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The role of analysts: An examination of the idiosyncratic volatility anomaly in the Chinese stock market ☆

Ming Gu [a,*], George J. Jiang [b], Bu Xu [c,*]

[a] Department of Finance at School of Economics & WISE, Xiamen University, China
[b] Department of Finance and Management Science, Carson College of Business, Washington State University, United States
[c] School of Economics and Management, Beijing University of Chemical Technology, China

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ABSTRACT

Given the unique institutional setting in the Chinese stock market, we investigate the effect of analyst activity on the idiosyncratic volatility (IVOL) anomaly. Our results show that the inverse relation between IVOL and future stock returns is more pronounced in stocks without analyst coverage. Furthermore, for stocks with analyst coverage, revision activity attenuates the IVOL anomaly. In fact, we find a positive relation between IVOL and future stock returns among stocks receiving analyst upgrades. We interpret our findings as evidence that analysts play an important role in disseminating information and reducing information asymmetry. As a result, news about firm fundamentals, particularly positive news, is incorporated more quickly into stock prices when analysts issue upgrade revisions. Finally, we show that our results are not subsumed by other potential explanations of the IVOL anomaly.

1. Introduction

The idiosyncratic volatility (IVOL) anomaly, first documented by Ang et al. (2006) in the US stock market, refers to the empirical finding that stocks with higher idiosyncratic volatility tend to have significantly lower future returns. This negative relation challenges classic asset pricing theories, which predict either no relation (e.g. the capital asset pricing model, CAPM) or a positive relation (e.g. Merton, 1987) between idiosyncratic volatility and stock returns.

Several studies have linked the negative pricing of idiosyncratic volatility to information asymmetry.[1] For example, Johnson (2004) demonstrates theoretically and empirically that adding idiosyncratic risk to a levered firm reduces its expected return, since rising uncertainty about the firm's cash flows increases the option value of its equity. As such, Johnson (2004) argues that firms may not have an incentive to disclose information in a timely and transparent way. Jiang et al. (2009) link the IVOL anomaly to selective corporate disclosure, i.e., management tends to disclose good news in a timely manner while withholding bad news.

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* Corresponding authors.
E-mail addresses: guming@xmu.edu.cn (M. Gu), george.jiang@wsu.edu (G.J. Jiang), buxu@mail.buct.edu.cn (B. Xu).

[1] Other explanations of the IVOL anomaly include the effect of illiquidity (Bali and Cakici, 2008; Han and Lesmond, 2011), return reversal (Fu, 2009; Huang et al., 2010), lottery preference (Boyer et al., 2010; Bali et al., 2011), risk exposure (Chen and Petkova, 2012), financial distress (Avramov et al., 2013), proportion of retail investors (Han and Kumar, 2013), short-sale constraints (George and Hwang, 2011; Stambaugh et al., 2015) and others. Hou and Loh (2016) provides an excellent survey and classification of potential explanations of the IVOL anomaly. In addition, they show that a sizable portion of the IVOL anomaly puzzle is still left unexplained.

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Thus, firms with bad news are more likely to have high information uncertainty; consequently, their stocks experience lower future returns. These arguments are consistent with studies by Brennan and Subrahmanyam (1995) and Verrecchia (2001), which show that greater information asymmetry reduces the speed of stock price discovery, causing more severe mispricing of idiosyncratic volatility.

Our study is motivated by the role that analysts play in information production and dissemination in the financial market. Previous studies show that financial analysts have a substantial impact on market efficiency. For example, Brennan et al. (1993) provide evidence that stocks followed by more analysts appear to be priced more accurately. Francis and Soffer (1997) show that the information from both analysts' earnings forecast revisions and their recommendations is incorporated into stock prices. Barth and Hutton (2000) find that the stock prices of firms with higher analyst followings incorporate information on accruals and cash flows more rapidly than the prices of less-followed firms' stocks. Chan and Hameed (2006) show that analyst coverage lessens the amount of firm-specific noise. In particular, using data on the U.S. market, George and Hwang (2011) show that the IVOL effect is stronger among firms with no analyst coverage. In this study, we extend the literature and examine the effect of analyst revisions, namely upgrades and downgrades, on the idiosyncratic volatility anomaly.

We focus on the Chinese stock market for the following reasons. First, analysts play a special role in the Chinese stock market given its unique institutional setting. Compared to other developed countries, institutional ownership in China is quite low and the market is dominated by retail investors.[2] In addition, there are fewer regulatory requirements for firms to disclose information to investors and the market in a transparent and timely manner. As such, information production and dissemination by financial analysts likely has a significant effect on the efficiency of stock prices in the Chinese stock market. While Ang et al. (2009) and George and Hwang (2011) provide evidence that the IVOL anomaly is stronger among stocks with low analyst coverage in developed markets,[3] we expect the effect of analyst activities on the IVOL anomaly to be stronger in China. As a result, data from the Chinese stock market should provide a sharper test on the effect of analyst information production on the IVOL anomaly. Second, Gu et al. (2018) show that the IVOL effect is stronger in China than in the US. They also find that the equally-weighted IVOL premium is higher than the value-weighted premium in the Chinese stock market. This is evidence that small firms have a strong IVOL effect. Moreover, the IVOL effect in China cannot be absorbed by the maximum daily return documented in Bali et al. (2011). That is, the IVOL anomaly is not a simple effect of investors chasing lottery-type stocks. Third, there are strong frictions in the Chinese stock market. For instance, short-sale trading is highly restricted in China. Prior studies have shown that short-sale constraints lead to stock overvaluation and slow down the price discovery process (Miller, 1977; Chang et al., 2007). In particular, Diamond and Verrecchia (1987) suggest that, due to short-sale constraints, negative information may not be immediately incorporated into stock prices. These unique features of the Chinese stock market provide a natural setting to examine the effect of analyst information production on the idiosyncratic volatility anomaly.

The stock sample in our study contains all A-listed stocks in the Chinese stock market from January 2005 to December 2014. We confirm a negative relationship between idiosyncratic volatility and subsequent stock returns. As predicted, the IVOL anomaly exists in the Chinese stock market for both equally-weighted and value-weighted returns. The monthly equally-weighted and value-weighted abnormal return spreads between the lowest- and highest-IVOL quintiles are 1.79% (t-stat = 9.82) and 0.74% (t-stat = 2.89), respectively. We find that the IVOL anomaly is particularly strong in stocks without analyst coverage, in comparison to stocks with analyst coverage. Specifically, the value-weighted abnormal returns spreads are 2.24% (t-stat = 8.67) vs. 0.39% (t-stat = 1.27) for stocks without analyst coverage and with coverage, respectively. Moreover, when we form the value-weighted IVOL-spread portfolio for non-covered stocks, the cumulative IVOL return spread persists up to a six-month horizon. In contrast, for covered stocks, the negative IVOL premium becomes positive after six months. Our results are consistent with the U.S. evidence documented in George and Hwang (2011) that analyst coverage reduces the IVOL anomaly.

More importantly, we categorize stocks with analyst coverage into three groups based on analyst activity: upgrade revision, downgrade revision, or no revision. The relation between IVOL and stock returns shows different patterns among these three subsamples. For stocks with no revision activity, the IVOL spread remains significantly negative and persists up to a six-month horizon. For stocks with downgrade revision, the negative IVOL effect is relatively weaker and reverses after 3 months. Most interestingly, for stocks with upgrade revisions, the negative IVOL effect turns much weaker or disappears: the value-weighted IVOL spread even turns positive over the next month and up to six-month horizon. That is, analysts seem to ensure that positive information is quickly incorporated into stock prices, leading to more efficient pricing of idiosyncratic risk.

Our results are consistent with the notion that analysts play an important role in disseminating information, particularly by reducing information asymmetry, and help incorporate information into security prices. As a result of analyst information production, stocks with analyst coverage are less mispriced. Moreover, earnings forecast revisions by analysts are evidence of their active role in information production. As documented in the literature (Jegadeesh and Kim, 2006; Jiang et al., 2014), investor responses to upgrades are faster than to downgrade in the Japanese and Chinese stock markets. This implies that positive news in analyst upgrades is incorporated into stock prices more quickly than negative news in analyst downgrades in the Chinese stock markets. Consistent with this argument, our results show that for stocks with analyst upgrade revision, there is actually a positive relation between IVOL and subsequent stock returns. Jiang et al. (2014) argue that the behavior of individual investors is a plausible explanation of weaker market reactions to downgrades. In this study, we conduct several tests and provide evidence substantiating the argument.

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2 Based on the 2010 data (China Securities Depository Clearing Corporation Limited, 2010), more than 99% of investor accounts in China belong to individual accounts.

3 George and Hwang (2011) use analyst coverage as a proxy of investor disagreement and document a stronger negative relation between IVOL and stock returns with low analyst coverage.

One potential concern is that our findings are simply manifestations of alternative explanations of the IVOL anomaly. For instance, the literature documents that the IVOL anomaly is more pronounced among stocks with strong limits-to-arbitrage or short-sale constraints. We show that non-covered stocks do indeed have stronger limits-to-arbitrage and short-sale constraints than those with analyst coverage. Nevertheless, our findings persist after controlling for both of these factors, showing that our results are not mainly driven by differences in limits-to-arbitrage or short-sale constraints among different subsamples. We also show that our findings are robust after controlling for several previously documented IVOL related variables, such as institutional ownership (Nagel, 2005; Ang et al., 2009; George and Hwang, 2011), return reversal (Huang et al., 2010), and preference lottery-type of returns (Bali et al., 2011).

An additional concern is that both analyst coverage and the presence of a relatively weak IVOL anomaly may be driven by the same firm characteristics or other unknown variables. Therefore, one might argue that a weaker IVOL effect among certain stock subsamples does not necessarily result from analyst coverage. As documented in Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013), both brokerage mergers and brokerage closures cause the decrease in analyst coverage and thus increase the information asymmetry. We employ two exogenous changes of analyst coverage and explore the causal impact of analyst coverage on IVOL anomaly. The first shock is the analyst coverage loss due to brokerage mergers. The second is a market-wide shock in the sudden decrease of analyst coverage occurred in the Chinese stock market in 2011. We show that the loss in analyst coverage aggravates the IVOL effect, evidence supporting our argument that analyst activities reduce the IVOL anomaly. We also perform further robustness checks, namely controlling for analyst earnings forecast dispersion and employing alternative measures of analyst revisions, and confirm that our main results are robust.

Our study contributes to the literature in several aspects. First, there are few studies examining the effect of analyst information production on the IVOL anomaly. The main premise of our study is that, through information production and dissemination, analysts play an important role in reducing information uncertainty and information asymmetry. Given the unique institutional setting of the Chinese stock market, analyst activity likely has a strong effect on the efficiency of stock prices. Second, using the recent quasi-natural experiment of Margin Trading and Short Selling (MTSS) in China, we are able to identify the effect of short-sale constraints. Previous studies attribute the IVOL anomaly to short-sale constraints, a form of limits-to-arbitrage. In this study, we show that the impact of information asymmetry on IVOL mispricing is robust after controlling for short-sale constraints. Third, our study extends the analysis in George and Hwang (2011) and shows that specific analyst actions (i.e. revisions) are indicators of active information production and have a stronger effect on stock prices than analyst coverage alone. Nevertheless, not all revisions have the same effect on stock prices.

The remainder of the paper is organized as follows: Section 2 describes the sample and variables; Section 3 examines the effect of analyst activity on the IVOL anomaly; Section 4 conducts further analyses to control for alternative explanations and Section 5 performs robustness checks; Section 6 concludes.

2. Data

The sample contains Chinese A-share firms listed on Shanghai and Shenzhen stock exchanges. Stock-trading data, financial data, and Fama–French three-factor are from China Stock Market and Accounting Research (CSMAR). Analyst related data are from Wind Info Database (Wind). The full sample period is from January 2005 to December 2014.[4] For the accessibility of financial data, we match the accounting data at the end of each fiscal year $y-1$ with the monthly returns from July of year y to June of year $y+1$. This treatment is conservative since China Securities Regulatory Commission (CSRC) requires all firms to file their last fiscal year reports before April 30 in the current calendar year. We exclude financial firms and special treated (ST) firms from the sample.[5] The final full sample contains 2458 firms, and the average firm number is 1456 per month.

The main variables include idiosyncratic volatility (*IVOL*), analyst coverage, and forecast revision. Following Ang et al. (2006), IVOL is calculated as the standard deviation of the residuals from Fama and French (1993) three-factor model. Specifically, the regression takes the form as:

$$r_d^i = \alpha^i + \beta^i_{RMRF} RMRF_d + \beta^i_{SMB} SMB_d + \beta^i_{HML} HML_d + \varepsilon^i_d \tag{1}$$

where r_d^i is stock i's excess return over daily deposit rate on day d in each month t, and $RMRF_d$, SMB_d, HML_d are daily Fama–French three factors. We treat IVOL missing for any stock less than 17 trading days in that month.

We construct analyst coverage (*COV*) and revision subsamples employing the following procedure. First, at the end of each month t, we divide all the stocks into two groups, those with analyst coverage and those without analyst coverage. In this step, analyst coverage is defined as the number of analysts covering a stock in the previous year (Zhang, 2006). Second, among stocks with analyst coverage, we further divide them into three groups — upgrade revision, downgrade revision, and no revision, based on revisions made by analysts in month t for earnings forecasts of the current fiscal year. We classify stocks as having upgrade (downgrade) revision if there are more (less) analysts of upgrade earnings forecast revisions than those of downgrade revisions to stocks. If there are no revisions made by analysts on a stock or the number of upgrades equals the number of downgrades, we classify these stocks as no revision.[6] On average, there are 201 stocks with upgrade revision, 382 stocks with downgrade revision, and 442

[4] The main reason of starting from 2005 is to ensure enough firms in all subsamples defined later, since there are few analyst reports released before year 2005.

[5] Special treatment is a kind of risk alert. ST firms usually have extremely bad financial situations. (e.g., negative earnings in the last two consecutive years.)

[6] Specifically, we include three cases in "no" revision subsample; (1) there is no analyst report in certain month for analyst covered firms; (2) there are several analyst reports but no analyst revision in certain month for analyst covered firms; (3) the number of upgrades equals the number of downgrades in certain month for analyst covered firms. The firm number of the third case accounts around 10% of no revision subsample.

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
RET(%)	2.36	9.96	−18.27	−4.12	0.98	7.33	38.57
IVOL(%)	1.93	0.77	0.44	1.37	1.80	2.35	5.53
COV	5.47	6.60	0.00	0.52	2.79	8.35	37.68
lnMV	0.71	0.96	−1.32	0.04	0.59	1.26	3.85
lnBM	−0.25	0.67	−1.97	−0.71	−0.26	0.20	1.57
MOM	0.30	0.47	−0.57	0.00	0.20	0.48	4.84
MAX5(%)	3.63	1.32	0.95	2.70	3.38	4.30	9.85
TURN	3.15	1.89	0.13	1.90	2.76	3.93	15.60

This table reports descriptive statistics of main variables used in our analysis. Each month, we calculate cross-sectional statistics of the variables. The table reports time-series average of these cross-sectional statistics. *RET* (in percent) is the monthly stock return; *IVOL* (in percent) is the standard deviation of the daily excess returns, estimated each month for each stock; *COV* is the number of analysts covering the stock in the previous year; *lnMV* is the natural log of market capitalization at the end of the month; *lnBM* is the natural log of book-to-market ratio at the end of last fiscal year; *MOM* is the cumulative return from month t−11 to month t−1. *MAX5* is the average of the five highest daily returns within the month; *TURN* is the turnover ratio in previous 6 months. The sample period is from January 2005 to December 2014.

stocks with no revision at the monthly level. As robustness check, we also use the sign of average revisions to define upgrade, downgrade, and no revision and confirm that the results are robust.

We include several commonly used control variables in our analysis. For example, *lnMV* is defined as the natural log of market capitalization at the end of a month; *lnBM* is defined as the natural log of book-to-market ratio at the end of last fiscal year; *MOM* is calculated as the cumulative return in the previous year (from each month $t-11$ to month $t-1$); *MAX5* is calculated as the average of the five highest daily returns within a month (Bali et al., 2011); *TURN* is defined as the turnover ratio of the previous 6 months.

Table 1 reports the time-series averages of monthly cross-sectional statistics. On average, stocks in the full sample have the average return of 2.36% per month, average monthly idiosyncratic volatility of 1.93%, and average covered analysts of 5.47.

3. Main empirical analysis

In this section, we investigate the role of analysts by relating analyst information to the pricing of idiosyncratic volatility. Previous studies suggest that analyst following may promote information production, lessen the amount of firm-level noise, and facilitate stocks to be accurately priced (Brennan et al., 1993; Walther, 1997; Barth and Hutton, 2000; Chan and Hameed, 2006). We hypothesize that if analysts help alleviate information asymmetry and accelerate efficient adjustment of prices, information produced by analysts will reduce the mispricing of idiosyncratic volatility. We confirm the existence of IVOL anomaly in the Chinese stock market and examine how analyst coverage affects the IVOL anomaly in Section 3.1, study whether different types of analyst revision affect the IVOL anomaly in Section 3.2, and verify the main results in multivariate regressions in Section 3.3.

3.1. The IVOL anomaly in the Chinese stock market

We sort stocks into quintiles based on IVOL, then compute the raw returns and abnormal returns of each quintile portfolio in the next month. We calculate both raw returns and abnormal returns, using value-weighted and equally-weighted methods across stocks in portfolios. Following Daniel et al. (1997, DGTW), at the end of each month t, we form benchmark portfolios by sequentially sorting stocks into terciles based size, book-to-market, and prior one-year return (i.e., 3*3*3 benchmark portfolios). The abnormal return of a stock in month $t+1$ is then computed as the difference between the stock return and the value-weighted average return of a benchmark portfolio.

Panel A of Table 2 reports the average returns of each quintile portfolio. Q1 (Q5) refers to the quintile portfolio with the lowest (highest) IVOL. The monthly equally-weighted return spreads between lowest- and highest-IVOL quintiles are 1.80% (t-stat = 6.77) for raw returns and 1.79% (t-stat = 9.82) for abnormal returns. The value-weighted return spreads between two extreme IVOL quintile portfolios are 0.58% (t-stat = 1.38) and 0.74% (t-stat = 2.89) for raw returns and abnormal returns, respectively. The result confirms the existence of IVOL anomaly in the Chinese stock market. Also, this anomaly is more evident in small-cap firms than in large-cap firms, since the IVOL return spreads are substantially higher in the equally-weighted results.

The one-way sorting results raise the research question why high idiosyncratic volatility stocks are associated with low future returns. If the market is fully efficient, no investor has an advantage in predicting returns. We argue that the IVOL anomaly exists because information asymmetry deters the price discovery process of high IVOL stocks. To test whether analyst following reduces the IVOL anomaly, we conduct portfolio sorting based on analyst coverage and IVOL. At the end of each month, we separate stocks into two subsamples — those with analyst coverage and those without. Then, within each subsample, we further sort stocks into quintiles by IVOL. Panel B of Table 2 reports the return spreads of quintile portfolios and examines whether there is a significant difference in IVOL spreads between covered stocks and non-covered stocks. For the subsample with analyst coverage, the equally-weighted (EW) raw returns/abnormal returns spreads are 1.13% (t-stat = 3.66)/1.23% (t-stat = 5.52). The value-weighted (VW) raw returns spreads (0.19% with t-stat = 0.41) and the abnormal returns spreads (0.39% with t-stat = 1.27) are not significantly different from zero. For the subsample without analyst coverage, the equally weighted raw-returns and abnormal-returns spreads are 2.75% (t-stat = 9.91) and 2.55% (t-stat = 10.73), respectively. The value-weighted return spreads are 2.42% (t-stat = 7.94)

Table 2
Average returns of idiosyncratic volatility portfolios.

Panel A: One-way sorting by IVOL

IVOL Quintile	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	3.02	0.78	1.78	0.05
	(2.61)	*(8.06)*	*(1.71)*	*(0.37)*
Q2	2.84	0.61	2.10	0.40
	(2.43)	*(7.32)*	*(1.91)*	*(3.59)*
Q3	2.52	0.33	1.96	0.24
	(2.18)	*(3.94)*	*(1.75)*	*(2.15)*
Q4	2.19	−0.07	1.76	−0.06
	(1.89)	*(−0.83)*	*(1.51)*	*(−0.57)*
Q5	1.22	−1.00	1.21	−0.69
	(1.10)	*(−8.08)*	*(1.06)*	*(−4.52)*
Q1–Q5	1.80	1.79	0.58	0.74
t-stat	*(6.77)*	*(9.82)*	*(1.38)*	*(2.89)*

Panel B: The return spreads of portfolios sorting by analyst coverage and IVOL

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Covered				
Q1–Q5	1.13	1.23	0.19	0.39
t-stat	*(3.66)*	*(5.52)*	*(0.41)*	*(1.27)*
Non-covered				
Q1–Q5	2.75	2.55	2.42	2.24
t-stat	*(9.91)*	*(10.73)*	*(7.94)*	*(8.67)*
Non-covered–Covered				
Q1–Q5	1.62	1.32	2.23	1.85
t-stat	*(5.74)*	*(5.86)*	*(4.98)*	*(5.46)*

This table conducts one-way portfolio sorting based on idiosyncratic volatility (IVOL), and two-way sorting based on analyst coverage and IVOL. At the end of each month *t*, we form the equally- and value-weighted quintile portfolios based on *IVOL* in month *t*. Q1(Q5) contains 20% stocks with the lowest (highest) IVOL. Following Ang et al. (2006, AHXZ), we construct $IVOL_{i,t}$ as the standard deviation of stock i's daily excess returns (relative to Fama and MacBeth (1973) three-factor model) in month *t*. We calculate average raw returns and abnormal returns for each quintile portfolio in month *t*+1. Following Daniel et al. (1997, DGTW), abnormal returns are computed as the difference between stock return and the value-weighted average returns of benchmark portfolios. At the end of each month *t*, we form benchmark portfolios by sequentially sorting stocks into size, book-to-market, and prior one-year return terciles. The row "Q1–Q5" refers to average monthly return spreads between Q1 and Q5. Panel A reports average raw returns and abnormal returns of quintile idiosyncratic volatility (IVOL) portfolios. Panel B reports the average return spreads of portfolios sorting by analyst coverage and IVOL, and the differences in IVOL spreads between stocks without analyst coverage and stocks with analyst coverage. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. The sample period is from January 2005 to December 2014.

for raw returns and 2.24% (*t*-stat = 8.67) for abnormal returns. We compare the IVOL spreads between two subsamples and find a large and significant discrepancy in IVOL spreads between covered and non-covered stocks. The differences in IVOL return spreads between two subsamples are 1.62% (*t*-stat = 5.74), 1.32% (*t*-stat = 5.86), 2.23% (*t*-stat = 4.98) and 1.85% (*t*-stat = 5.46) for EW raw returns, EW abnormal returns, VW raw returns, and VW abnormal returns, respectively. The results indicate that the presence of analysts reduces the effect of IVOL, consistent with the US evidence in George and Hwang (2011).

So far we have presented that the IVOL anomaly is less evident in analyst-covered stocks. Our main argument is that analysts can mitigate information asymmetry by producing and disseminating information, thus accelerate efficient adjustment of stock prices and reduce the IVOL anomaly. Someone may argue that if an analyst does not release information related to her/his covered firm every month, then coverage might not be a competent proxy for updated analyst information. Indeed, we may not receive analyst reports every month of a particular year. Moreover, the degree of information update varies across different analyst reports. Therefore, we go deeper to address these issues in the next subsection by considering the types of analyst forecast revisions.

3.2. Two-way portfolio sorting based on analyst revision and IVOL

Analyst coverage can help alleviate information asymmetry of a stock, but itself does not produce information. In particular, what really matters is the content of reports. In this subsection, we go one step further and analyze the effect of analyst forecast revisions on IVOL return spreads. Specifically, we conduct portfolio sorting based on analyst revision and IVOL. We separate stocks into three revision subsamples – upgrade revision, downgrade revision, and no revision – at the end of each month *t*. Within each subsample, we further sort stocks into quintiles by IVOL. We calculate the average equally-weighted and value-weighted raw returns and abnormal returns for these 3*5 portfolios.

Table 3 reports the pricing effects of IVOL among upgrade-revision stocks, down upgrade-revision stocks, and no-revision stocks. In Panel A, for stocks with upgrade revision, the IVOL return spreads become less significant, compared to the whole analyst-covered

Table 3
Subsample results based on analyst forecast revisions.

Panel A: Stocks with upgrade revision

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	2.92	1.01	1.60	0.15
	(2.72)	*(5.71)*	*(1.59)*	*(0.54)*
Q2	3.18	1.18	2.36	0.60
	(3.00)	*(7.14)*	*(2.23)*	*(1.95)*
Q3	3.01	0.90	2.78	0.85
	(2.84)	*(4.68)*	*(2.44)*	*(3.23)*
Q4	2.92	0.93	2.30	0.56
	(2.61)	*(4.88)*	*(2.03)*	*(2.24)*
Q5	2.46	0.32	2.66	0.73
	(2.27)	*(1.21)*	*(2.28)*	*(2.37)*
Q1–Q5	0.46	0.69	−1.06	−0.59
t-stat	*(1.06)*	*(2.07)*	*(−1.90)*	*(−1.38)*

Panel B: Stocks with downgrade revision

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	2.30	0.33	1.42	−0.27
	(2.12)	*(2.25)*	*(1.36)*	*(−1.27)*
Q2	2.26	0.31	1.76	0.11
	(2.01)	*(2.27)*	*(1.56)*	*(0.50)*
Q3	2.12	0.10	1.57	0.08
	(1.80)	*(0.52)*	*(1.37)*	*(0.37)*
Q4	2.07	0.00	1.56	−0.09
	(1.78)	*(0.01)*	*(1.30)*	*(−0.36)*
Q5	1.29	−0.84	0.97	−0.88
	(1.22)	*(−4.13)*	*(0.87)*	*(−4.19)*
Q1–Q5	1.01	1.16	0.45	0.61
t-stat	*(2.79)*	*(4.74)*	*(0.86)*	*(1.76)*

Panel C: Stocks with no revision

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	3.03	0.74	2.22	0.39
	(2.60)	*(4.87)*	*(2.03)*	*(2.03)*
Q2	2.81	0.53	1.94	0.20
	(2.41)	*(4.00)*	*(1.70)*	*(1.14)*
Q3	2.49	0.21	2.04	0.15
	(2.10)	*(1.68)*	*(1.68)*	*(0.87)*
Q4	2.05	−0.19	1.75	−0.15
	(1.75)	*(−1.13)*	*(1.41)*	*(−0.64)*
Q5	1.35	−0.89	1.18	−0.71
	(1.24)	*(−4.65)*	*(1.02)*	*(−3.01)*
Q1–Q5	1.68	1.63	1.04	1.10
t-stat	*(5.42)*	*(6.31)*	*(2.63)*	*(3.48)*

Panel D: Differences in IVOL spreads

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
no–upgrade	1.22	0.94	2.10	1.68
t-stat	*(3.74)*	*(3.13)*	*(5.15)*	*(4.73)*
no–downgrade	0.67	0.47	0.59	0.48
t-stat	*(3.07)*	*(2.41)*	*(1.87)*	*(2.01)*
downgrade–upgrade	0.55	0.47	1.51	1.20
t-stat	*(1.77)*	*(1.55)*	*(3.22)*	*(2.96)*

This table reports average raw returns and abnormal returns of portfolios sorting by analyst forecast revision and IVOL. At the end of each month t, we divide covered stocks into three groups depending on their revision types — upgrade, downgrade, or no revision. Within each revision type, we further sort stocks into quintiles, based on IVOL calculated over month t, from the lowest (Q1) to the highest (Q5). For each subsample stocks, we form equally- and value-weighted portfolios and report average raw returns and abnormal returns in month $t+1$. Panel A, B, and C separately report results for stocks with "upgrade" revision, "downgrade" revision, and "no" revision. Panel D presents the return differences in IVOL spreads between these three subsamples. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. The sample period is from January 2005 to December 2014.

stocks. The equally-weighted average raw returns and abnormal returns are 0.46% (t-stat = 1.06) and 0.69% (t-stat = 2.07); the

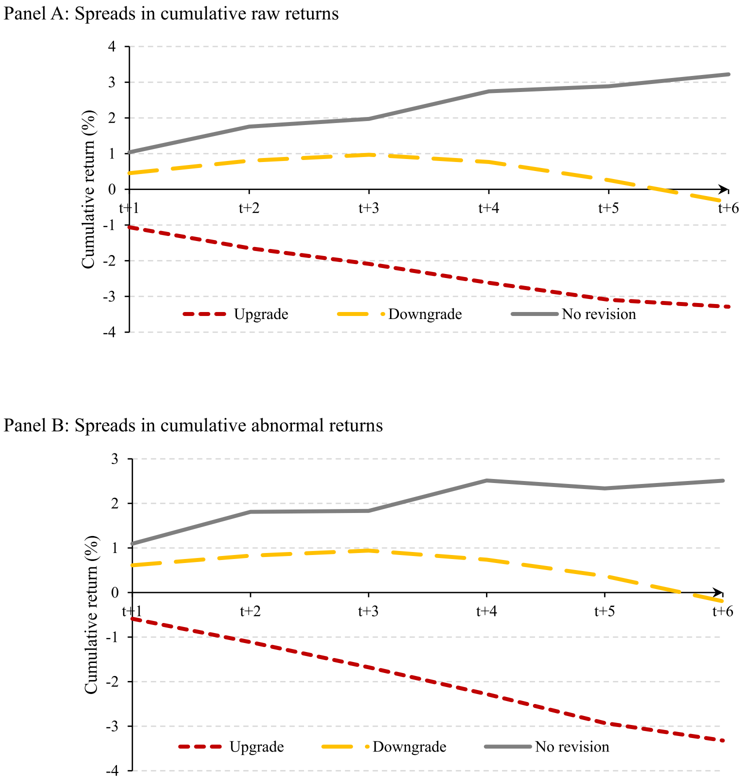

Fig. 1. Cumulative idiosyncratic volatility spread of three forecast revision subsamples. Panel A plots average cumulative raw returns (in percent) of value-weighted "Q1–Q5" spread portfolio. At the end of each month *t*, we form zero-cost "spread portfolios" by going long the lowest IVOL quintile (Q1) and shorting the highest IVOL quintile (Q5) across three analyst-revision types. For each revision type, we add up the raw returns of the spread portfolio from month *t*+1 to *t*+6 and calculate average cumulative raw returns. Panel B plots average abnormal returns of value-weighted "Q1–Q5" spread portfolio for three revision types. The abnormal returns are adjusted following Daniel et al. (1997, DGTW), controlling for size, value, and momentum effect. The sample period is from January 2005 to December 2014.

value-weighted average raw returns and abnormal returns are −1.06% (*t*-stat = −1.90) and −0.59% (*t*-stat = −1.38). In Panel B, for stocks with downgrade revision, the IVOL return spreads are relatively small, compared to the whole analyst-covered stocks. The equally-weighted raw returns and abnormal returns are 1.01% (*t*-stat = 2.79) and 1.16% (*t*-stat = 4.74); the value-weighted raw returns and abnormal returns are 0.45% (*t*-stat = 0.86) and 0.61% (*t*-stat = 1.76). In Panel C, for stocks with no revision, the IVOL return spreads are economically large and statistically significant at the 1% level, compared to the whole analyst-covered stocks. The EW average raw returns and abnormal returns are 1.68% (*t*-stat = 5.42) and 1.63% (*t*-stat = 6.31); the value-weighted raw returns and abnormal returns are 1.04% (*t*-stat = 2.63) and 1.10% (*t*-stat = 3.48).

To test whether the IVOL spreads vary among three analyst revision types, we further examine the differences in IVOL spreads among three revision groups in Panel D. We first calculate the difference of IVOL spreads between no-revision and upgrade-revision groups. The EW raw returns and abnormal returns are 1.22% (*t*-stat = 3.74) and 0.94% (*t*-stat = 3.13), respectively. The VW raw returns and abnormal returns are 2.10% (*t*-stat = 5.15) and 1.68% (*t*-stat = 4.73), respectively. All four differences in spread are significant at the 1% level, indicating that the IVOL effect presents significantly stronger in no-revision stocks than in upgrade-revision stocks. Similarly, the discrepancies between no-revision stocks and downgrade-revision stocks are relatively smaller but still significant (0.67% with *t*-stat = 3.07, 0.59% with *t*-stat = 1.87, 0.47% with *t*-stat = 2.41, and 0.48% with *t*-stat = 2.01 for EW raw returns, VW raw returns, EW abnormal returns, and VW abnormal returns, respectively). In addition, there are substantial differences between down-revision stocks and upgrade-revision stocks. The EW raw returns and abnormal returns are 0.55% (*t*-stat = 1.77) and 0.47% (*t*-stat = 1.55), respectively. The VW raw returns and abnormal returns are 1.51% (*t*-stat = 3.22) and 1.20% (*t*-stat = 2.96), respectively.

Table 3 shows the different patterns of IVOL spreads among upgrade-revision, downgrade-revision, and no-revision stocks. To understand the differences between upgrade (or downgrade) revision and no revision stocks, the former has concrete information update that mitigates the effect of information asymmetry on IVOL, the latter has no update. As for the substantial difference between upgrades and downgrades stocks, previous studies argue that investors response to upgrades are faster than to downgrade in the Japanese and Chinese stock markets (e.g., Jegadeesh and Kim, 2006; Jiang et al., 2014). Thus, the stock price is more efficient in the presence of good news relative to bad news. Furthermore, given the difference between EW and VW results, large-cap stock prices are confirmed to be more efficient.

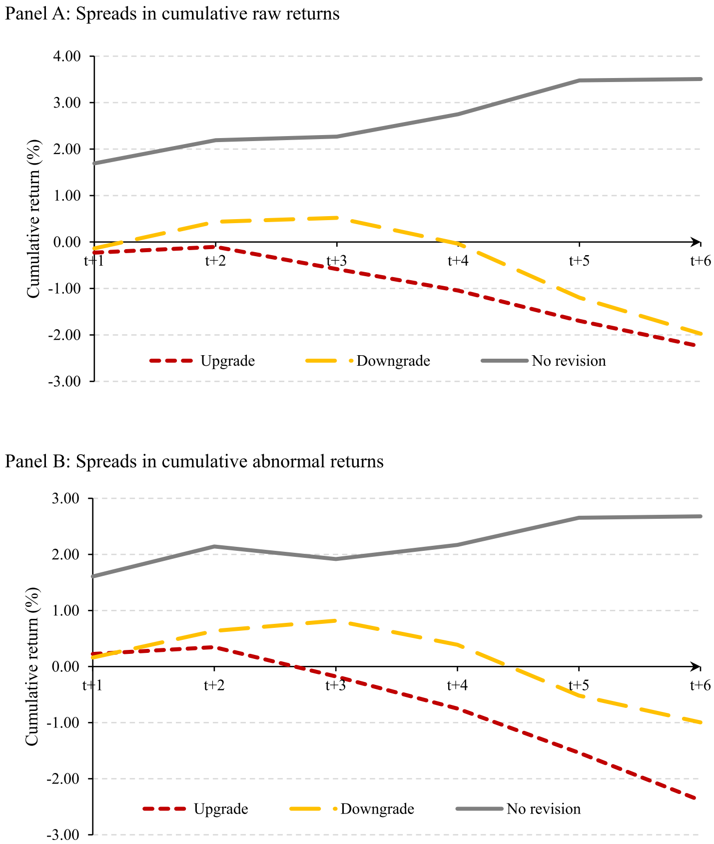

Fig. 2. Cumulative idiosyncratic volatility spread using an alternative measure of revisions. This figure is based on an alternative measure of analyst earnings forecast revision. We classify stocks as having upgrade (downgrade) revision in month t if the average revision of earnings forecasts is positive (negative) and no revision if the average revision is zero. Panel A and Panel B are constructed in the same way as Fig. 2. The abnormal returns are adjusted following Daniel et al. (1997, DGTW), controlling for size, value, and momentum effect. The sample period is from January 2005 to December 2014.

In Fig. 1, we plot the cumulative IVOL spreads (Q1–Q5) among three analyst revision groups. We form zero-cost portfolios of IVOL spreads of three revision types at the end of each month t, and then we draw their cumulative raw returns and abnormal returns up to 6-month holding period. For upgrade-revision stocks, both cumulative raw returns and abnormal returns gradually decrease up to 6 months. For downgrade-revision stocks, the IVOL spreads start decreasing at t+3 and reverse to negative at t+6. For no-revision stocks, the IVOL return spreads gradually increase in 6 months. The evidence shows that the distinguishable pattern among three revision groups holds up to 6 months. Therefore, we argue that stocks with upgrade revision generally have the least information asymmetry since the information updates from analysts are quickly incorporated into prices. Stocks with downgrade-revision also have information updates, but investors react to downgrade slowly in the Chinese stock markets. Stocks with no-revision have the most severe information asymmetry among these three revision types. In the latter section, we conduct several empirical tests to understand the difference between upgrade and downgrade revisions.

3.3. Fama-MacBeth regressions

In this subsection, we perform multivariate tests by controlling for relevant variables in the value-weighted Fama and MacBeth (1973) regression. In each month, we run the following cross-sectional regressions of stock returns on *IVOL*, interaction terms of *IVOL* and coverage dummies or revision dummies, and control variables.

$$\begin{aligned}\mathrm{Ret}_{\mathrm{i},t+1} &= \alpha + \beta_1 * IVOL_{\mathrm{i},t} + \beta_2 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}^{COV} + \beta_3 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}^{NCOV} + \gamma * controls \\ \mathrm{Ret}_{\mathrm{i},t+1} &= \alpha + \beta_1 * IVOL_{\mathrm{i},t} + \beta_2 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}^{\mathrm{UP}} + \beta_3 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}^{\mathrm{DOWN}} + \beta_4 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}^{\mathrm{NO}} + \gamma * controls\end{aligned} \tag{2}$$

Where *Ret* is the next month stock return; $\mathrm{d}^{\mathrm{COV}}/\mathrm{d}^{\mathrm{NCOV}}$ is assigned one if a stock is covered by at least one analyst/not covered in the previous year; $\mathrm{d}^{\mathrm{UP}}/\mathrm{d}^{\mathrm{DOWN}}/\mathrm{d}^{\mathrm{NO}}$ is assigned one if analysts release upgrade/downgrade/no revision on a stock. Control variables include *lnMV* defined as the natural log of market capitalization, *lnBM* defined as the natural log of book-to-market ratio, *MOM* defined as the cumulative stock return from month $t-11$ to month $t-1$, *MAX5* defined as the average of the five highest daily stock returns within a month, and *TURN* defined as the turnover ratio of a stock in previous 6 months.

Table 4
Fama–MacBeth Regressions.

Panel A: Mean and medians of variables in stock subsample with and without coverage

	Covered		Non-covered		Non-covered–Covered	
Average number of firms	1025		431			
	Mean	Median	Mean	Median	Mean	t-stat
lnMV	0.95	0.87	0.27	0.24	−0.68	(−23.31)
lnBM	−0.28	−0.31	−0.20	−0.17	0.09	(4.98)
MOM	0.32	0.21	0.28	0.20	−0.03	(−1.73)
MAX5	3.58	3.34	3.72	3.43	0.14	(4.14)
TURN	3.03	2.64	3.42	3.01	0.40	(3.39)

Panel B:Fama–MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IVOL		−2.75***		−2.43***		−1.05**		−1.15**
		(−7.79)		(−5.01)		(−2.37)		(−2.51)
IVOL* d^{COV}	−0.09	2.66***	−0.38	2.05***				
	(−0.16)	(5.41)	(−0.86)	(4.71)				
IVOL* d^{NCOV}	−2.75***		−2.43***					
	(−7.79)		(−5.01)					
IVOL* d^{UP}					0.51	1.56***	0.19	1.34***
					(0.83)	(3.67)	(0.34)	(3.46)
IVOL* d^{DOWN}					−0.17	0.88*	−0.52	0.63*
					(−0.26)	(1.92)	(−1.01)	(1.64)
IVOL* d^{NO}					−1.05**		−1.15**	
					(−2.37)		(−2.51)	
lnMV			−2.12***	−2.12***			−2.12***	−2.12***
			(−3.21)	(−3.21)			(−2.90)	(−2.90)
lnBM			0.43	0.43			0.36	0.36
			(0.87)	(0.87)			(0.68)	(0.68)
MOM			0.53	0.53			0.62	0.62
			(1.18)	(1.18)			(1.29)	(1.29)
MAX5			−0.21	−0.21			−0.26	−0.26
			(−0.52)	(−0.52)			(−0.58)	(−0.58)
TURN			−0.87**	−0.87**			−0.75	−0.75
			(−2.13)	(−2.13)			(−1.66)	(−1.66)
Sample	Full	Full	Full	Full	Covered	Covered	Covered	Covered
Adj. R^2	0.033	0.033	0.160	0.160	0.045	0.045	0.174	0.174

The table runs the value-weighted Fama and MacBeth (1973) regressions of stock returns on idiosyncratic volatility controlling for analyst coverage (Columns 1 to 4) and forecast revisions (Columns 5 to 8). Specifically, we run cross-sectional regressions of stock excess return in month t+1 on *IVOL*, interaction terms of *IVOL* and coverage/revision dummies, and control variables calculated in month t. Then we test whether the time-series average coefficients are significantly different from zero. d^{COV}/d^{NCOV} is assigned one if a stock is covered by at least an analyst/not covered in the previous year. $d^{UP}/d^{DOWN}/d^{NO}$ is assigned one if analysts release upgrade/downgrade/no revision on a stock. Panel A reports the means and medians of control variables, both for stocks with analyst coverage and stocks without coverage. Panel B reports the results of Fama–MacBeth regressions. *lnMV* is the natural log of market capitalization. *lnBM* is the natural log of book-to-market ratio. *MOM* is the cumulative stock return from month $t-11$ to month $t-1$. *MAX5* is the average of the five highest daily stock returns within a month. *TURN* is the turnover ratio of a stock in previous 6 months. All explanatory variables and control variables are standardized at the cross-sectional level each month. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to December 2014.

Panel A of Table 4 presents firm characteristics of stocks with and without analysts coverage. On average, there are 1025 stocks in the covered subsample and 431 stocks in the non-covered subsample. We notice the significant differences between two subsamples for our control variables — firm size, book-to-market, past twelve-month returns, maximum daily return, and turnover ratio.

Panel B of Table 4 reports Fama and MacBeth (1973) regressions controlling for analyst coverage (Columns 1 to 4) and three analyst revisions (Columns 5 to 8). We focus the interaction terms between *IVOL* and analyst related dummy variables. In Column 1, the coefficient of the interaction terms of *IVOL**d^{NCOV} is −2.75 (t-stat = −7.79), and the coefficient of the interaction terms of the *IVOL**d^{COV} dummy is insignificant (−0.09 with t-stat = −0.16). When non-covered subsample is used as a baseline in Column 2, we find that the regression coefficient of *IVOL**d^{COV} is positively significant (2.66 with t-stat = 5.41). When adding control variables in Columns 3 and 4, we find both regressions yield coefficients similar to regressions without control variables. The first four columns confirm that there is a significant difference of IVOL effect between covered stocks and non-covered stocks, in line with portfolio sorting results in Table 2.

We report the regression results of revision effect from Columns 5 to 8. In Column 5, the coefficients of *IVOL**d^{UP}, *IVOL**d^{DOWN}, and *IVOL**d^{NO} are 0.51 (t-stat = 0.83), −0.17 (t-stat = −0.26), −1.05 (t-stat = −2.37), respectively. The negatively significant coefficient of the interaction term *IVOL**d^{NO} implies that no analyst revision makes an additional contribution to the IVOL negative premium. When we use no-revision stocks as a baseline in Column 6, the coefficients of interaction terms *IVOL**d^{UP} and *IVOL**d^{DOWN} are 1.56 (t-stat = 3.67) and 0.88 (t-stat = 1.92), respectively. Column 6 shows that both upgrade revision and downgrade revision groups add a positive number to the IVOL negative premium, and thus decrease the IVOL return spreads. In particular, upgrade

Table 5
Abnormal returns following analyst revisions.

Panel A: Analyst revisions and subsequent abnormal returns					
Revision	Holding days after revision date				
	5	22	44	62	125
Upgrade	1.49	2.11	2.97	3.62	5.80
	(4.16)	*(3.34)*	*(2.97)*	*(2.83)*	*(2.24)*
Downgrade	−0.24	−0.51	−1.02	−1.40	−2.26
	(−1.97)	*(−2.07)*	*(−2.34)*	*(−2.02)*	*(−1.67)*
Up–Down	1.25	1.60	1.95	2.21	3.53
t-stat	*(4.46)*	*(3.91)*	*(3.68)*	*(3.58)*	*(3.49)*

Panel B: Analyst coverage and the reactions to downgrades					
Holding days after revision date	5	22	44	62	125
d^{UP}	1.48***	2.15***	3.02***	3.68***	5.96***
	(15.28)	(12.46)	(12.15)	(12.13)	(11.05)
d^{DOWN}	−0.26***	−0.52***	−0.99***	−1.34**	−2.20**
	(−5.64)	(−5.53)	(−5.55)	(−2.10)	(−2.06)
COV^R *d^{DOWN}	−0.34***	−0.40**	−0.40*	−0.44	−0.75
	(−3.09)	(−1.97)	(−1.79)	(−1.25)	(−1.21)
N	51129	51129	51129	51129	51129
Adj.R^2	0.025	0.018	0.021	0.023	0.022

This table reports the average buy-and-hold abnormal returns (BHARs) of stocks after revisions and the effects of analyst coverage on market reactions to revisions. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The average buy-and-hold abnormal returns with holding periods of 5, 22, 44, 62, 125 days are separately reported. The sample period is from January 2005 to December 2014.
Panel A reports the average buy-and-hold abnormal returns (BHARs) of stocks after a revision of earnings forecast. For each stock with an upgrade or downgrade revision, we calculate its buy-and-hold abnormal returns as the difference between the cumulative returns of the stock and the cumulative value-weighted returns of the benchmark portfolio of that stock. The benchmark portfolio is constructed by triple sorting all the stocks into quartiles by size, book-to-market ratio, and lagged returns. Panel B reports the effects of analyst coverage on market reactions to downgrade revisions of earnings forecast. We regress stocks' buy-and-holding abnormal returns (BHARs) on upgrade dummy, downgrade dummy, the interaction term of downgrade dummy and residual coverage (COV^R), as well as control variables. d^{UP}/d^{Down} is assigned one if a revision is upgrade/downgrade and zero otherwise. We control quarterly size, book-to-market, lagged returns, leverage and volatility. COV^R is calculated as the residual of regressing log of one plus the number of analysts on log of size. COV^R and other control variables are all standardized to a mean of 0 and standard deviation of 1. To save space, coefficient estimates of control variables are not reported. All explanatory variables and control variables are standardized at the cross-sectional level each month.

revision decreases even more than downgrade revision, in terms of IVOL return spreads. The results of Columns 5 and 6 hold when we include more control variables in Columns 7 and 8.

Overall, the results of Fama–MacBeth regressions are consistent with two-way portfolio sorting results. We confirm the findings in George and Hwang (2011) that the IVOL anomaly is much stronger among firms without analyst coverage. More importantly, we make an extension by studying the effect of analyst revision on IVOL anomaly. Among covered stocks, stocks with no-revision have the most severe information asymmetry, resulting in more prominent IVOL anomaly than other two revision groups. We will focus on the results of analyst revision from the next section.

4. Further analysis

In this section, we perform further analysis to examine potential explanations of the IVOL anomaly. In Section 4.1, we provide empirical tests to understand the difference between upgrade and downgrade revision stocks. In Section 4.2, we examine whether limits-to-arbitrage proxies have potential effects on our results. In Section 4.3, we investigate the role of short-sale constraints by incorporating the Chinese pilot program of margin trading and short selling. In Section 4.4, we show that the main results are not driven by limits-to-arbitrage or short-sale constraints.

4.1. Difference between upgrade and downgrade revisions

Our previous results show the significant difference in IVOL anomaly between upgrade and downgrade revisions, and we try to explore the economic mechanisms behind this difference. As shown in Jegadeesh and Kim (2006) and Jiang et al. (2014), investors' responses to upgrade are stronger than to downgrade in the Japanese and Chinese stock markets. In other words, compared to stocks with downgrade revision, stocks with upgrade revision generally have less information asymmetry since the information updates from analysts are more quickly incorporated into prices. To demonstrate this point, we first examine market reactions to upgrade revisions and downgrade revisions in Panel A of Table 5. Following Daniel et al. (1997, DGTW) and Jiang et al. (2014), we triple-sort the sample by size, book-to-market ratio, and lagged returns, and calculate value-weighted benchmark returns. Then we calculate the buy-and-hold abnormal returns (BHAR) of each stock after an upgrade or downgrade revision as the difference between the cumulative return of the stock and that of the benchmark portfolio with holding periods of 5, 22, 44, 62, 125 days.

Panel A shows that the market reacts significantly to both upgrade revisions and downgrade revisions. The buy-and-hold abnormal returns following upgrades are significantly positive at the 1% level up to 3-month holding period (62 days) and 5% level at

Table 6
Analyst revisions and limits-to-arbitrage.

Panel A: The limits-to-arbitrage proxies of three revision subsamples						
	Up		Down		No	
	Mean	*Median*	Mean	*Median*	Mean	*Median*
NLIM	0.30	*0.08*	0.32	*0.11*	0.39	*0.15*
AMIHUD	0.74	*0.53*	0.87	*0.63*	1.29	*0.98*
(-)VOLUME	−2.59	*−1.52*	−2.08	*−1.24*	−1.53	*−0.99*
(-)PRICE	−17.34	*−13.78*	−13.66	*−11.19*	−11.23	*−9.15*

Panel B: Comparison of limits-to-arbitrage proxies in three revision subsamples						
	No–Up		No–Down		Down–Up	
	Mean	*t-stat*	Mean	*t-stat*	*t-stat*	Mean
NLIM	0.09	*(4.64)*	0.07	*(5.63)*	0.02	*(1.19)*
AMIHUD	0.55	*(4.65)*	0.42	*(4.27)*	0.13	*(4.10)*
(-)VOLUME	1.05	*(9.32)*	0.54	*(8.70)*	0.51	*(5.20)*
(-)PRICE	6.12	*(11.07)*	2.43	*(12.57)*	3.68	*(8.14)*

This table reports the mean and median of four limits-to-arbitrage proxies among different analyst subsamples. In each month *t*, we calculate the mean and median of a proxy within a subsample. We then take the time-series average of these means and medians across all the sample months. *NLIM* is the number of price-limit-hitting days of a stock in a month. *AMIHUD* is Amihud (2002) monthly illiquidity measure. *VOLUME* is monthly CNY trading volume (in billion yuan). *PRICE* is monthly closing price (in yuan). T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. The sample period is from January 2005 to December 2014.

the 6-month horizon (125 days), whereas the BHARs following downgrades are significantly negative at the 5% level up to 3-month and 10% level at the 6-month horizon. In particular, abnormal returns following upgrades have larger magnitude than abnormal returns following downgrades. For example, over 1-week, 1-month and 2-month horizons, the BHARs following upgrades are, respectively, 1.49%, 2.11%, and 2.97%, whereas the BHARs following downgrades are −0.24%, −0.51%, and −1.02%, respectively. Formal tests on the differences show that the magnitudes of abnormal returns following upgrade revisions are significantly higher than those of following downgrade significant at 1% level at the 6-month horizon, confirming that market reactions to upgrades are significantly stronger than to downgrades in the Chinese stock market.

We further explore one potential reason for such pattern by linking the unique Chinese feature that the Chinese stock market is dominated by retail investors. We use the residual coverage in Hong et al. (2000) to proxy for investor sophistication and examine the effect of analyst coverage on market reactions to analyst revisions. Following Jiang et al. (2014), we conduct the regression as follows:

$$BHAR_{i,D} = \beta_1 * d^{UP} + \beta_2 * d^{DOWN} + \beta_3 * COV^R * d^{DOWN} + \gamma * controls \tag{3}$$

Where $BHAR_{i,D}$ is the D-day cumulative buy-and-hold abnormal return following a revision. The dummy variable d^{UP} / d^{DOWN} is assigned one if a revision is upgrade/downgrade and zero otherwise. COV^R is the residual coverage of the firm. We control size, book-to-market, lagged returns, leverage, and volatility.

Panel B of Table 5 presents the effect of analyst coverage on market reactions to downgrades. Coefficient estimates of control variables are not reported for brevity. If investor sophistication is the reason for weaker market reactions to downgrades in the Chinese stock market, then there should be stronger market reactions to downgrades for stocks with more analyst overage. Thus, the coefficient of $COV^R * d^{DOWN}$ expects to be significantly negative.

Indeed, Panel B shows that β_3 is negatively significant at the 1% level for one-week horizon, at the 5% level for one-month horizon, and at the 10% level for two-month horizon. The results imply that the behavior of individual investors is a plausible explanation of weaker market reactions to downgrades.

Overall, this subsection shows that investor reactions to downgrades are weaker than to upgrades in the Chinese stock markets. As such, the mitigating effect of information production and dissemination on the IVOL anomaly is less prominent among stocks with downgrade revisions than with upgrade revisions. In other words, positive news is incorporated into stock prices more quickly than negative news in the Chinese stock markets. The above empirical analysis offer evidence to substantiate our argument on the differences between upgrade and downgrade revisions.

4.2. Analyst revision and limits-to-arbitrage

DeLong et al. (1990) and Shleifer and Vishny (1997) show that limits-to-arbitrage makes the arbitrage process risky and costly. As a consequence, market mispricing can persist and market efficiency will not be achieved instantaneously. In this subsection, we investigate four firm characteristics proxied for limits-to-arbitrage and examine any cross-variation of these proxies among different analyst revision subsamples.

George and Hwang (1995) and Kim and Rhee (1997) argue that price limits postpone price discovery and desired trading activity, so we employ the unique Chinese trading feature "price-limit-hitting" as one proxy for limits-to-arbitrage.[7] The price-limit-hitting

[7] Since December 1996, the Chinese stock market has imposed the daily price change limit on trading of stocks. There is a 10% limit of daily price up or down for regular stocks. Investors cannot post limit buy (sell) order whose limit price is 10% higher (lower) than yesterday close price. In other words, when

NLIM is measured as the number of price-limit-hitting days of a stock in a month, and the higher *NLIM* suggests the higher level of limits-to-arbitrage. We also consider three other commonly used limits-to-arbitrage proxies. For example, the illiquidity measure *AMIHUD* is defined as the Amihud (2002) monthly illiquidity measure because Chordia et al. (2008) show that liquidity improves market efficiency by stimulating arbitrage activity. Mashruwala et al. (2006) show that transaction costs proxied by low price and low volume incur obstacles to exploiting accrual mispricing, so we also consider trading volume and stock price as the limits-to-arbitrage proxies, where *VOLUME* is monthly Chinese Yuan (CNY) trading volume (in billion yuan), and *PRICE* is monthly closing price (in yuan).[8] For each proxy, we employ the Fama and MacBeth (1973) two-step approach and report its time-series average of cross-sectional means and medians in Table 6.

Table 6 reports the means of four limits-to-arbitrage proxies, and difference in means between three analyst revision subsamples. We find that the means and medians of limits-to-arbitrage proxies are the highest in stocks with no revision; the stocks with upgrade revision have the lowest level of limits-to-arbitrage, and stocks with downgrade revision are in the middle. Among three revisions groups, Panel B shows that the differences of limits-to-arbitrage proxies in means are most significant at the 1% level.[9] Overall, there are significant differences of the limits-to-arbitrage proxies among each revision subsample, implying that limits-to-arbitrage may contribute to the return discrepancies in IVOL spread among different subsamples.

4.3. Analyst revision, and short-sale constraints

Miller (1977) argues that the dispersion of opinion and short-sale constraints lead to overpricing. Since stronger information asymmetry leads to more pronounced Miller effect, we conjecture that our main findings might be due to Miller's overpricing effect. In this subsection, we utilize a recent quasi-natural experiment in the Chinese stock market to measure the effect of short-sale constraints and test whether short-sale constraints affect our main results. The pilot program, named "Margin Trading and Short-Selling" (MTSS), launched in March 2010 and has gradually included more A-listed stocks in the pilot program. For stocks in the pilot program, investors can borrow stocks and short sell them. For stocks that are not included in this program, it will be very difficult for arbitrageurs to short sell.

We run Fama and MacBeth (1973) regressions by adding the dummy variables of MTSS and non-MTSS for the years from 2012 to 2014.[10] d^{MTSS} (d^{NMTSS}) is assigned one if a stock is included (not included) in the MTSS pilot program in each month *t*. We include other dummies and control variables defined in the previous section. Panel A of Table 7 reports the average monthly firm numbers of each category to make sure we have sufficient observations to conduct the cross-sectional regression, and Panel B reports the Fama–MacBeth regression results.

Column 1 of Panel B simply shows the effect of short-sale constraints on IVOL return spreads. The regression coefficient of $IVOL{*}\ d^{MTSS}$ is insignificant (−0.34 with *t*-stat = −0.42), and the coefficient of $IVOL{*}\ d^{NMTSS}$ is negatively significant (−1.64 with *t*-stat = −2.43), suggesting that the short-sale constraints contribute the negative premium of idiosyncratic volatility. Columns 2&3 compare the effect of short-sale constraints on IVOL in the upgrade, downgrade and no-revision groups. We find that short-sale constraints do not have a strong impact on IVOL in the upgrade group, mainly because IVOL effect does not exist in the upgrade group. For the downgrade group, we find a significant difference between $IVOL{*}d^{DOWN}{*}d^{NMTSS}$ (−1.89 with *t*-stat = −2.21) and $IVOL{*}d^{DOWN}{*}d^{MTSS}$ (0.16 with *t*-stat = 0.18), suggesting short-sale constraints have a significant on IVOL effect in the downgrade subsample. For stocks in the no-revision group, both the coefficients of $IVOL{*}d^{NO}{*}d^{MTSS}$ *and* $IVOL{*}d^{NO}{*}d^{NMTSS}$ are negatively significant, which implies that the negative IVOL return spreads in the no-revision subgroup are so strong that the short-sale constraints cannot fully explain. To summarize, Table 7 shows that short-sale constraints partially explain the return discrepancies in IVOL spreads among three revision groups.

4.4. Controlling for the effects of limits-to-arbitrage and short-sale constraints

In Table 8, we simultaneously control for limits-to-arbitrage and short-sale constraints. Panel A reports the correlations of *IVOL* and control variables. Given that some limits-to-arbitrage proxies are highly correlated, for example, the correlation between *AMIHUD* and *VOLUME* is −0.90, we take an average of standardized *NLIM*, *AMIHUD*, *VOLUME*, and *PRICE*, and obtain a comprehensive limits-to-arbitrage measure *LA* in each month. In Panel B of Table 8, we control for proxies of both short-sale constraints and limits-to-arbitrage in the regression.[11] Overall, the regression results of Panel B are quite similar to Panel B of Table 7, suggesting that our main results are robust to controlling for limits-to-arbitrage and short-sale constraints.

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stocks hit the price-limit, the trading execution probability is low. We measure the "price-limit-hitting" as the number of price-limit-hitting days of a stock in a month.

[8] Since lower price and lower volume suggest higher level of limits-to-arbitrage, we put a negative sign in front of these three measures to make all variables in the same direction.

[9] For three out of four proxies, the difference in means between downgrade-revision stocks and upgrade-revision stocks are significant, while the difference in average NLIM is insignificant (0.02 with *t*-stat = 1.19).

[10] The number of MTSS stocks is only 90 in its infancy. To ensure enough regression observations when considering subsample dummies, we start the period from Jan 2012.

[11] In an un-reported table, we separately control each limits-to-arbitrage indicator in the regression, and the results show the qualitatively similar pattern as Panel B of Table 7.

Table 7
Analyst revisions and short-sale constraints.

Panel A: Monthly firm number of analyst revision subsample in MTSS program	Mean
Full Sample	2008
MTSS stocks	456
Non-MTSS stocks	1552
Stocks with different revision types	
Up & MTSS	94
Up & non-MTSS	161
Down & MTSS	231
Down & non-MTSS	520
No & MTSS	89
No & non-MTSS	492

Panel B: Controlling for short-sale constraints	(1)	(2)	(3)
$IVOL*d^{MTSS}$	−0.34	−0.33	
	(−0.42)	(−0.39)	
$IVOL*d^{NMTSS}$	−1.64**		−1.62**
	(−2.43)		(−2.40)
$IVOL*d^{UP}*d^{MTSS}$			−0.74
			(−0.79)
$IVOL*d^{UP}*d^{NMTSS}$		−0.61	
		(−0.58)	
$IVOL*d^{DOWN}*d^{MTSS}$			0.16
			(0.18)
$IVOL*d^{DOWN}*d^{NMTSS}$		−1.89**	
		(−2.21)	
$IVOL*d^{NO}*d^{MTSS}$			−1.88**
			(−2.60)
$IVOL*d^{NO}*d^{NMTSS}$		−1.66***	
		(−3.11)	
lnMV	−2.65**	−2.66**	−2.61**
	(−2.49)	(−2.50)	(−2.47)
lnBM	0.60	0.60	0.55
	(0.58)	(0.58)	(0.53)
MOM	1.15	1.14	1.16
	(1.38)	(1.36)	(1.41)
MAX5	0.32	0.29	0.27
	(0.42)	(0.38)	(0.36)
TURN	−0.44	−0.44	−0.43
	(−0.78)	(−0.77)	(−0.77)
Sample	Covered	Covered	Covered
Adj. R^2	0.170	0.172	0.177

The table reports Fama and MacBeth (1973) regressions on Margin Trading and Short-Selling (MTSS). Specifically, we run cross-sectional regressions of stock excess return in each month $t+1$ on IVOL, interaction terms of IVOL and dummies, and control variables in month t. Then we test whether the time-series average coefficients are significantly different from zero. d^{MTSS} (d^{NMTSS}) is assigned one if a stock is (is not) in the MTSS program in month t. $d^{UP}/d^{DOWN}/d^{NO}$ is assigned one if analysts release upgrade/downgrade/no revision on a stock. All explanatory variables and control variables are standardized at the cross-sectional level each month. Panel A reports the average monthly firm numbers of each revision subsample in MTSS program. Panel B shows the Fama–MacBeth regression results after controlling for short-sale constraints. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2012 to December 2014.

5. Robustness checks

5.1. Change of analyst coverage and the effect on IVOL anomaly

Someone may argue that analysts' decision to follow a particular stock may depend on some unobservable variables. It raises the concern that the weak IVOL effect among analyst-covered stocks is not necessarily the effect of analyst information production but is due to the characteristics of certain stocks. We utilize two exogenous shocks on analysts to address this concern. Following Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013), we argue that both brokerage mergers and brokerage closures cause the decrease in analyst coverage and thus increases the information asymmetry. We then examine whether the shock to analyst coverage has any effect on the IVOL anomaly.

Table 8
Controlling for the effects of limits-to-arbitrage and short-sale constraints.

Panel A: Correlation matrix

	MV	BM	MOM	MAX5	TURN	NLIM	AMIHUD	VOLUME	PRICE	LA
IVOL	−0.05	−0.20	0.27	0.82	0.35	0.29	−0.15	0.43	0.30	−0.24
MV		0.22	*0.03*	−0.05	−0.50	0.07	−0.70	0.58	*−0.01*	−0.49
BM			−0.11	−0.16	−0.30	0.04	−0.03	−0.04	−0.56	0.24
MOM				0.19	0.22	0.03	−0.14	0.20	0.33	−0.26
MAX5					0.34	0.27	−0.12	0.41	0.27	−0.21
TURN						0.07	−0.06	0.21	0.28	−0.19
NLIM							−0.11	0.21	*0.01*	0.28
AMIHUD								−0.90	−0.17	0.80
VOLUME									0.25	−0.79
PRICE										−0.57

Panel B: Controlling for limit-to-arbitrage and short-sale constraints

	(1)	(2)	(3)
IVOL*d^{MTSS}	−0.64	−0.62	
	(−0.77)	(−0.75)	
IVOL*d^{NMTSS}	−1.54**		−1.53**
	(−2.37)		(−2.34)
IVOL*d^{UP}*d^{MTSS}			−0.96
			(−1.03)
IVOL*d^{UP}*d^{NMTSS}		−0.63	
		(−0.60)	
IVOL*d^{DOWN}*d^{MTSS}			−0.16
			(−0.18)
IVOL*d^{DOWN}*d^{NMTSS}		−1.70**	
		(−2.17)	
IVOL*d^{NO}*d^{MTSS}			−2.18***
			(−2.97)
IVOL*d^{NO}*d^{NMTSS}		−1.65***	
		(−2.85)	
lnMV	−1.29	−1.32	−1.27
	(−1.18)	(−1.20)	(−1.18)
lnBM	0.12	0.12	0.07
	(0.11)	(0.12)	(0.07)
MOM	1.31	1.30	1.33
	(1.48)	(1.47)	(1.53)
MAX5	0.51	0.48	0.46
	(0.66)	(0.62)	(0.59)
TURN	0.05	0.04	0.05
	(0.08)	(0.07)	(0.07)
LA	2.48**	2.45**	2.45**
	(2.23)	(2.22)	(2.26)
Sample	Covered	Covered	Covered
Adj. R^2	0.179	0.180	0.186

The table reports Fama and MacBeth (1973) regressions on Margin Trading and Short-Selling (MTSS) and limit-to-arbitrage proxies. d^{MTSS} (d^{NMTSS}) is assigned one if a stock is (is not) in the MTSS program in month *t*. $d^{UP}/d^{DOWN}/d^{NO}$ is assigned one if analysts release upgrade/downgrade/no revision on a stock. *NLIM* is the number of price-limit-hitting days of a stock in a month. *AMIHUD* is Amihud (2002) monthly illiquidity measure. *VOLUME* is monthly CNY trading volume (in billion yuan). *PRICE* is monthly closing price (in yuan). *LA* is a comprehensive limit-to-arbitrage index combining four limits-to-arbitrage proxies. Specifically, we take an average of standardized *NLIM, AMIHUD, VOLUME, and PRICE* to obtain *LA* in each month t. All explanatory variables and control variables are standardized at the cross-sectional level each month. Panel A presents the average monthly Pearson correlation matrix of explanatory variables. Correlations insignificant at 5% are italicized. Panel B shows the Fama–MacBeth regression results controlling for short-sale constraints and limits-to-arbitrage proxied by the comprehensive limit-to-arbitrage index. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2012 to December 2014.

First, we manually collect data on brokerage mergers during our sample period. Panel A of Table 9 lists the bidders (Broker 1) and the targets (Broker 2) as well as the date of brokerage merger. We employ Fama–MacBeth regression to test this potential effect of exogenous coverage loss.

$$Ret_{i,t+1} = \alpha + \beta_1 * IVOL_{i,t} + \beta_2 * IVOL_{i,t} * D_{i,t}^{LOSS} + \gamma * controls \tag{4}$$

If firm i loss at least one analyst covering it in month t, $D_{i,t}^{LOSS}$ equals one from month t to t+11. We include similar control variables as in the previous tests. We argue that a loss in analyst coverage results in less information production and dissemination of the firm, so the coefficient of β_2 is expected to be negative, which denotes more severely negative IVOL effect.

In Panel B of Table 9, the coefficient estimates of the interaction terms of IVOL and coverage loss dummy are significantly negative in both column 1 (β_2 = −0.76, t-stat = −1.98) and column 2 (β_2 = −1.11, t-stat = −2.43). The results show that the

Table 9
The effect of coverage loss by brokerage mergers on IVOL anomaly.

Panel A: Brokerage merger events

Merger Event	Broker 1	Broker 2	Merger date
1	China Jianyin Investment Securities	Southern Securities	2005/9/28
2	Hong Yuan Securities	Xinjiang Securities	2006/2/17
3	Essence Securities	China Sci-Tech Securities	2006/2/24
4	Qilu Securities	Tiantong Securities	2006/3/1
5	Western Securities	Jianqiao securities	2006/3/1
6	Everbright Securities	Tianyi Securities	2006/7/1
7	Essence Securities	Centergates Securities	2006/9/1
8	Merchants Securities	Jutian Securities	2006/10/13
9	United Bank of Switzerland	Beijing Securities	2006/12/11
10	Huatai Securities	United Securities	2011/9/5

Panel B: The effect of coverage loss by brokerage mergers

	(1)	(2)
IVOL	−0.11	−0.54
	(−0.22)	(−1.18)
IVOL* D^{LOSS}	−0.76*	−1.11**
	(−1.98)	(−2.43)
lnMV		−2.07***
		(−2.94)
lnBM		0.47
		(0.91)
MOM		0.74
		(1.50)
MAX5		−0.13
		(−0.28)
TURN		−0.81*
		(−1.85)
Sample	Covered	Covered
Adjusted R^2	0.034	0.172

Panel A lists the brokerage mergers events during our sample period. Panel B presents the Fama–MacBeth regression results of analyst loss dummy. D^{LOSS} is assigned one in 12 months if a firm loses at least one analyst due to brokerage mergers. Specifically, we run cross-sectional regressions of stock excess return in month t+1 on *IVOL*, interaction terms of *IVOL* and D^{LOSS}, and control variables calculated in month t. Then we test whether the time-series average coefficients are significantly different from zero. All explanatory variables and control variables are standardized at the cross-sectional level each month. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to December 2014.

negative relation between IVOL and future return is stronger for firms losing coverage due to brokerage mergers, evidence that the decline in analyst coverage exacerbates the IVOL effect.

Second, we use negative shock of market downturn to analyst following to provide more evidence on the effect of analyst coverage. After a steady increase of analyst coverage from the year 2005 to 2010, there is a negative shock to both the number of analysts and the number of following analysts per firm in 2011 (see Panel A of Table 10) as a result of market downturn. We examine this potential effect using the following Fama–MacBeth regression:

$$Ret_{i,t+1} = \alpha + \beta_1 * IVOL_{i,t} + \beta_2 * IVOL_{i,t} * D_{i,t}^{SHOCK} + \gamma * controls \tag{5}$$

$D_{i,t}^{SHOCK}$ is assigned one in month t if the analyst following number of a firm in month t of year y is less than that in year $y-1$. The same control variables are used as in the previous section. Similar to Eq. (4), we expect that β_2 to be negative.

In Panel B of Table 10, the coefficient estimates of the interaction terms of IVOL and the market-wide shock dummy are significantly negative in both column 1 ($\beta_2 = -0.43$, t-stat $= -1.90$) and column 2 ($\beta_2 = -0.57$, t-stat $= -2.40$). The results show that the coefficient estimates of the interaction terms are indeed significantly negative, additional evidence that the decline in analyst coverage aggravates the IVOL effect.

5.2. Other potential explanations of IVOL anomaly

In this subsection, we investigate whether other potential explanations documented in the literature for IVOL anomaly, such as institutional ownership (Nagel, 2005; Ang et al., 2009) and the short-term return reversal (Huang et al., 2010), can subsume our findings. For example, Nagel (2005) and Ang et al. (2009) show that institutional ownership can explain the idiosyncratic volatility anomaly to some extent. Huang et al. (2010) suggest that return reversals can explain the negative relation between idiosyncratic volatility and stock returns. We re-do the Fama–MacBeth regression of Eq. (2) by including more control variables: institutional ownership (INSOWN) and return reversal (STREV). Table 11 reports the regression results and we focus the interaction terms between *IVOL* and analyst related dummy variables. Overall, after controlling for institutional ownership and return reversal, our main findings hold. Among covered stocks, stocks with no-revision have more prominent IVOL anomaly than other two revision groups.

Table 10
The effect of coverage loss by market downturn on IVOL anomaly.

Panel A: Number of analysts and brokerages over time

Year	Number of followed stocks	Number of analysts	Number of following analysts per firm		Number of brokerages	Number of analysts per brokerage	
			Mean	Median		Mean	Median
2005	595	749	4.91	3	67	11.18	9
2006	783	680	4.73	3	56	12.14	8
2007	862	957	5.45	4	59	16.22	11
2008	1050	1399	9.49	6	74	18.91	16
2009	1259	1507	9.51	6	80	18.84	18
2010	1637	1742	10.92	9	87	20.02	16
2011	1931	1447	10.31	8	90	16.08	13
2012	1903	1574	10.30	7	85	18.52	14
2013	1733	1637	9.53	6	75	21.83	16
2014	1928	1543	7.95	6	79	19.53	14

Panel B: Fama–MacBeth regressions — The effect of analyst coverage on IVOL anomaly

	(1)	(2)
IVOL	−0.71	−1.23***
	(−1.23)	(−3.85)
IVOL* D^{SHOCK}	−0.43*	−0.57**
	(−1.90)	(−2.40)
lnMV		−2.41***
		(−3.57)
lnBM		−0.11
		(−0.15)
MOM		1.39**
		(2.60)
MAX5		0.29
		(0.74)
TURN		−1.16***
		(−3.37)
Sample	Covered	Covered
Adjusted R^2	0.022	0.112

Panel A reports the number of security analysts and brokerages during our sample period. Panel B presents the Fama–MacBeth regression results of analyst following shock dummy. D^{SHOCK} is assigned one in year y+1 if the number of analysts following of a firm in year y is less than that in year y−1. Specifically, we run cross-sectional regressions of stock excess return in month t+1 on *IVOL*, interaction terms of *IVOL* and D^{SHOCK}, and control variables calculated in month t. Then we test whether the time-series average coefficients are significantly different from zero. All explanatory variables and control variables are standardized at the cross-sectional level each month. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The regression sample period is from January 2011 to December 2014.

5.3. Further robustness checks

In this subsection, we control for the effect of analyst earnings forecast dispersion. In the previous analysis, we separate stocks into revision groups by comparing the numbers of upgrade revision and downgrade revision. We do not rule out the possibility that analysts' forecast revision explains the IVOL anomaly via their differences of opinion. Following Diether et al. (2002), analyst forecast dispersion (DISP) is defined as the standard deviation of earnings forecasts over the absolute value of the average earnings forecast. To calculate dispersion, a firm must be followed by two or more analysts during that month. We run Fama–MacBeth regressions controlling for *DISP*. The results presented in Table 12 are consistent with our main findings.

Second, we consider the sign of average revisions as an alternative analyst revision measure. We classify stocks as having upgrade (downgrade) revision in month t if the average revision of earnings forecasts is positive (negative) and no revision if the average revision is zero. In Fig. 2, we find similar distinguishable patterns as the previous findings among stocks with upgrade revision, downgrade revisions, and no revision.

6. Conclusions

This study examines how analyst information updates affect the pricing of idiosyncratic volatility. Given the unique institutional settings in the Chinese stock market, we investigate idiosyncratic volatility among different analyst subsamples. We find that the IVOL anomaly is particularly strong in stocks without analyst coverage, but becomes much weaker or even disappears in covered stocks, suggesting that the presence of analysts reduces the IVOL anomaly.

In particular, we categorize stocks into three groups, based on whether they experience upgrade revision, downgrade revision, or no revision; the IVOL effect presents different patterns among these groups. For stocks with upgrade revision, the negative IVOL effect disappears or even becomes positive; for stocks with downgrade revision, the negative IVOL effect is relatively weaker; for stocks with no revision, the IVOL spread is highly negatively significant. The long-term IVOL effect patterns are different among

Table 11
Controlling for institutional ownership and return reversal.

	(1)	(2)	(3)	(4)
IVOL		−1.05**		−1.33***
		(−2.37)		(−3.47)
IVOL*d^{UP}	0.51	1.56***	−0.18	1.15***
	(0.83)	(3.67)	(−0.39)	(4.32)
IVOL* d^{DOWN}	−0.17	0.88*	−0.88**	0.45*
	(−0.26)	(1.92)	(−2.24)	(1.73)
IVOL* d^{NO}	−1.05**		−1.33***	
	(−2.37)		(−3.47)	
lnMV			−1.95***	−1.95***
			(−2.82)	(−2.82)
lnBM			0.49	0.49
			(0.93)	(0.93)
MOM			0.63	0.63
			(1.23)	(1.23)
MAX5			0.31	0.31
			(0.54)	(0.54)
TURN			−1.04***	−1.04***
			(−3.09)	(−3.09)
STREV			−0.92*	−0.92*
			(−1.83)	(−1.83)
INSOWN			0.28	0.28
			(0.87)	(0.87)
Sample	Covered	Covered	Covered	Covered
Adj. R^2	0.045	0.045	0.198	0.198

The table reports the results of value-weighted Fama and MacBeth (1973) regressions of stock returns on idiosyncratic volatility controlling for revisions. Specifically, we run cross-sectional regressions of stock excess return in month t+1 on *IVOL*, interaction terms of *IVOL* and revision dummies, and control variables calculated in month t. Then we test whether the time-series average coefficients are significantly different from zero. $d^{UP}/d^{DOWN}/d^{NO}$ is assigned one if analysts release upgrade/downgrade/no revision on a stock. *lnMV* is the natural log of market capitalization. *lnBM* is the natural log of book-to-market ratio. *MOM* is the cumulative stock return from month t−11 to month t−1. *MAX5* is the average of the five highest daily stock returns within a month. *TURN* is the turnover ratio of a stock in previous 6 months. *STREV* is the return reversal, measured as the previous-month stock return. *INSOWN* is the institutional ownership of each stock. All explanatory variables and control variables are standardized at the cross-sectional level each month. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to December 2014.

Table 12
Controlling for earnings forecast dispersion.

	(1)	(2)	(3)	(4)
IVOL		−0.44		−0.80
		(−0.78)		(−1.62)
IVOL*d^{UP}	0.60	1.03**	0.20	1.00**
	(0.93)	(2.21)	(0.36)	(2.29)
IVOL* d^{DOWN}	−0.05	0.38	−0.43	0.36
	(−0.08)	(0.75)	(−0.81)	(0.84)
IVOL* d^{NO}	−0.44		−0.80	
	(−0.78)		(−1.62)	
DISP	−0.13	−0.13	0.13	0.13
	(−0.17)	(−0.17)	(0.28)	(0.28)
lnMV			−2.39***	−2.39***
			(−3.04)	(−3.04)
lnBM			0.39	0.39
			(0.75)	(0.75)
MOM			0.60	0.60
			(1.20)	(1.20)
MAX5			−0.33	−0.33
			(−0.71)	(−0.71)
TURN			−0.51	−0.51
			(−1.08)	(−1.08)
Sample	Covered	Covered	Covered	Covered
Adj. R^2	0.045	0.045	0.174	0.174

The table reports Fama and MacBeth (1973) regressions controlling for analyst forecast dispersion. Specifically, we run cross-sectional regressions of stock excess return in month t+1 on *IVOL*, interaction terms of *IVOL* and revision dummies, and control variables calculated in month t. Then we test whether the time-series average coefficients are significantly different from zero. As in Diether et al. (2002), dispersion (DISP) is calculated as the standard deviation of earnings forecasts divided by the absolute value of the mean earnings forecast. All explanatory variables and control variables are standardized at the cross-sectional level each month. T-statistics based on Newey et al. (1987) standard errors are reported in parentheses. '*', '**' and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2005 to December 2014.

the three revision subsamples as well. We provide a possible explanation for these discrepancies. Both upgrades and downgrades offer additional information, which mitigates the effect of information asymmetry relative to stocks that experience no revision at all. Further, it is known that negative news is incorporated into stock prices more slowly than positive news, due to short sale constraints, limits-to-arbitrage, etc. Thus, stock prices are more efficient in the presence of good news relative to bad news.

We conduct extended analysis to investigate the interaction of the negative pricing of idiosyncratic volatility and the role of financial analysts from two perspectives: limits-to-arbitrage and short-sale constraints. We find that both contribute to return discrepancies in IVOL spreads among the three revision groups but neither subsumes our findings. Several endogeneity tests and robustness checks do not change our main results. In contrast to previous studies focusing on the relationship between analyst revisions and stock returns (Diether et al., 2002; Barron et al., 2009), our study highlights the effect of analyst information updates on the IVOL anomaly.

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