portfolios and then hold the portfolios over the next quarter. As in Ang et al. (2006a), we refer to the IVOL estimation quarter as the portfolio formation period (denoted by Q0) and the subsequent quarter as the portfolio holding period. In calculating holding-period returns, we follow Shumway (1997) to treat delisting returns and replace missing delisting returns with -30% if delisting is performance-related, and zero otherwise. For each of the 10 decile portfolios, we calculate the time series means of the quarterly holding-period returns and their t-statistics. The time series t-statistics are computed using the Newey-West heteroskedasticity and autocorrelation consistent covariance estimator (see Newey and West (1987)).

Table 2 confirms the inverse cross-sectional relation between IVOL and future stock returns reported in Ang et al. (2006a). Stocks in the lowest decile of IVOL (D1) significantly outperform those in the highest decile of IVOL (D10) by 3.28% per quarter. The Newey-West t-statistic is significant at the 1% critical level. Furthermore, the return difference is mainly between the highest two deciles (D9 and D10) and the other eight deciles (D1 to D8). Returns exhibit only a slight downward trend from the first decile (D1) to the eighth decile (D8), but drop off sharply for the ninth (D9) and 10th (D10) decile portfolios. A similar pattern is noted in Ang et al. (2006a) based on quintile portfolios. Untabulated results based on value-weighted decile portfolios also have the same patterns.

TABLE 2

Returns and Characteristics: Portfolios Sorted by Idiosyncratic Volatility

Table 2 reports the time series means of the idiosyncratic volatility (IVOL) and various characteristics, including ln(SIZE), ln(B/M), and momentum (PrRet), of equal-weighted decile portfolios formed at the end of each quarter based on IVOL. It also reports the average quarterly portfolio returns (r) and the α estimates (alpha), together with t-statistics, of the Carhart (1997) four-factor model. Return and IVOL are in percentage points. The Newey-West t-statistics are computed with a four-quarter lag for portfolio characteristics and a one-quarter lag for returns and alphas.

IVOL Decile	IVOL	ln(SIZE)	ln(B/M)	PrRet	Return (r)	Alpha	
D1(L)	0.83	5.68	0.85	1.35	3.83	0.25	(0.52)
D2	1.18	6.01	0.80	1.46	4.00	0.30	(0.91)
D3	1.43	5.74	0.80	1.48	4.21	0.30	(0.90)
D4	1.67	5.39	0.81	1.59	4.25	0.34	(1.03)
D5	1.93	5.10	0.80	1.73	4.39	0.41	(1.33)
D6	2.21	4.82	0.79	1.90	4.49	0.30	(1.16)
D7	2.54	4.59	0.77	2.14	4.11	−0.01	(−0.03)
D8	2.93	4.37	0.76	2.34	3.66	−0.43	(−1.28)
D9	3.48	4.14	0.73	2.43	2.73	−1.28	(−2.95)
D10(H)	4.88	3.80	0.70	2.69	0.55	−3.21	(−5.12)
D1–D10	−4.05	1.88	0.15	−1.34	3.28	3.46	
t-stat.	(−30.8)	(10.0)	(3.62)	(−2.13)	(2.56)	(4.23)	

Table 2 also reports various portfolio characteristics. For each decile portfolio, we calculate the time series means of log market capitalization, log book-to-market ratio, and momentum at the end of each portfolio-formation period. Consistent with Panel B of Table 1, the results in Table 2 suggest that firms with high IVOL overall tend to be smaller in size and have lower book-to-market ratios and higher past returns. Based on the Newey-West *t*-statistics, the differences in stock characteristics between the low-IVOL portfolio (D1) and high-IVOL portfolio (D10) are all statistically significant.

Since these portfolio characteristics are also related to the cross-section of stock returns, we further control for their effects by estimating the alpha for each portfolio using the following Carhart (1997) four-factor model:

$$(2) \qquad r_t - r_{f,t} = \alpha + b_1(r_{m,t} - r_{f,t}) + b_2\mathrm{SMB}_t + b_3\mathrm{HML}_t + b_4\mathrm{UMD}_t + e_t,$$

where r_t is the quarterly portfolio return, $r_{f,t}$ is the three-month T-bill yield, and $r_{m,t}$ is the quarterly return of the CRSP value-weighted index. SMB_t, HML_t, and UMD_t are the Fama-French size, book-to-market, and momentum factors, respectively, which are aggregated from monthly data to quarterly observations. The results are also reported in Table 2. The difference in alphas between the D1 and D10 portfolios is 3.46% and statistically significant. In other words, factor exposure cannot explain the inverse relation between IVOL and stock returns. Moreover, the portfolio alphas exhibit a similar pattern to the raw portfolio returns. Namely, the main difference in alphas between the low and high IVOL portfolios is due to the very low alphas of the two highest IVOL deciles (D9 and D10). The alpha estimates are insignificant for deciles D1 to D8 but significantly negative for deciles D9 and D10.

C. Idiosyncratic Volatility and Future Earnings

In Section II.C, we further document that IVOL is predictive of future earnings and earning shocks. We use the following measures of earnings and earning shocks in our analysis:

i) Return on equity (ROE): quarterly net income divided by beginning-of-quarter book value of equity. The data is from Compustat.

ii) Standardized unexpected earnings (SUE): quarterly unexpected earnings (UE) divided by the standard deviation of UE. UE is the reported quarterly earnings per share (EPS) in excess of EPS four quarters ago. The standard deviation is calculated from UE over the past eight quarters or a minimum of four quarters. The data is from Compustat.

iii) Analyst forecast error (FER): realized quarterly EPS in excess of the mean of analysts' EPS forecasts at the last month of the portfolio formation quarter (Q0), divided by the previous year's book value of equity per share. Both realized EPS and EPS forecasts are from IBES. We adjust the number of shares outstanding from Compustat so that the book value per share from Compustat and EPS from IBES are consistent. Due to data availability, the variable FER is constructed over the period from 1980 to 2002.

As a measure of earning shock, SUE is based on the assumption that earnings follow a seasonal random walk. On the other hand, FER uses analysts' mean earnings forecast as a direct measure of expected earnings.

Similar to the analysis in Section II.B, at the end of each quarter we sort stocks on IVOL to form equal-weighted decile portfolios. Panel A of Table 3 reports the time series average of median ROE, SUE, and FER measures for each portfolio during the portfolio formation quarter (Q0), the following quarter (Q1), and the four quarters following portfolio formation. Specifically, ROE4 (SUE4) is the aggregate ROE (SUE) over quarters Q1 to Q4. Since IBES only provides analysts' earnings forecasts for four quarters from Q0 to Q3, FER4 is defined as the aggregate FER over quarters Q0 to Q3. We include Q0 earnings in our analysis because of the financial reporting time lag. Q0 earnings are typically not released at the end of Q0. On the other hand, we consider earnings up to the next four quarters, because such information may affect stock returns in Q1 through information updating (e.g., corporate guidance or analyst forecasts).

The results show that stocks with the lowest IVOL, on average, have high future earnings and positive earning shocks, while stocks with the highest IVOL, on average, have low future earnings and negative earning shocks for Q0, Q1, and subsequent quarters. The differences in ROE, SUE, and FER between the lowest and highest IVOL portfolios are all statistically significant. We also note that these earnings measure declines steadily among low IVOL deciles but drop at a faster pace among high IVOL deciles. For the two highest IVOL deciles (D9 and D10), the SUE measures are mostly negative. We note that FER is mostly negative in Table 3, suggesting an overall optimistic bias in analysts' forecasts (Richardson, Teoh, and Wysocki (2004)). Finally, untabulated results based on value-weighted decile portfolios show the same patterns.

To provide further evidence on the persistence of the relation between IVOL and earnings, we perform the following analysis. In each quarter t, we form equal-weighted quintile portfolios based on IVOL. We then compute the average IVOL, ROE, and SUE of the quintile portfolios during each of the four quarters before and after the portfolio formation quarter (i.e., from quarter $t-4$ to $t+4$). The differences in IVOL, SUE, and ROE between the bottom and top quintile portfolios are plotted in Figure 1. The figure shows that IVOL is persistent over time. Interestingly, ROE exhibits a very similar pattern of persistence. The difference in SUE between the top and bottom quintiles decays at a relatively faster pace. However, the SUE difference remains positive even at quarter $t+4$. This is in contrast with the well-known mean-reverting pattern of SUE documented in the literature. For example, Bernard and Thomas (1989) report that the top decile of stocks sorted on SUE in quarter t typically have negative SUEs in quarter $t+4$ (i.e., four quarters after the portfolio formation quarter). The patterns of ROE and SUE in Figure 1 illustrate a persistent relation of IVOL with earnings and earning shocks.

Note that portfolios formed on IVOL involve turnover. As a result, some stocks will no longer be in the same portfolio in future quarters (e.g., at Q4 when ROE4, SUE4, and FER4 are computed). Tracking the transition of stocks across different quintiles, we find that among stocks in the highest IVOL quintile at Q0, on average 63% (42%) of them remain in the same quintile at Q1 (Q4). On the

TABLE 3

Idiosyncratic Volatility and Future Earnings

At the end of each quarter, stocks are sorted on idiosyncratic volatility to form equal-weighted decile portfolios. Panel A of Table 3 reports the time series averages of the median return on equity (ROE) in percentage points, standardized unexpected earnings (SUE), and errors of analyst consensus earnings forecast (FER) over the current quarter, the next quarter, and the next four quarters. SUE is defined as the earnings change from four previous quarters divided by the standard deviation of earnings changes in the past eight quarters. FER is defined as the realized quarterly earnings minus analyst consensus forecasts, scaled by the previous year's book value of equity. The Newey-West *t*-statistics are computed with a four-quarter lag. Panel B reports the results of the Fama-MacBeth regression of future earnings on IVOL with various control variables.

Panel A. Earnings and Earning Shocks of Portfolios Formed on IVOL

IVOL Decile	ROEQ0	ROEQ1	ROE4	SUEQ0	SUEQ1	SUE4	FERQ0	FERQ1	FER4
D1(L)	3.61	3.59	14.38	0.23	0.19	0.46	−0.05	−0.06	−0.36
D2	3.77	3.75	14.84	0.22	0.20	0.48	−0.08	−0.10	−0.60
D3	3.64	3.61	14.36	0.18	0.17	0.49	−0.13	−0.12	−0.63
D4	3.52	3.51	14.03	0.15	0.14	0.36	−0.17	−0.16	−0.86
D5	3.44	3.42	13.64	0.12	0.10	0.31	−0.17	−0.17	−1.01
D6	3.28	3.31	13.41	0.08	0.08	0.27	−0.23	−0.25	−1.41
D7	3.16	3.15	13.03	0.07	0.07	0.26	−0.33	−0.37	−1.80
D8	2.80	2.83	12.30	0.01	0.02	0.15	−0.48	−0.45	−2.27
D9	2.26	2.34	10.64	−0.07	−0.03	0.07	−0.73	−0.64	−2.62
D10(H)	1.03	1.40	8.51	−0.23	−0.13	−0.03	−1.32	−0.88	−2.76
D1–D10	2.58	2.19	5.87	0.46	0.33	0.49	1.27	0.82	2.40
t-stat.	(5.90)	(5.39)	(4.76)	(13.4)	(9.88)	(3.34)	(9.02)	(7.20)	(5.73)

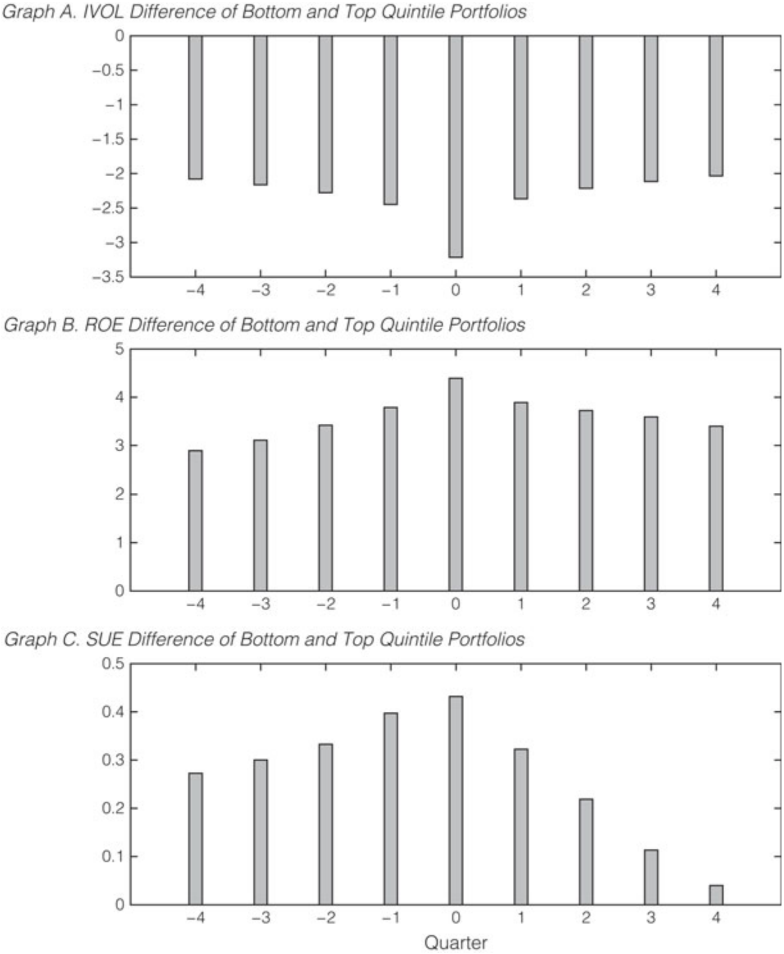
Panel B. Fama-MacBeth Regressions of ROE

	ROEQ0	ROEQ1	ROE4	IBESROEQ0	IBESROEQ1	IBESROE4
IVOL	−0.79	−0.67	−1.74	−0.67	−0.62	−1.63
	(−12.9)	(−11.5)	(−10.1)	(−12.8)	(−13.3)	(−7.37)
ln(SIZE)	0.14	0.15	0.17	0.12	0.11	0.41
	(2.71)	(3.36)	(1.66)	(2.72)	(3.96)	(3.22)
ln(B/M)	−0.56	−0.5	−2.86	−1.16	−1.10	−4.29
	(−2.51)	(−3.04)	(−6.65)	(−5.50)	(−5.91)	(−7.16)
PrRet	2.79	2.02	4.72	1.93	1.56	4.22
	(20.3)	(18.5)	(11.6)	(15.0)	(11.87)	(8.24)
LAGROE/FROE	0.42	0.42	0.47	0.51	0.51	0.54
	(26.4)	(26.6)	(21.1)	(12.8)	(12.91)	(12.68)
Adj. R^2	0.33	0.30	0.39	0.51	0.48	0.56

FIGURE 1

Differences of IVOL, ROE, and SUE: Portfolios Sorted on IVOL at Q0

In each quarter, we form equal-weighted quintile portfolios based on IVOL. Figure 1 plots the differences of IVOL, ROE, and SUE between bottom and top quintile portfolios during the formation period, and in each of the four quarters before and after the formation period.



other hand, among stocks in the lowest IVOL quintile at Q0, on average 66% (55%) of them remain in the same quintile at Q1 (Q4). These numbers further confirm the persistence of IVOL. Such portfolio turnover can have a direct effect on the dynamic relation of IVOL with future earnings. To examine such effect, we use the information at Q1 to divide the stocks in the highest IVOL quintile at Q0 into two groups. One group consists of stocks remaining in the same quintile at Q1, which we refer to as the "remaining" group, and the other consists of stocks migrating to other quintiles at Q1, which we refer to as the "migrating" group. We calculate the average future earnings for each of the groups. The time series averages of median ROEQ1 for the "remaining" and "migrating" groups are, respectively, 1.58 and 1.83. Both numbers are significantly below that of the middle quintile (the average of D5 and D6 in Table 3). That is, both groups of stocks are contributing to the inverse relation between IVOL at Q0 and ROE at Q1. In addition, the time series averages of median ROE4 for the "remaining" and "migrating" groups are, respectively, 11.65 and 7.66. While the average ROE4 of the "migrating" group is below that of the middle quintile, the difference is not statistically significant. We confirm that the inverse relation between IVOL at Q0 and ROE4 is mainly driven by the "remaining" group.

In the examination of event-study methodologies, Barber and Lyon (1996) show that when measuring abnormal operating performance, it is important to control for the effects of industry and size, as well as past operating performance. Therefore, we perform Fama-MacBeth regressions with the factors suggested by Barber and Lyon, as well as two additional firm characteristics (book-to-market and momentum) as control variables.[3] Specifically, in each quarter we perform the following cross-sectional regressions on individual stocks:

$$\text{(3)} \qquad \text{ROE} = \sum_{k=1}^{12} \alpha_k \text{IND}_k + b_1 \text{IVOL} + b_2 \ln(\text{SIZE}) + b_3 \ln(\text{B/M}) + b_4 \text{PrRet} + b_5 \text{LAGROE} + e,$$

where ROE refers to the return on equity for Q0 (ROEQ0), Q1 (ROEQ1), and four quarters after Q0 (ROE4). LAGROE is the four-quarter lagged corresponding ROE variable. Stocks are classified into 12 industries using classification from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/), where IND_k is the industry dummy. All other explanatory variables, including IVOL, SIZE, B/M, and PrRet, are as defined previously.

We also perform Fama-MacBeth regressions using realized earnings and analysts' earnings forecasts from IBES:

$$\text{(4)} \qquad \text{IBESROE} = \sum_{k=1}^{12} \alpha_k \text{IND}_k + b_1 \text{IVOL} + b_2 \ln(\text{SIZE}) + b_3 \ln(\text{B/M}) + b_4 \text{PrRet} + b_5 \text{FROE} + e,$$

where IBESROE is EPS from IBES divided by the previous year's book value of equity per share from Compustat. IBESROE is measured over the fiscal quarter Q0 (IBROEQ0), Q1 (IBROEQ1), and aggregated over four quarters from Q0 to Q3 (IBROE4). FROE refers to the mean analyst EPS forecasts for the corresponding quarters divided by the previous year's book value of equity per share (i.e., FROEQ0, FROEQ1, and FROE4). These forecasts are measured during the last month of Q0. Due to data availability, this regression is performed for the sample period from 1980 to 2002.

[3]Barber and Lyon (1996) suggest a matching-portfolio approach that identifies a matching portfolio for each event stock. This is difficult to implement here because our analysis involves the entire cross-section of firms.

The time series averages of the coefficients and their Newey-West t-statistics from quarterly cross-sectional regressions, excluding industry dummies, are reported in Panel B of Table 3. Using either earnings from the Compustat database or the IBES database, the average coefficients on IVOL are significantly negative in all regressions. That is, IVOL is predictive of future unexpected earnings, and such predictive power cannot be explained away by the control variables.

Finally, we perform subsample analysis to ensure robustness of the results. We first sort stocks into five subgroups according to one of the following firm characteristics: size, book to market, momentum, and leverage. Then within each subgroup we form quintile portfolios based on IVOL. Future earnings and earning shocks are computed for all quintile portfolios. Untabulated results show that the top and bottom quintile differences in future earnings and earning shocks are highly significant for all but one subgroup.[4]

D. Idiosyncratic Volatility Anomaly: Controlling for Future Earning Shocks

The finding that IVOL contains information about future earnings points to the possibility that the return-predictive power of idiosyncratic volatility may be induced by its information content about future earnings. To test this hypothesis, in each quarter we cross-sectionally regress next-quarter stock returns onto current-quarter IVOL, future earning shocks, as well as a number of control variables:

$$r_{t+1} = b_0 + b_1\text{IVOL} + b_2\ln(\text{SIZE}) + b_3\ln(\text{B/M}) + b_4\text{PrRet} + b_5\text{LEV} + b_6\text{LIQ} + b_7\text{SHOCK} + e, \tag{5}$$

where r_{t+1} is stock return in Q1. SHOCK is one of the following six unexpected earning measures: SUEQ0, SUEQ1, SUE4, FERQ0, FERQ1, and FER4. As in Ang et al. (2006a), we also include LIQ, the Pastor and Stambaugh (2003) liquidity measure estimated using daily returns in Q0, as a control variable.

The time series averages of the quarterly cross-sectional regression coefficients and their Newey-West t-statistics are reported in Table 4. When none of the earning shock variables are used as control variable (Model 1), the coefficient for IVOL is significantly negative. When SUEQ0 is included as a control variable (Model 2), the coefficient for IVOL is reduced but remains significantly negative. However, when SUEQ1 is included (Model 3), the coefficient for IVOL becomes insignificantly negative. When the unexpected earnings over the next four quarters (SUE4) are used as a control variable (Model 4), the coefficient for IVOL becomes positive, although statistically insignificant. Similarly, when FERQ0 or FERQ1 is included as control variable, the coefficient for IVOL becomes insignificant. When FER4 is included, the coefficient for IVOL is not only positive but also marginally significant (at the 10% level).[5]

[4]In the subgroup of stocks of the largest size, the differences in future earnings and earning shocks between top and bottom IVOL quintiles are positive but statistically insignificant.

[5]Merton (1987) shows that when investors cannot fully diversify away firm-specific risk, IVOL may be priced, and thus stocks with higher IVOL have higher expected returns.

TABLE 4

Idiosyncratic Volatility Anomaly: Controlling for Future Earning Shocks

Table 4 reports the results of the Fama-MacBeth regression of future stock return on idiosyncratic volatility (IVOL) with various control variables. In each quarter, we perform cross-sectional regressions of next-quarter returns (RETQ1) on current-quarter IVOL and future earning shocks as measured by standardized unexpected earnings (SUEQ0/SUEQ1/SUE4) and errors of analyst consensus earnings forecast (FERQ0/FERQ1/FER4). Control variables include ln(SIZE), ln(B/M), PrRet (momentum), LEV (leverage), and LIQ (liquidity measure of Pastor and Stambaugh (2003)). The Newey-West *t*-statistics are computed with a one-quarter lag.

	Model						
	1	2	3	4	5	6	7
Intercept	7.92 (7.81)	7.28 (6.76)	7.07 (6.54)	6.85 (6.51)	5.84 (4.09)	5.74 (3.89)	6.28 (4.45)
IVOL	−0.91 (−4.11)	−0.67 (−3.01)	−0.16 (−0.69)	0.21 (0.85)	−0.15 (−0.42)	0.22 (0.54)	0.90 (1.93)
ln(SIZE)	−0.35 (−2.90)	−0.31 (−2.38)	−0.43 (−3.39)	−0.46 (−3.95)	−0.33 (−2.30)	−0.39 (−2.55)	−0.46 (−2.83)
ln(B/M)	0.91 (2.77)	1.35 (3.73)	1.14 (3.41)	0.74 (2.14)	−0.20 (−0.48)	0.06 (0.14)	0.22 (0.51)
PrRet	3.05 (8.60)	2.01 (4.41)	1.62 (3.75)	1.74 (3.83)	0.47 (0.81)	1.03 (1.73)	1.43 (2.13)
LEV	−0.11 (−0.38)	−0.14 (−0.50)	−0.12 (−0.42)	−0.26 (−0.93)	0.60 (1.57)	0.59 (1.57)	0.29 (0.73)
LIQ	−0.05 (−1.74)	−0.04 (−1.63)	−0.04 (−1.01)	0.00 (0.02)	0.08 (0.17)	0.59 (0.81)	0.19 (0.43)
SUEQ0		2.08 (26.2)					
SUEQ1			2.10 (24.0)				
SUE4				0.63 (15.4)			
FERQ0					1.48 (10.11)		
FERQ1						1.24 (10.52)	
FER4							0.41 (10.34)
Adj. R^2	0.08	0.10	0.10	0.10	0.13	0.12	0.12

The above findings suggest that IVOL predicts stock returns through information on future earnings. It is important to point out that the statistical significance for the coefficients of ln(SIZE), ln(B/M), and PrRet is not affected by including future earning shocks as a control variable. That is, these firm characteristics predict stock returns for economic reasons other than information on future earnings. Therefore, in terms of information content, the IVOL anomaly is distinct from the three classical "anomalies" in the asset pricing literature—size, book-to-market, and momentum.

Since earning is an important determinant of contemporaneous stock returns, an interesting question is to what extent IVOL captures the earnings-return relation. To address this question, in each quarter we first sort stocks to form equal-weighted quintile portfolios based on IVOL. Different from the sample used in Table 2, here we restrict our analysis to the sample of stocks with a valid measure of SUEQ1. This is to ensure the consistency between the results reported in Panels A and B of Table 5. Panel A of Table 5 shows that the average alpha spread, based on the Carhart four-factor model, between the top and bottom IVOL quintile portfolios is 2.57% in the following quarter. For comparison, we also estimate

TABLE 5

Return Predictive Power of Idiosyncratic Volatility and Earnings

At the end of each quarter, stocks are sorted on idiosyncratic volatility (IVOL) to form equal-weighted quintile portfolios. Panel A reports the time series means of the holding-period returns (RETQ1) and the α estimates (alpha) of the Carhart (1997) four-factor model of the quintile portfolios over the following quarter. Within each IVOL quintile portfolio, stocks are further divided into quintiles based on standardized unexpected earnings over the following quarter (SUEQ1). Panel B reports the time series means of the quarterly returns (RETQ1) of all 25 stock groups, as well as their averages across IVOL quintiles. The Newey-West t-statistics are computed with a one-quarter lag.

Panel A. Alphas of Portfolios Sorted on IVOL

	Ranks of IVOL						
	1(L)	2	3	4	5(H)	1(L)–5(H)	t-Stat.
	0.28	0.30	0.26	−0.34	−2.29	2.57	(3.74)

Panel B. Alphas of Portfolios Sorted on IVOL and SUEQ1

		Ranks of SUEQ1						
		1(L)	2	3	4	5(H)	5(H)–1(L)	t-Stat.
IVOL quintile	1(L)	−1.58	0.20	0.25	1.23	1.71	3.29	(10.39)
	2	−2.67	−0.93	0.36	1.58	2.60	5.27	(13.90)
	3	−4.15	−1.13	0.74	2.11	4.38	8.53	(16.32)
	4	−5.61	−1.73	0.12	2.64	5.38	10.99	(17.78)
	5(H)	−5.64	−3.26	0.07	2.64	6.43	12.07	(21.73)
Controlling for IVOL		−3.93	−1.37	0.31	2.04	4.10	8.03	(23.20)

the alpha spread between top and bottom quintiles of stocks formed on SUEQ1 but after removing the effect of IVOL. To achieve this, within each IVOL quintile, we further sort stocks into quintiles based on SUEQ1. Note that these stock groups are not tradable portfolios, because they are formed on ex post information of SUEQ1. Alphas of these equal-weighted stock groups are reported in Panel B. In particular, after averaging over the five different IVOL groups with the same SUEQ1 rank, we find that the contemporaneous alpha spread between stocks with low SUEQ1 and high SUEQ1 is 8.03%. The alpha spread between top and bottom IVOL quintiles in Panel A is just below 1/3 of the above number. This suggests that IVOL contains a relatively small but statistically and economically meaningful fraction of earnings information relevant for explaining stock returns.

Finally, as robustness checks, we extend the analysis in a few additional directions. For brevity, the results of additional analyses are summarized below without being tabulated.

First, since results in Table 2 suggest a nonlinear relation between IVOL and future returns, we test whether the earnings information captures the nonlinear relation. We construct a dummy variable TOP for stocks in the top ninth and 10th IVOL deciles and include the product term of IVOL and TOP (TOP · IVOL) as an additional explanatory variable in the regression of (5). With earning shocks (SUE4 or FER4) included in the regression, the coefficient for TOP · IVOL is statistically insignificant. That is, the nonlinear relation between IVOL and future returns is also explained by information about future earnings.

Second, in a related study, Fu (2009) reports that expected IVOL, estimated using the EGARCH model, is positively correlated with stock returns. We estimate expected IVOL using the EGARCH model and then include it as an explanatory variable (together with SUE4) in the cross-sectional regression of quarterly returns. The results show that the coefficient of the EGARCH volatility is significant even after controlling for earning shocks. That is, the relation between EGARCH volatility and stock returns is not induced by the information related to earnings.

Third, we perform the same analysis on various subsamples of stocks sorted on size, book-to-market, momentum, and leverage. Within each characteristic-sorted group, we perform Fama-MacBeth regressions of next-quarter individual stock returns onto current-quarter IVOL and future earning shocks (SUE4), as well as various control variables. The IVOL coefficient is no longer significantly negative for all but one subgroup once we control for SUE4.[6]

III. The Link between Idiosyncratic Volatility and Earnings

The finding that the return-predictive power of IVOL is largely induced by future earnings information provides an important perspective for assessing potential explanations of the IVOL anomaly. In Section III, we focus on hypotheses that explicitly predict an inverse relation between IVOL and future earning shocks. We first examine whether the idiosyncratic volatility anomaly is related to several anomalies previously documented in the literature. They include excess extrapolation of firms' future growth, managerial over-investment, the accruals anomaly, and investor underreaction to earnings news. We then explore a potential link between IVOL and the selective disclosure of corporate information. Below, we describe these hypotheses in detail and empirically examine each of them as potential explanations of the IVOL anomaly.

A. Hypotheses and Variables

1. Excessive Extrapolation on Firm Growth

Lakonishok et al. (1994) argue that when forming expectations on future growth, investors tend to excessively extrapolate from firms' past growth. Thus, firms with high past growth (and often high idiosyncratic return volatility) are more likely to have negative earning shocks in the future. Therefore, investors' extrapolation bias may explain why firms with high IVOL tend to have negative future earning shocks.

Consistent with Lakonishok et al. (1994) and Chan, Karceski, and Lakonishok (2003), we measure a firm's past growth using the previous year's annual SG rate. In addition, we measure investors' expectation of a firm's future growth using average long-term earnings growth forecasts (LTG) by brokerage firm analysts. According to La Porta (1996), analyst long-term growth forecasts are also subject to the extrapolation bias. Moreover, Xu and Malkiel (2003) show that both SG and analyst forecasts of long-term growth are positively correlated with idiosyncratic stock return volatility. Annual sales data is from Compustat and analysts' long-term growth forecasts are from IBES. Since SG and many other accounting variables used in subsequent analysis are measured annually, all analysis

[6]In the group of stocks with the lowest book-to-market ratio, the IVOL coefficient remains significantly negative. However, when we further include SUEQ0 as an explanatory variable, the IVOL coefficient becomes insignificantly positive.

in this section is performed at the annual frequency. The portfolio formation period is thus from July of year $t-1$ to June of year t, and the holding period is after July of year t. IVOL is averaged over the four quarters in the portfolio holding period. SG is measured for the fiscal year that ends in calendar year $t-1$, and LTG is measured in June of year t. Note that due to data availability, all analysis involving LTG is for the sample period from 1982 to 2002. Analysis involving SG (and all other Compustat accounting variables used in subsequent analysis) is for the entire sample period from 1974 to 2002.

2. The Investment Anomaly

When firms engage in large investments, their business fundamentals often change dramatically, with increased uncertainty about future cash flows. Therefore, there may be a positive link between idiosyncratic stock return volatility and firms' capital expenditure. Literature (e.g., Titman et al. (2004)) also documents that firms with high capital expenditures tend to have low returns in the future. Titman et al. (2004) attribute this relation to agency problems and the over-investment tendency of empire-building managers. As a result, capital investments may also induce the empirically documented relations among IVOL, future earnings, and future returns.

We measure the intensity of capital investment (CAPEX) using the capital expenditure in the fiscal year that ends in calendar year $t-1$, scaled by total assets at the beginning of the fiscal year. Note that CAPEX only captures the effect of tangible investments. To take into account the effect of intangible investments, we also follow Chan, Sougiannis, and Lakonishok (2001) and construct a measure for the R&D expenditure. Specifically, the R&D intensity (R&D) is defined as the ratio of R&D expenditure in the fiscal year that ends in calendar year $t-1$ to the market capitalization of the firm at the end of June of year t.[7] Data used to construct CAPEX and R&D measures are from Compustat.

3. The Accruals Anomaly

Sloan (1996) shows that stocks with high ACCs have low future returns. He provides an explanation to this finding based on investors' misreaction to information; although the accrual component of earnings is less persistent than the cash flow component, naive investors fail to recognize such a difference when valuing stocks. Under this hypothesis, stocks with higher accruals, which tend to be associated with higher uncertainty about future cash flows and higher return volatility, are more likely to have negative news about cash flows in the future. In this study, we examine whether the IVOL anomaly is actually a manifestation of the ACCs anomaly.

[7] There is, however, no evidence that firms on average overinvest in R&D projects. In fact, Chan et al. (2001) show that R&D intensity is positively correlated with future stock returns, making intangible investments an unlikely cause of the IVOL-return anomaly.

Following Sloan (1996), we measure accruals for individual firms using the annual balance sheet and income statement data from Compustat:

$$\text{(6)} \quad \text{Accruals} = [(\Delta\text{CA} - \Delta\text{CASH}) - (\Delta\text{CL} - \Delta\text{STD} - \Delta\text{TP}) - \text{DEP}]/\text{ATA},$$

where ΔCA is the change in current assets from the previous fiscal year; ΔCASH is the change in cash and cash equivalents; ΔCL is the change in current liabilities; ΔSTD is the change in debt included in current liabilities; ΔTP is the change in income taxes payable; DEP is depreciation and amortization expense; and ATA is the average of the beginning and ending total assets of the fiscal year. Similar to CAPEX and R&D, the accruals variable is measured for the fiscal year that ends in year $t-1$.

4. Underreaction to Bad News

The literature has long documented that investors tend to underreact to information on earnings. For instance, Ball and Brown (1968) and Bernard and Thomas (1989), (1990) document that stock price drifts in the direction of earnings surprise for several months after earnings announcements. This anomaly is often referred to as the post earnings announcement drift. In general, when investors underreact to bad news about firms' cash flows (for example, profit warnings issued by firms, news reports about corporate product failure, and unfavorable litigation outcomes), it is likely that stocks are overvalued with low future returns. Since unfavorable information on firms' future cash flows usually results in high idiosyncratic volatility, the inverse relation between IVOL and future earnings as well as stock returns can simply be caused by investor underreaction.

In our analysis, we consider two measures of public information about firms' earnings. The first is analysts' revisions of earning forecasts. In each quarter, we calculate analysts' revisions, defined as the change of consensus annual EPS forecasts from the previous quarter, divided by the quarter-end stock price. We then calculate the average analysts' revisions over the past four quarters from July of year $t-1$ to June of year t, and denote this variable as REV. Data on analysts' earnings forecasts are from IBES. The second measure of public news is the average SUE over the past four quarters from July of year $t-1$ to June of year t. We denote this variable as LAGSUE. Due to data availability, analysis involving REV is over the sample period from 1980 to 2002.

5. Selective Corporate Disclosure

Various theoretical models on voluntary corporate information disclosure have been developed in the literature (see, e.g., Verrecchia (1983), Dye (1986), and Shin (2003)). These models show that under certain conditions firms have incentives to engage in selective disclosure by releasing good news about future earnings while withholding bad news. Several empirical studies have provided evidence consistent with theoretical predictions of selective disclosure. For example, using stock price reactions to news announcements, Kothari, Shu, and Wysocki (2009) show that firms, on average, delay the release of bad news to investors but leak and immediately reveal good news. In addition, Hutton, Miller, and Skinner (2003) find that when making earnings forecasts, managers often provide detailed supportive information when expected earnings are good and provide relatively vague information when expected earnings are poor. The evidence in Anilowski, Feng, and Skinner (2007) suggests that managers leak good news about quarterly earnings to investors weeks before the end of the fiscal quarter, but bad news is delayed until the end of the quarter.

Generally, when firms disclose less information, investors are more likely to have divergent beliefs, leading to higher return volatility (Fishman and Hagerty (1989), He and Wang (1995)). Thus, firms with timely disclosure of good news about future earnings tend to have low IVOL, while firms withholding bad news tend to have high IVOL. In other words, IVOL is negatively associated with future earnings due to selective disclosure. Further, when marginal investors in the stock market are not sophisticated enough to gauge the information content of corporate selective disclosure, favorable earnings information released by firms is more likely to be efficiently priced, relative to unfavorable earnings information withheld by firms. Therefore, subsequent stock returns for high IVOL firms are likely to be "abnormally" low, while subsequent returns to low IVOL firms may not necessarily be "abnormally" high. This implication is consistent with the nonlinear relation between IVOL and stock return documented in Ang et al. (2006a) and this study. For example, in Table 2, the alphas (based on the Carhart (1997) four-factor model) of the low IVOL deciles are insignificantly different from zero, whereas alphas of the high idiosyncratic volatility deciles are significantly negative.

To examine the potential link between the IVOL anomaly and corporate disclosure, we follow existing studies and use the annual rating of corporate disclosure practices released by the AIMR as a proxy for the extent and quality of corporate disclosure.[8] The AIMR disclosure score data set covers the period from 1986 to 1996, with 8,735 firm-year observations, averaging about 1,000 firms per year. Each year, AIMR selects leading analysts to serve on industry committees that decide on the set of firms to be evaluated and the criteria for the assessment. Each committee member then assigns a score on a scale of 0 to 100 to each firm based on the adequacy, timeliness, and clarity of its information disclosure in three categories: annual reports, quarterly reports, and investor relations. These scores are averaged across committee members and aggregated into a total disclosure score. To ensure a uniform standard, AIMR provides each committee member with a comprehensive checklist of scoring criteria and guidelines on the weights for each disclosure category. The use of industry specialists and the consensus scoring procedure reduce the ad hoc element of the ratings. Furthermore, individual analyst scores are never made public, reducing the influence firms may exert on analysts' ratings.

Admittedly, the AIMR disclosure score has several limitations for measuring the quality of corporate information disclosure. Ideally, we need a measure of the amount or quality of private information about future earnings disclosed by corporate managers. Rather, the AIMR score measures the transparency of overall

[8]We thank Russell Lundholm and Fan Yu for providing the data set. For more detailed accounts of this data, see Lang and Lundholm (1993), (1996), and Yu (2005).

accounting information. It thus serves as a proxy for the unobservable corporate behavior we try to quantify in our study. In addition, the data are available only for a relatively short period of time, covering a subsample of large and medium size firms (relative to the entire CRSP database). These factors may limit the power of statistical analysis based on the AIMR score.

B. Empirical Results

We first examine how variables corresponding to various hypotheses are related to idiosyncratic return volatility. In June of each year, we sort stocks on IVOL to form decile portfolios and report the time series mean of the average of each variable for all deciles. The results are reported in Table 6. Indeed, idiosyncratic return volatility is positively related to SG, long-term earnings growth forecasts (LTG), the intensity of both tangible and intangible investments (CAPEX and R&D), as well as ACCs. However, most of the relations are U-shaped. The only monotonic relations are with LTG and R&D. On the other hand, IVOL is negatively related to analyst revisions (REV) and earning surprises (LAGSUE), but only the relation with LAGSUE is monotonic. Table 6 also shows that IVOL is inversely related to the AIMR disclosure quality score (DISC) with a monotonic pattern. This result is consistent with the effect of corporate disclosure (i.e., less disclosure tends to increase the degree of heterogeneity in investors beliefs, resulting in higher stock return volatility).

We next test whether the above variables can explain the inverse relation between IVOL and future earnings. We perform annual Fama-MacBeth regressions of future return on equity (ROE4) on these variables, with control variables including four-quarter lagged ROE4 (LAGROE4), as well as 12 industry dummies. The results, reported in Table 7, confirm that all variables are significantly related to future earnings. In particular, firms' past sales growth (SG), long-term earnings

TABLE 6

Relation between Idiosyncratic Volatility and Other Variables

Table 6 reports the average sales growth (SG), analyst forecasts of long-term earnings growth (LTG), capital expenditure intensity (CAPEX), R&D intensity (R&D), accruals (ACC), analyst forecast revision (REV), lagged earning surprises (LAGSUE), and the AIMR disclosure score (DISC) of decile portfolios formed on idiosyncratic volatility. Numbers in parentheses below the variable names are the sample period for each variable. The Newey-West *t*-statistics are computed with a four-quarter lag.

IVOL Decile	SG (1974–2002)	LTG (1982–2002)	CAPEX (1974–2002)	R&D (1974–2002)	ACC (1974–2002)	REV (1980–2002)	LAGSUE (1974–2002)	DISC (1986–1996)
D1(L)	8.58	9.02	10.08	3.40	−3.38	−0.10	0.59	72.65
D2	9.87	11.65	8.56	3.96	−3.37	−0.12	0.59	72.47
D3	10.52	12.81	8.67	3.98	−3.21	−0.40	0.59	72.47
D4	11.07	14.34	9.65	4.55	−2.88	−0.26	0.53	72.10
D5	12.49	15.90	11.40	4.83	−2.51	−0.51	0.52	71.50
D6	13.72	17.73	13.48	5.49	−1.98	−0.69	0.52	71.07
D7	15.75	19.99	15.38	5.69	−1.35	−0.87	0.51	70.39
D8	17.46	22.53	18.37	5.99	−0.86	−1.50	0.49	69.98
D9	17.38	25.63	21.76	6.26	−0.89	−1.58	0.42	67.74
D10(H)	15.31	27.02	23.66	7.11	−1.70	−2.10	0.38	64.76
D1–D10	−6.73	−18.00	−13.58	−3.71	−1.67	1.99	0.21	6.89
t-stat.	(−4.43)	(−8.18)	(−4.59)	(−8.00)	(−3.32)	(6.22)	(3.99)	(6.48)

TABLE 7

Alternative Explanations: Idiosyncratic Volatility and Future Earning Shocks

Table 7 reports the results of Fama-MacBeth regressions of return on equity over the next four quarters (ROE4) on SG, LTG, CAPEX, R&D, ACC, REV, LAGSUE, DISC, and control variables ln(SIZE), ln(B/M), PrRet, lagged return on equity (LAGROE4), and industry dummies. The coefficients of industry dummies are not reported for brevity. R^2 is the time series average of adjusted R-squares. The Newey-West t-statistics are computed with a four-quarter lag.

	Model										
	1	2	3	4	5	6	7	8	9	10	11
IVOL	−1.51	−1.64	−1.62	−1.46	−1.48	−1.44	−1.58	−1.90	−1.56	−1.83	−1.07
	(−7.53)	(−5.20)	(−5.81)	(−4.84)	(−4.35)	(−4.19)	(−5.06)	(−4.58)	(−6.56)	(−4.37)	(−1.82)
ln(SIZE)	0.61	0.50	0.40	0.73	0.94	0.97	0.72	0.72	0.65	0.68	0.23
	(2.63)	(2.23)	(1.71)	(2.93)	(2.96)	(2.97)	(2.86)	(2.91)	(3.39)	(3.35)	(0.38)
ln(B/M)	−2.04	−3.64	−5.35	−0.94	−0.62	−0.74	−0.44	−1.72	−0.99	−2.21	−0.92
	(−2.48)	(−3.28)	(−6.06)	(−0.90)	(−0.49)	(−0.57)	(−0.40)	(−1.57)	(−1.08)	(−2.18)	(−2.10)
PrRet	1.80	1.82	1.92	1.68	1.69	1.68	1.56	1.58	1.69	1.55	2.01
	(10.20)	(8.02)	(9.27)	(8.47)	(7.43)	(7.33)	(8.36)	(6.76)	(8.69)	(7.20)	(7.46)
LAGROE4	0.48	0.45	0.43	0.50	0.49	0.49	0.53	0.49	0.52	0.49	0.41
	(27.65)	(18.93)	(17.97)	(27.89)	(24.23)	(23.99)	(25.87)	(23.68)	(27.71)	(20.77)	(6.94)
SG	−2.31		−4.04								
	(−2.52)		(−2.78)								
LTG		−0.16	−0.12								
		(−4.58)	(−3.25)								
CAPEX				−2.81		−2.55					
				(−2.79)		(−1.80)					
R&D					−6.96	−6.70					
					(−2.12)	(−2.10)					
ACC							−1.13				
							(−2.04)				
REV								0.89		0.83	
								(5.54)		(5.84)	
LAGSUE									0.14	0.06	
									(3.77)	(1.97)	
DISC											1.84
											(2.16)
Adj. R^2	0.39	0.40	0.40	0.43	0.47	0.48	0.43	0.45	0.45	0.46	0.47

growth forecasts (LTG), the intensity of both tangible and intangible investments (CAPEX and R&D), as well as ACCs are all inversely related to future earnings. However, with the variables under each hypothesis added to the regression either separately or jointly, the coefficient of IVOL remains significantly negative. In other words, IVOL contains information about future earnings beyond the predictive power of these variables. Table 7 also suggests that both REV and LAGSUE are positively related to future earnings. That is, firms with downward analyst revisions of earning forecasts and negative earning surprises are more likely to have negative earning shocks in the future. Nevertheless, the coefficient of IVOL remains highly significant even after controlling for REV and LAGSUE.[9] That is, the information on future cash flows contained in analyst revisions of earning forecasts and past earning surprises does not fully explain the predictive power of IVOL on future earnings.

In addition to the above results, Table 7 also reports the Fama-MacBeth regression of future return on equity (ROE4) on the disclosure score (DISC). The result suggests a significantly positive relation between DISC and future earnings. This finding is consistent with the prediction of theoretical models (i.e., firms with poor future earnings tend to be selective in information disclosure). It also extends the finding in Lang and Lundholm (1993) that corporate disclosure is positively related to *contemporaneous* earnings. In addition, when DISC is included as a control variable, the coefficient of IVOL is reduced and statistically significant only at the 10% level.[10] Given that DISC is only a noisy measure of information disclosure, the result is favorable evidence that the predictive power of IVOL on future earnings is related to corporate information disclosure.

Finally, we examine whether the above variables can explain the return-predictive power of IVOL. We perform annual Fama-MacBeth regressions of stock returns over the next quarter (RETQ1) on these variables with various control variables. The results in Table 8 show that the coefficients of SG and LTG are statistically insignificant when they are added to the regression separately or jointly. While CAPEX is negatively related to future stock returns, R&D is positively related to future stock returns. The result on ACC is consistent with the findings of Sloan (1996) (i.e., ACCs are inversely related to future stock returns). In addition, Table 8 shows that both REV and LAGSUE are significantly related to future stock returns. These findings are consistent with the existing literature that investors tend to underreact to earnings news. However, the coefficient of IVOL remains significantly negative in all regressions. That is, none of these variables can explain the return-predictive power of IVOL. We note that with REV and LAGSUE included as control variables in the regression, the return-predictive power of IVOL is reduced, particularly when both REV and LAGSUE are included as control variables. These results show that investor underreaction to earnings news seems to contribute partially to the IVOL anomaly but does not fully account for the predictive power of IVOL on future earnings and returns.

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[9]In unreported analysis, we also perform regressions using IBES earnings (in place of ROE4) and IBES analyst earnings forecasts (in place of LAGROE4), with the same conclusion.

[10]When DISC is not included, the coefficient of IVOL is -1.46, with a t-statistic of -2.01, in the regression based on the same sample of stocks with valid observations of DISC.

TABLE 8

Alternative Explanations: Idiosyncratic Volatility and Future Stock Returns

Table 8 reports the results of Fama-MacBeth regressions of stock returns over the next quarter (RETQ1) on SG, LTG, CAPEX, R&D, ACC, REV, LAGSUE, DISC, and control variables. Adj. R^2 is the time series average of adjusted *R*-squares. The Newey-West *t*-statistics are computed with a one-quarter lag.

	Model										
	1	2	3	4	5	6	7	8	9	10	11
IVOL	−1.62	−1.75	−1.67	−1.60	−1.64	−1.59	−1.61	−2.06	−1.37	−1.73	−1.20
	(−2.46)	(−3.12)	(−2.69)	(−2.40)	(−2.43)	(−2.36)	(−2.27)	(−2.30)	(−2.26)	(−2.09)	(−1.62)
ln(SIZE)	−0.30	−0.21	−0.21	−0.34	−0.19	−0.19	−0.39	−0.36	−0.38	−0.37	−0.25
	(−2.04)	(−1.37)	(−1.40)	(−1.88)	(−0.87)	(−0.81)	(−2.18)	(−1.81)	(−2.28)	(−1.73)	(−1.02)
ln(B/M)	0.55	0.47	0.42	0.50	0.32	0.26	0.41	0.77	0.54	0.79	1.28
	(1.19)	(1.02)	(0.90)	(1.13)	(0.54)	(0.46)	(0.93)	(1.38)	(1.12)	(1.29)	(0.97)
PrRet	4.77	5.30	5.32	4.66	4.31	4.22	4.69	4.62	4.67	4.46	6.83
	(7.01)	(5.09)	(5.11)	(6.50)	(6.34)	(6.09)	(6.88)	(4.55)	(5.93)	(3.88)	(2.03)
LEV	−0.45	−0.46	−0.40	−0.41	−0.51	−0.57	−0.50	−0.99	−0.30	−0.60	−0.84
	(−1.08)	(−1.19)	(−1.07)	(−0.94)	(−0.79)	(−0.91)	(−1.21)	(−1.46)	(−0.80)	(−1.18)	(−0.31)
LIQ	−0.11	−0.15	−0.14	−0.10	0.06	0.06	−0.09	−0.57	−0.10	−0.08	0.22
	(−1.53)	(−0.25)	(−0.24)	(−1.68)	(0.67)	(0.63)	(−1.68)	(−1.27)	(−1.60)	(−0.16)	(1.50)
SG	−0.16		−0.04								
	(−0.24)		(−0.06)								
LTG		−0.05	−0.06								
		(−1.16)	(−0.69)								
CAPEX				−0.07		−0.08					
				(−0.67)		(−0.96)					
R&D					0.41	0.40					
					(2.36)	(2.34)					
ACC							−0.30				
							(−2.77)				
REV								1.11		1.16	
								(3.12)		(3.26)	
LAGSUE									0.29	0.22	
									(2.86)	(1.99)	
DISC											9.05
											(1.84)
Adj. R^2	0.07	0.08	0.08	0.08	0.09	0.09	0.08	0.09	0.08	0.09	0.09

Turning to the question of whether corporate disclosure explains the return-predictive power of IVOL, the results of the Fama-MacBeth regression in Table 8 indicate that there is a positive relation between DISC and future stock returns, with the coefficient of DISC statistically significant at the 10% level.[11] Further, after controlling for corporate disclosure the return-predictive power of IVOL is no longer statistically significant.[12]

In summary, the above results show that the idiosyncratic volatility anomaly is not a simple manifestation of other market anomalies documented in existing literature. On the other hand, the AIMR disclosure score exhibits a monotonic negative relation with IVOL. Controlling for DISC substantially reduces the predictive power of IVOL on future earnings and to a large extent explains its predictive power on future returns. Overall, these results are consistent with the implications of adverse selection in corporate information disclosure.

IV. The Effect of Investor Sophistication

The evidence that IVOL is related to future returns suggests that marginal investors are not sophisticated enough to fully understand earnings information content in IVOL. This is because in an efficient market with rational investors, such information should be reflected in current stock prices, not in future returns. In Section IV, we further explore this implication. If the IVOL anomaly is due to investor misreaction to the earnings information content in IVOL, then we should expect the anomaly to be stronger among stocks with a less sophisticated investor base.

We start with a simple measure of the sophistication of a stock's investor base—institutional ownership, defined as the percentage of shares outstanding held by institutional investors at the end of the portfolio formation quarter. This measure is constructed using the Thomson Financial 13F data. A double-sort procedure is used in our analysis. In each quarter, we first sort stocks into quintiles according to institutional ownership. We then sort stocks into five equal-weighted portfolios based on IVOL within each quintile. The Carhart four-factor α and standardized unexpected earnings (SUEQ1) for each portfolio in the next quarter are reported in Panel A of Table 9. The difference in α between the bottom (D1) and top (D5) quintile IVOL portfolios is only significant for the two subgroups with low institutional ownership. It is worth noting that the differences in SUEQ1 between the top and bottom quintile portfolios are statistically significant across all

[11] Similar to the relation between IVOL and future returns, the relation between DISC and RET4 is stronger for smaller firms. To show this, we perform the following regression:

$$\text{RET4} = a + b_1\ln(\text{SIZE}) + b_2\ln(\text{B/M}) + b_3\text{PrRet} + b_4\text{DISC} + b_5\text{SMALL}\cdot\text{DISC} + \epsilon, \quad (7)$$

where SMALL is a size dummy that is set to 1 if the firm size is below the median and 0 otherwise. The estimate of coefficient b_5 has a value of 0.29, with t-statistic of 2.34. This suggests a significantly stronger relation of disclosure score with small-cap stock returns.

[12] When DISC is not included, the coefficient of IVOL has a value of −1.37, with t-statistic of −1.89, in the regression based on the same sample of stocks.

TABLE 9

Idiosyncratic Volatility Anomaly: Effect of Investor Sophistication

At the end of each quarter, we first sort stocks into five groups based on one of the following variables: institutional ownership, residual institutional ownership (orthogonal to short-sale constraint), active mutual fund ownership, and analyst coverage. Then within each group, we further sort stocks into quintiles based on IVOL. Table 9 reports the average Carhart (1997) four-factor alpha (α) and SUE of the next quarter (SUEQ1) for each quintile portfolio, and the differences between the top and bottom quintiles. The Newey-West t-statistics are computed with a one-quarter lag for alphas and a four-quarter lag for SUEQ1.

	1(L)		2		3(M)		4		5(H)	
IVOL Quintile	α	SUEQ1	α	SUEQ1	α	SUEQ1	α	SUEQ1	α	SUEQ1
Panel A. Stocks Sorted by Institutional Ownership										
D1(L)	0.07	0.13	0.17	0.12	−0.11	0.13	0.07	0.16	0.10	0.26
D2	0.24	0.10	−0.32	0.10	0.13	0.07	0.33	0.07	−0.07	0.15
D3	−0.40	0.04	0.41	0.07	0.33	0.06	0.46	0.04	−0.33	0.14
D4	−0.57	0.05	−0.52	−0.03	−0.55	−0.03	0.33	−0.01	0.42	0.09
D5(H)	−2.90	−0.13	−2.79	−0.22	−1.44	−0.22	0.19	−0.16	−0.22	0.01
D1–D5	2.97	0.26	2.96	0.34	1.34	0.35	−0.12	0.32	0.32	0.25
t-stat.	(2.67)	(4.14)	(2.77)	(6.11)	(1.28)	(7.33)	(−0.14)	(6.26)	(0.36)	(3.47)
Panel B. Stocks Sorted by Residual Institutional Ownership										
D1(L)	0.12	0.05	0.07	0.01	0.04	0.08	0.06	0.18	0.02	0.23
D2	0.84	0.06	0.80	0.02	0.13	0.03	0.31	0.06	−0.03	0.13
D3	0.42	0.04	0.74	0.05	0.49	0.00	0.49	0.02	−0.47	0.10
D4	1.34	−0.01	−0.93	−0.06	0.33	−0.05	−0.03	−0.04	0.14	0.10
D5(H)	−2.11	−0.15	−1.57	−0.14	−1.08	−0.21	−0.04	−0.17	−0.74	−0.04
D1–D5	2.23	0.20	1.64	0.15	1.12	0.29	0.11	0.35	0.76	0.26
t-stat.	(2.43)	(3.94)	(2.03)	(3.39)	(1.37)	(7.04)	(0.11)	(7.11)	(0.83)	(3.53)
Panel C. Stocks Sorted by Active Mutual Fund Ownership										
D1(L)	0.53	0.12	0.37	0.15	0.01	0.17	−0.26	0.16	−0.26	0.18
D2	0.03	0.11	−0.03	0.06	0.26	0.09	−0.17	0.11	−0.13	0.16
D3	−0.49	0.04	−0.12	−0.01	−0.07	0.00	−0.21	0.06	−0.21	0.15
D4	−1.90	−0.01	−0.64	−0.08	−0.01	−0.02	−0.42	0.01	−0.10	0.09
D5(H)	−3.56	−0.13	−1.98	−0.19	−2.48	−0.16	−1.76	−0.15	−0.37	−0.12
D1–D5	4.09	0.24	2.35	0.34	2.08	0.34	1.50	0.31	0.11	0.30
t-stat.	(3.76)	(5.36)	(2.12)	(5.95)	(1.97)	(7.74)	(1.76)	(7.03)	(0.13)	(8.55)
Panel D. Stocks Sorted by Analyst Coverage										
D1(L)	0.19	0.21	0.23	0.27	0.38	0.22	−0.11	0.31	−0.57	0.28
D2	0.62	0.20	0.17	0.20	0.16	0.24	0.26	0.29	−0.41	0.33
D3	0.06	0.15	−0.23	0.18	0.28	0.18	0.03	0.23	−0.30	0.23
D4	−0.99	0.10	−0.66	0.09	0.02	0.11	−0.20	0.09	0.05	0.07
D5(H)	−2.15	−0.09	−2.65	−0.14	−1.31	−0.06	−0.78	−0.07	0.56	−0.04
D1–D5	2.34	0.30	2.88	0.41	1.69	0.28	0.67	0.37	−1.13	0.32
t-stat.	(2.60)	(7.01)	(3.35)	(7.92)	(1.85)	(6.10)	(0.74)	(5.98)	(−1.15)	(4.58)

subgroups. This suggests that while IVOL contains earnings information across all subsamples of stocks, only sophisticated investors are able to incorporate such information into current stock prices.

Institutional ownership has also been used in existing studies as a proxy of the short-sale supply, since institutional investors may lend their shares to short-sellers (see, e.g., D'Avolio (2002), Nagel (2005), and Asquith, Pathak, and Ritter (2005)). To control for the effect of short-sale constraints, we construct a measure of institutional ownership that is orthogonal to short-sale constraints. Using data from a large institutional lending intermediary, D'Avolio (2002) identifies stock characteristics that are significantly related to the probability of binding short-sale constraints. He reports that the likelihood of binding short-sale constraints is a logit transformation of the following expression (Panel C of Table 6 in D'Avolio (2002)):[13]

$$(8) \qquad y = -0.46\text{SIZE} + 1.59\text{TURN} - 0.09\text{CF} + 0.41\text{GLAM} + 0.86\text{IPO},$$

where SIZE, TURN, and CF denote the market capitalization, trading volume, and cash flow of the firm, respectively; GLAM is a dummy variable for book-to-market ratio; and IPO is firm age since IPO, with the IPO date determined by the first stock return observation in the CRSP database. Details of these variables can be found in D'Avolio (2002). We regress institutional ownership against y at each quarter, and the residual is the institutional ownership orthogonal to short-sale constraints. This residual institutional ownership serves as an alternative measure of investor sophistication.

We further consider two additional measures of investor sophistication. One is active mutual fund ownership, defined as the percentage of shares outstanding held by actively-managed U.S. domestic equity mutual funds. We identify active equity mutual funds as those with the following investment objectives: aggressive growth, growth, growth and income, and balanced. Passive index funds are excluded. The data is from Thomson Financial CDA/Spectrum. The advantage of using active mutual fund ownership is that active mutual funds generally do not lend stocks to short-sellers and thus are not directly correlated with short-sale supply. The other is analyst coverage, defined as the number of brokerage-firm analysts following a stock, using data from IBES. Prior literature has shown that analyst coverage helps investors gain access to sophisticated analysis on stocks and improves informational efficiency in the market (see, e.g., Brennan, Jegadeesh, and Swaminathan (1993) and Hong, Lim, and Stein (2000)). Similar to active mutual fund ownership, analyst coverage is not directly correlated with short-sale supply.

We perform similar double-sort analysis using the above three alternative measures of investor sophistication. The results are reported in Panels B to D of Table 9. The patterns are similar to those reported in Panel A using institutional ownership. For all three measures—residual institutional ownership, active mutual fund ownership, and analyst coverage—the earnings information contained in IVOL remains significant across all stock subsamples, whereas higher investor sophistication results in less mispricing of idiosyncratic volatility.

V. Conclusion

This paper extends the analysis of Ang, Hodrick, Xing, and Zhang (2006a) by documenting that stocks with high idiosyncratic volatility (IVOL) tend to have

[13] The cross-sectional regression performed by D'Avolio (2002) also includes several other stock characteristics, such as institutional ownership, stock return volatility, dispersion of analyst earnings forecasts, being a pure-play Internet company, the number of authors on a stock's Yahoo! Finance message board, and momentum. He reports that, except for institutional ownership, these additional characteristics tend to be much less significantly related to short-sale constraints. We therefore do not include them in (8). In addition, the probability of short-sale constraints is the logit transformation of y. In our analysis, instead of using the logit transformation, we use y_{it} directly to capture the first-order effect of various stock characteristics on the likelihood of short-sale constraints.

low future earnings and earning shocks. More importantly, it provides evidence that the return-predictive power of IVOL is induced by future earnings information. This finding distinguishes the IVOL anomaly documented by Ang et al. (2006a) from other classical asset pricing anomalies related to size, value, and momentum.

The fact that IVOL contains information about future earnings provides a new perspective in assessing potential explanations of the IVOL anomaly. The triangular relation among IVOL, future earnings, and future stock returns rules out hypotheses such as those based on tax-timing option, financial leverage, and short-sale constraints. These theories link idiosyncratic volatility only with future stock returns but are silent as to why IVOL is predictive of future earnings.

We examine various potential explanations of the idiosyncratic volatility anomaly from the perspective of its information content on future earnings. We investigate whether the idiosyncratic volatility anomaly is an alternative form of stock return anomalies documented in existing studies and further explore a potential link with strategic corporate behavior in information disclosure. The results suggest that the IVOL anomaly is not a simple manifestation of other known market anomalies. Rather, there is evidence linking the idiosyncratic volatility anomaly to corporate information disclosure. We note that while the findings are promising, more conclusive evidence requires further research using a more reliable measure of corporate disclosure on a larger sample of firms.

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