The Role of Analysts:

An Examination of the Idiosyncratic Volatility Anomaly in the Chinese Stock Market

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February 10, 2017

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Abstract

Given the unique institutional setting and the role of analysts in the Chinese stock markets, we investigate the effect of analyst activities on idiosyncratic volatility (IVOL) anomaly. Our results show that the inverse relation between IVOL and future stock returns is more pronounced in the subsample of stocks without analyst coverage. For stocks with analyst coverage, revision activities further attenuate the negative relation between IVOL and future stocks returns. In fact, we find a positive relation between IVOL and future stock returns among the subsample of stocks with analyst upgrade revisions. We argue that our results are evidence of analysts playing the role of disseminating information and particularly reducing information asymmetry in the Chinese stock markets. Moreover, positive news is incorporated into stock prices more quickly in the Chinese stock markets. Finally, we show that our results are not driven by differences in limits-to-arbitrage or short-sale constraint among different stock subsamples.

Keywords: Financial analysts, idiosyncratic volatility, China stock markets

JEL classification: G12 G15

Introduction

The idiosyncratic volatility (IVOL) anomaly, first documented in Ang et al. (2006, 2009) in the US stock market, refers to the phenomenon that stocks with higher idiosyncratic volatility have significantly lower future returns. This negative relation challenges the traditional asset pricing theories since the classic theories suggest no relation (the capital asset pricing model, CAPM) or a positive relation (Merton, 1987) between idiosyncratic volatility and stock returns.[1]

Several studies have linked the negative pricing role of idiosyncratic volatility to information asymmetry. For example, Johnson (2004) theoretically and empirically demonstrate that adding idiosyncratic risk on a levered firm reduces its expected return, because raising uncertainty about cash flows of the firm increases the option value of equity. In this regard, Johnson (2004) argues that firms may not have an incentive to disclose information in a timely and transparent way. Jiang, Xu and Yao (2009) argue that idiosyncratic volatility anomaly is related to corporate selective disclosure, and the anomaly is stronger among stocks with a less sophisticated investor base. Firm-specific stock price variations reflect noise, thereby causing stock prices to deviate from their fundamental values (DeLong et al., 1990; Shleifer and Vishny, 1997). Greater information asymmetry reduces the speed of stock price discovery (Brennan and Subrahmanyam, 1995; Verrecchia, 2001), and then greater information asymmetry may cause the more severe mispricing of idiosyncratic volatility.

Our study is motivated by the role of analysts in information production and dissemination in the financial market. Previous studies indicate that financial analysts play a valuable role in improving market efficiency. For example, Brennan, Jegadeesh, and

[1] Existing explanations for this anomaly includes size effect (Bali and Cakici, 2008; Fu, 2009), corporate information disclosure (Jiang, Xu and Yao, 2009), return reversal (Huang et al., 2010), lottery preference (Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011), illiquidity (Han and Lesmond, 2011), risk exposure (Chen and Petkova, 2012), financial distress (Avramov et al., 2013), and arbitrage asymmetry (Stambaugh, Yu and Yuan, 2015). In a recent survey paper, Hou and Loh (2016) show that a sizable portion of this puzzle is still left unexplained.

Swaminathan (1993) suggest that stocks followed by more analysts appear to be priced more accurately. Francis and Soffer (1997) show that analysts' earnings forecasts and recommendations affect stock prices. Barth and Hutton (2000) find that stock prices for firms with higher analyst following more rapidly incorporate information on accruals and cash flows than prices of less followed firms. Chan and Hameed (2006) show that more analyst coverage lessens the amount of firm-specific noise. In this study, we try to link the analyst information to the idiosyncratic volatility. In the spirit of the valuable role of analysts in capital markets, we argue financial analysts could reduce the information asymmetry, and thus decrease the mispricing of idiosyncratic volatility.

We focus on the Chinese mainland stock markets because the role of analysts in the Chinese stock markets has some unique institutional settings. For example, the Chinese stock markets are dominated by individual investors.[2] As such, analysts play an important role in information production and dissemination in the Chinese stock market. Their activities may have a significant effect on the efficiency of stock prices. In addition, 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, Cheng and Yu, 2007). In particular, Diamond and Verrecchia (1987) suggest that, due to the short-sale constraints, negative information may not be immediately incorporated into stock prices. These unique features of the Chinese stock markets provide us a great opportunity to examine the effect of analyst information production on the idiosyncratic volatility anomaly.

We employ a sample containing A-listed stocks in the Chinese stock markets from January 2005 to December 2014, and our main results are as follows. 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

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

value-weighted results. We find that the IVOL anomaly is particularly strong in stocks without analyst coverage, in comparison with stocks with analyst coverage. Moreover, when we form value-weighted IVOL-spread portfolio, for non-covered stocks, the cumulative IVOL return spread persists up to 12 months holding period. As a comparison, for covered stocks, the negative IVOL premium reverses to positive after 6 months. This is evidence that analyst coverage or the presence of analysts reduces the IVOL anomaly.

For stocks with analyst coverage, we further categorize them into three groups: upgrade revision, downgrade revision, and no revision, based on their analysts' revisions in the current month. The IVOL effect demonstrates the different pattern among these three revisions. For stocks with upgrade revision, the negative IVOL effect almost disappears or even reverses to 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. There exist distinguishable patterns of long-term IVOL effect among three revision types as well. For upgrade-revision stocks, a positive relation between IVOL and future stock returns holds throughout 12 months holding period; for downgrade-revision stocks, the negative IVOL effect reverses after 3 months and cumulates to positive after 6 months; as a sharp contrast, the negative IVOL effect persists for no-revision stocks up to 12 months.

Our results are consistent with the notion that analysts play an important role in disseminating information, particularly reducing information asymmetry, and helping incorporating information into security prices. As a result of analyst information production, stocks with analyst coverage are less mispriced. Our results show an insignificant IVOL anomaly among these stocks. Moreover, earnings forecast revisions made by analysts are indicators of an active role by analysts in information production or update. There is an even weaker IVOL anomaly among these stocks. As documented in the literature, positive news is more quickly incorporated into stock prices than negative news in the Chinese market due to short-sale constraint. For stocks with analyst upgrade, we actually find a positive relation between IVOL and subsequent stock returns.

One potential concern of our findings is that they are simply manifestations of alternative explanations in the literature. For instance, the literature documents that IVOL anomaly is more pronounced among stocks with strong limits-to-arbitrage or short-sale constraints. We show that indeed there are stronger limits-to-arbitrage or short-sale constraints for non-covered stocks than those with analyst coverage. We perform further analysis to control for the effects of limits-to-arbitrage and short-sale constraints, and show that our results are not driven by differences in limits-to-arbitrage or short-sale constraint among different stock subsamples.

Our study contributes to the related literature in several aspects. Firstly, there are few studies directly attributing the IVOL anomaly to the lack of analyst information update. A notable exception is Jiang, Xu, and Yao (2009), which present evidence linking the IVOL anomaly to corporate selective disclosure. Unlike their work, our study emphasizes the role of analyst information update. Secondly, given the recent pilot program of Margin Trading and Short Selling (MTSS) in China, we are able to identify the IVOL mispricing is affected by information asymmetry after controlling for short-sale constraints. In addition, different from several recent studies in the Chinese stock markets, we investigate the interaction between analyst information update and idiosyncratic volatility anomaly, where Jiang, Lu and Zhu (2014) focus on the information content of analyst recommendation revisions, and Gu, Kang and Xu (2016) study on the effect of limits-to-arbitrage on idiosyncratic volatility. Our study provides additional insights into IVOL anomaly in an emerging market where individual investors are in the majority.

The remainder of the paper is organized as follows. Section 2 describes the sample and variables used in this study. Section 3 examines the effect of analyst information on the IVOL return premium. Section 4 provides extended analysis to examine possible explanations for the negative pricing of idiosyncratic volatility and the role of financial analyst. Section 5 concludes our paper.

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 data are from Wind Info Database (Wind). The full sample period is from January 2005 to December 2014.[3] 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 annual reports before April 30 in the current calendar year. We exclude financial firms and special treated (ST) firms from the sample.[4] The final full sample contains 2,458 firms, and the average firm number is 2,008 per month.

The main interest of 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-French (1993) three-factor model. Specifically, the regression takes the form as:

$$r_d^i = \alpha^i + \beta_{RMRF}^i RMRF_d + \beta_{SMB}^i SMB_d + \beta_{HML}^i HML_d + \varepsilon_d^i \tag{1}$$

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 when there are less than 17 trading days in that month.

[3] 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.

[4] 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.)

We construct analyst coverage (*COV*) and revision subsamples employing the following procedure. Firstly, 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). Secondly, among stocks with analyst coverage, we further divide them into three groups – upgrade revision, downgrade revision, and no revision, based on their revisions made by analysts in month *t*. We classify stocks as having upgrade (downgrade) revision if there are more (less) analysts of upgrade earnings forecast revisions than that of downgrade revisions to stocks. If there is 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.[5]

We employ several commonly used control variables. 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 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, Cakici, and Whitelaw, 2011); *TURN* is defined as the turnover ratio in the previous 6 months.

<Table 1>

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. The Main Analysis

[5] 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. On average, the firm number of the third case accounts around 10% of no revision subsample.

In this section, we investigate the role of security analysts by relating analyst information to the pricing of idiosyncratic volatility. Previous studies suggest that analyst following may promote information production, lessens the amount of firm-level noise, and facilitates stocks to be more accurately priced (Brennan, Jegadeesh, and Swaminathan, 1993; Walther, 1997; Barth and Hutton, 2000; Chan and Hameed, 2006). We propose that if analysts can help alleviate information asymmetry and accelerate efficient adjustment of prices, more incorporated analyst information will reduce the mispricing of idiosyncratic volatility. We examine our argument by section 3.1 confirming the existence of IVOL anomaly in the Chinese stock markets, section 3.2 examining how analyst coverage affects the IVOL anomaly, section 3.3 studying whether different types of analyst revision affect the IVOL anomaly, and section 3.4 verifying our results in multivariate regressions.

3.1 The IVOL anomaly in the Chinese stock markets

We sort stocks into quintiles based on *IVOL*, then compute the raw returns and abnormal returns of each quintile portfolio in 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 market capitalization, 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.

<Table 2>

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 suggests that the IVOL anomaly exists in the Chinese stock markets. Also, this anomaly is more evident in small cap firms than in large cap firms, since the 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. In next section, we will incorporate the effect of information asymmetry proxy by analyst information, and show how analyst information affects the IVOL anomaly.

3.2 Two-way portfolio sorting based on the analyst coverage and IVOL

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*. We report the average raw returns, abnormal returns, and the return spreads of quintile portfolios in Panel A and B of Table 3. Panel C examines whether there is a significant difference in IVOL spreads between covered stocks and non-covered stocks.

<Table 3>

Panel A shows that the return spreads of IVOL decrease largely in subsample with analyst coverage. For example, 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. Compared to the return spreads of IVOL in the full sample, the spreads decrease substantially in subsample with analyst coverage. As a sharp contrast in Panel B, the IVOL anomaly is more significant in 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) for raw returns and 2.24% (*t*-stat = 8.67) for abnormal returns.

In Panel C, we compare the IVOL spreads between two subsamples, and find a large discrepancy in IVOL spreads between covered and non-covered stocks. The IVOL spreads in stocks without analyst coverage are significantly larger than those in covered stocks. For instance, 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 IVOL anomaly become much weak or insignificant in covered stocks.

Most of the time, security analysts follow certain firms for a long-term period, and continuously produce and disseminate information by releasing reports. In this regard, we examine the effect of analyst coverage on the IVOL anomaly in a long-run period as well. For both covered stocks and non-covered stocks, we form a value-weighted IVOL-spread portfolio by longing the lowest IVOL quintile and shorting the highest IVOL quintile at the end of each month t. Then we calculate cumulative raw returns and DGTW-adjusted returns from month t+1 to t+12. Figure 1 shows the spreads in cumulative raw returns and abnormal returns between covered stocks and non-covered stocks, holding for up to 12 months. Interestingly, the "Q1-Q5" spread portfolio of covered stocks reverses to negative and further declines after t+6, which denotes that stocks with high IVOL tend to have higher return in the covered subsample. For non-covered stocks, the IVOL return spread gradually increases up to 12-month holding period. These results show that analyst following not only mitigates the mispricing of idiosyncratic volatility, but it also has a long-term pricing effect on IVOL. In summary, the results combined in Table 3 and Figure 1 demonstrate that the presence of analysts reduces the effect of IVOL.

<Figure 1>

So far we have shown that the IVOL anomaly is less evident in analyst-covered stocks than in stocks without coverage. 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 need 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 try to address these issues in the next subsection by considering the types of analyst forecast revisions of covered stocks.

3.3 Two-way portfolio sorting based on the 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. As defined in section 2.1, 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 average equal-weighted and value-weighted raw returns and abnormal returns for these 3*5 portfolios.

<Table 4>

Table 4 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 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 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 smaller, 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 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 4 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 negative news is incorporated into stock price more slowly than positive news, due to short-sale constraint or limits to arbitrage (e.g., Hong, Lim, and Stein, 2000; Bris, Goetzmann, and Zhu, 2007). Thus, stock price are 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.

<Figure 2>

In Figure 2, we plot the cumulative IVOL spreads 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 12-month holding period. For upgrade-revision stocks, both cumulative raw returns and abnormal returns gradually decrease up to 12 months. For downgrade-revision stocks, the IVOL spreads start decreasing at *t*+3, reverse to negative at *t*+6, and further decrease at the end of *t*+12. For no-revision stocks, the IVOL return spreads gradually increase in the first 6 months, and then the IVOL spreads become flat from *t*+7 to *t*+12. The evidence shows that the distinguishable pattern among three revision groups holds up to 12 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 negative news travels more slowly into current prices. Stocks with no-revision have the most severe information asymmetry among these three revision types.

3.4 Fama-MacBeth regression

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

$$\mathrm{Re}t_{\mathrm{i},t+1} = \alpha + \beta_1 * IVOL_{\mathrm{i},t} + \beta_2 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}{}^{COV} + \beta_3 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}{}^{NCOV} + \gamma * controls$$
$$\mathrm{Re}t_{\mathrm{i},t+1} = \alpha + \beta_1 * IVOL_{\mathrm{i},t} + \beta_2 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}{}^{\mathrm{UP}} + \beta_3 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}{}^{\mathrm{DOWN}} + \beta_4 * IVOL_{\mathrm{i},t} * d_{\mathrm{i},t}{}^{\mathrm{NO}} + \gamma * controls \tag{2}$$

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 5>

Table 5 reports Fama-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 $IVOL$*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. The regression results from Columns 1 to 4 are in line with portfolio sorting results in Table 3.

In accordance with portfolio sorting in Table 4, we show 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 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, Fama-MacBeth regression results are consistent with the two-way portfolio sorting results. The IVOL spread is significant higher in non-covered than in covered subsample; among covered stocks, stocks with no-revision have the most severe information asymmetry, resulting in more prominent IVOL anomaly than other two revision groups.

4. Further Analysis

In this section, we provide several possible explanations for our main findings. In section 4.1, we examine whether limits-to-arbitrage proxies have potential effects on our results. In section 4.2, we specifically investigate the role of short-sale constraint by incorporating the Chinese pilot program of margin trading and short selling

4.1 The role of 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 five firm characteristics proxied for limits-to-arbitrage, and examine any cross-variation of these proxies among different analyst subsamples. For each proxy, we employ a Fama-MacBeth (1973) two-step approach, and report its time-series average of cross-sectional means and medians in Table 6.

<Table 6>

Since Kim and Rhee (1997) argue that price limits postpone price discovery and desired trading activity, we employ the unique Chinese trading feature "price-limit-hitting" as one proxy for limits-to-arbitrage.[6] The price-limit-hitting *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 other four commonly used limits-to-arbitrage proxies. For example, the illiquidity measure *AMIHUD* is defined as the Amihud (2002) monthly illiquidity measure because Chordia, Roll, and Subrahmanyam (2008) show that liquidity improves market efficiency by stimulating arbitrage activity. Mashruwala, Rajgopal, and Shevlin (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). Since Hong, Lim, and Stein (2000) suggest that analyst coverage can reflect differences in transaction costs, the fifth variable we employ is analyst coverage *COV*, defined as the number of analysts covering a stock in the previous year.[7]

Panel A of Table 6 reports the results of subsamples of analyst covered stocks and non-covered stocks. The mean and median of limits-to-arbitrage proxies are always higher in non-covered subsample than in covered subsample. For all of the five proxies, the differences in means between non-covered stocks and covered stocks are significant at 1% level. Specifically, the mean values of *NLIM* are 0.35 and 0.51 for non-covered subsample and in covered subsample, respectively. The difference in *NLIM* between two subsamples is 0.16 with t-stat=4.88. The other four limits-to-arbitrage proxies perform the similar pattern between these two subsamples.

Panel B presents the results of three analyst revision subsamples and reports the difference in means among three revisions. We find that the means and medians of

[6] 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 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.

[7] Since lower price, lower volume, lower analyst coverage 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.

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 range; among three revisions groups, the differences of limits-to-arbitrage proxies in means are mostly significant at the 1% level.[8]

Overall, there are significant differences of limits-to-arbitrage proxies among each analyst subsample, implying that limits-to-arbitrage may have certain explanatory power for the return discrepancies in IVOL spread.

4.2 The effect of short-sale constraints

Miller (1977) argues that dispersion of opinion and short-sale constraints lead to overpricing. Since stronger information asymmetry leads to more pronounced Miller effect, we conjecture that one channel of our main findings about the analyst coverage might be due to Miller's overpricing effect. In this subsection, we utilize a recent pilot program in the Chinese stock markets as a natural experiment to separate stocks with low short-sale constraints from those with short-sale constraints, and test whether short-sale constraint affects 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 money and buy stocks, or to 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 these stocks

We run Fama-MacBeth (1973) regressions by adding the dummy variables of MTSS and non-MTSS for the years from 2012 to 2014.[9] 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

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[8] For four out of five 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).

[9] 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, when there are 285 stocks in the MTSS list.

dummies and control variables defined the previous section in the regression. 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.

<Table 7>

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 (-0.37 with *t*-stat = -0.46), and the coefficient of *IVOL** d^{NMTSS} is negatively significant (-1.82 with *t*-stat = -2.85), suggesting that the short-sale constraints contributes the negative premium of idiosyncratic volatility. Column 3 reports the similar regression as Column using the analyst-covered subsample other than the full sample.

Column 2 compares the effect of short-sale constraints of on the covered and non-covered groups, including the dummy variables of d^{MTSS} and d^{NMTSS} in the regression. For example, the coefficient of $IVOL*d^{COV}*d^{MTSS}$ is insignificant (-0.31 with *t*-stat = -0.38) and $IVOL*d^{COV}*d^{NMTSS}$ is significant at the 5% level (-1.61 with *t*-stat = -2.51), suggesting that short-sale constraints have the impact on IVOL in the covered subsample. The significant difference in the coefficients of $IVOL*d^{NCOV}*d^{MTSS}$ and $IVOL*d^{NCOV}*d^{NMTSS}$ suggests short-sale constraints have the impact on IVOL in the non-covered subsample as well. More importantly, the coefficient of $IVOL*d^{NCOV}*d^{NMTSS}$ is -2.74 (*t*-stat=-4.03), which is substantially higher than that of $IVOL*d^{COV}*d^{NMTSS}$, implying that the effect of short-sale constraints on IVOL is stronger in non-covered subsample than in covered subsample.

Following the same logic, column 4 compares 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^{MTSS} (0.17 with *t*-stat = 0.19) and *IVOL**d^{DOWN}*d^{NMTSS} (-1.88 with *t*-stat = -2.20), 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 digest. In sum, Table 7 shows that short-sale constraint is a partly explanation for the return discrepancies in IVOL spreads among three revision groups.

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

<Table 8>

In Table 8, we conduct an additional robustness check by simultaneously controlling for limits-to-arbitrage and short-sale constraints. Panel A of Table 8 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. Then in Panel B of Table 8, we control for proxies of both "short-sale constraints" and "limits to arbitrage" in the regression. In addition, we control all four limits to arbitrage indictors in Panel C. Overall, the regression results of Panel B and Panel C are quite similar to Panel B of Table 7, suggesting that our main results are fully driven by short-sale constraints and limits-to-arbitrage.

5. Conclusions

This study examines how analyst information updates can affect the pricing of idiosyncratic volatility. Given the unique institutional settings of the role of analysts in the

Chinese stock markets, we investigate the idiosyncratic volatility among different analyst subsamples. We find that the IVOL anomaly is particularly strong in stocks without analyst coverage, and it is much weaker or disappears in analyst-covered stocks, suggesting the presence of analysts reduces the IVOL anomaly.

We further categorize them into three groups –upgrade revision, downgrade revision, and no revision, and the IVOL effect presents different patterns among three revisions. For stocks with upgrade revision, the negative IVOL effect almost disappears or even reverses to 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. There exist distinguishable patterns of long-term IVOL effect among three revision types as well. We provide a possible explanation to understand the return discrepancy of IVOL among different analyst subsamples. For the difference between upgrade/downgrade and no revisions, the former has information update, thus mitigating effect of information asymmetry, the latter has no update. It's known that negative news is incorporated into stock price more slowly than positive news, due to short sale constraint, limits to arbitrage, etc. Thus, stock prices are more efficient in the presence of good news relative to bad news.

We conduct the extended analysis to investigate the interaction of the negative pricing of idiosyncratic volatility and the role of financial analyst from two perspectives: limits-to-arbitrage and short-sale constraints. We find that both limits-to-arbitrage and short-sale constraint have certain explanation power for the return discrepancies in IVOL spreads among three revision groups. Different from previous studies focusing on the relationship between analyst revision and stock returns (Diether, Malloy and Scherbina, 2002; Barron, Stanford, and Yu, 2009), we highlight the effect of analyst information update on the prominent financial anomaly-IVOL.

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Table 1: Descriptive statistics

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 (relative to Fama-French (1993) three-factor model) estimated each month for each stock; *COV* is the number of analysts covering the stock in the previous year; *NLIM* is the number of price-limit-hitting days within the month; *VOLUME* is the CNY trading volume (in billion yuan) in the month; *PRICE* is the monthly closing price (in yuan); *AMIHUD* is Amihud (2002) illiquidity measure in the month (multiplied by 10^9). *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 January 2005 to December 2014.

	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
NLIM	0.41	0.69	0.00	0.07	0.17	0.43	6.50
VOLUME	1.68	2.28	0.12	0.57	1.00	1.89	32.62
PRICE	11.74	9.30	2.68	6.44	9.17	13.97	149.10
AMIHUD	1.65	4.43	0.02	0.56	1.15	2.09	124.20
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	0.04	0.01	0.01	0.03	0.03	0.04	0.10
TURN	3.15	1.89	0.13	1.90	2.76	3.93	15.60

Table 2: Average returns of idiosyncratic volatility portfolios

This table reports average raw returns and abnormal returns of quintile idiosyncratic volatility (IVOL) portfolios. 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-French (1993) 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 market cap, book-to-market, and prior one-year return terciles (27 benchmark portfolios). The row "Q1-Q5" refers to average monthly return spreads between Q1 and Q5. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. The sample period is January 2005 to December 2014.

	Equally-weighted		Value-weighted	
IVOL Quintile	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)*

Table 3: Average returns of idiosyncratic volatility portfolios:
Subsample results based on stocks with and without analyst coverage

This table reports average raw returns and abnormal returns of portfolios sorting by analyst coverage and IVOL. Panel A and Panel B show the pricing of IVOL among subsamples for stocks with analyst coverage and stocks without analyst coverage. Panel C presents the differences in IVOL spreads between stocks without analyst coverage and stocks with analyst coverage. At the end of each month t, we separate stocks into stocks with analyst coverage and stocks without analyst coverage, based on whether a stock is covered by at least an analyst in the previous year. Within each coverage subsample, we further sort stocks into quintiles, based on IVOL calculated over month t, from the lowest (Q1) to the highest (Q5). For each subsample, we form equally- and value-weighted portfolios and report the average raw returns and abnormal returns in month t+1. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. The sample period is January 2005 to December 2014.

Panel A: Stocks with analyst coverage

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	2.75	0.64	1.65	-0.04
	(2.45)	*(5.62)*	*(1.63)*	*(-0.24)*
Q2	2.69	0.58	1.98	0.32
	(2.38)	*(6.22)*	*(1.87)*	*(2.76)*
Q3	2.53	0.40	2.07	0.37
	(2.23)	*(3.98)*	*(1.82)*	*(2.82)*
Q4	2.16	0.02	1.73	-0.02
	(1.90)	*(0.15)*	*(1.48)*	*(-0.18)*
Q5	1.62	-0.59	1.46	-0.44
	(1.49)	*(-3.49)*	*(1.29)*	*(-2.35)*
Q1-Q5	1.13	1.23	0.19	0.39
t-stat	*(3.66)*	*(5.52)*	*(0.41)*	*(1.27)*

Panel B: Stocks without analyst coverage

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Q1	3.60	1.05	3.12	0.84
	(2.95)	*(7.85)*	*(2.50)*	*(4.58)*
Q2	3.13	0.62	2.84	0.65
	(2.53)	*(4.81)*	*(2.22)*	*(3.62)*
Q3	2.76	0.28	2.40	0.22
	(2.26)	*(2.03)*	*(1.95)*	*(1.15)*
Q4	2.08	-0.39	1.79	-0.42
	(1.70)	*(-2.67)*	*(1.46)*	*(-1.92)*
Q5	0.85	-1.50	0.70	-1.40
	(0.72)	*(-7.92)*	*(0.57)*	*(-5.37)*
Q1-Q5	2.75	2.55	2.42	2.24
t-stat	*(9.91)*	*(10.73)*	*(7.94)*	*(8.67)*

Panel C: Differences in IVOL spreads

	Equally-weighted		Value-weighted	
	Raw returns	Abnormal returns	Raw returns	Abnormal returns
Non-covered - Covered	1.62	1.32	2.23	1.85
t-stat	*(5.74)*	*(5.86)*	*(4.98)*	*(5.46)*

Table 4: Average returns of idiosyncratic volatility portfolios: Subsample results based on analyst forecast revisions

This table reports average raw returns and abnormal returns of portfolios sorting by analyst forecast revision and IVOL. Panel A, B, and C separately report results for stocks with “up” revision, “down” revision, and “no” revision. Panel D presents the return differences in IVOL spreads between these three subsamples. 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. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. The sample period is January 2005 to December 2014.

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)*

Table 5: Fama-MacBeth (1973) Regressions

The table reports the results of value-weighted Fama-MacBeth (1973) regressions of stock returns on idiosyncratic volatility controlling for analyst coverage (Columns 1 to 4) and three forecast revisions (Columns 5 to 8). We use firm size in each month t as the weight and run the value-weighted Fama-MacBeth (1973) regressions. 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. *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-West (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 January 2005 to December 2014.

	(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	0.0330	0.0330	0.160	0.160	0.0450	0.0450	0.174	0.174

Table 6: The role of limits-to-arbitrage

This table reports means and medians of five 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). *COV* is the number of analysts covering a stock in the previous year. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. The sample period is January 2005 to December 2014.

Panel A: Covered stocks versus non-covered stocks

	Covered		Non-covered		Non-covered - Covered	
	Mean	*Median*	Mean	*Median*	Mean	*t-stat*
NLIM	0.35	*0.13*	0.51	*0.23*	0.16	*(4.88)*
AMIHUD	1.02	*0.73*	2.14	*1.62*	1.12	*(2.89)*
(-)VOLUME	-1.94	*-1.16*	-1.10	*-0.74*	0.85	*(8.59)*
(-)PRICE	-13.33	*-10.60*	-8.15	*-7.13*	5.19	*(12.49)*
(-)COV	-7.52	*-5.32*	-0.00	*-0.00*	7.52	*(13.38)*

Panel B: Comparison of three analyst revision types

	Up		Down		No		No - Up		No - Down		Down - Up	
	Mean	*Median*	Mean	*Median*	Mean	*Median*	Mean	*t-stat*	Mean	*t-stat*	Mean	*t-stat*
NLIM	0.30	*0.08*	0.32	*0.11*	0.39	*0.15*	0.09	*(4.64)*	0.07	*(5.63)*	0.02	*(1.19)*
AMIHUD	0.74	*0.53*	0.87	*0.63*	1.29	*0.98*	0.55	*(4.65)*	0.42	*(4.27)*	0.13	*(4.10)*
(-)VOLUME	-2.59	*-1.52*	-2.08	*-1.24*	-1.53	*-0.99*	1.05	*(9.32)*	0.54	*(8.70)*	0.51	*(5.20)*
(-)PRICE	-17.34	*-13.78*	-13.66	*-11.19*	-11.23	*-9.15*	6.12	*(11.07)*	2.43	*(12.57)*	3.68	*(8.14)*
(-)COV	-10.13	*-8.42*	-9.84	*-8.35*	-4.24	*-2.54*	5.89	*(9.01)*	5.60	*(9.15)*	0.29	*(2.14)*

Table 7: The short-sale constraints

The table reports Fama-MacBeth (1973) regressions on Margin Trading and Short-Selling (MTSS). We use firm size in each month t as the weight and run the value-weighted Fama-MacBeth (1973) regressions. 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^{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. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. '*', '**'and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. 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 category. Panel B shows the Fama- MacBeth regression results, where column 1&2 correspond to the full sample and column 3&4 correspond to analyst-covered subsample. The sample period is January 2012 to December 2014.

Panel A: Monthly number of firms

	Mean	Min	Max
Full Sample	2008	1005	2216
MTSS stocks	456	142	784
Non-MTSS stocks	1552	863	1866
Stocks with coverage vs. stocks without coverage			
Covered & MTSS	414	141	674
Covered & non-MTSS	1173	710	1584
Not covered & MTSS	42	1	110
Not covered & non-MTSS	379	153	535
Stocks with different revision types			
Up & MTSS	94	15	165
Up & non-MTSS	161	42	219
Down & MTSS	231	98	352
Down & non-MTSS	520	313	810
No & MTSS	89	28	170
No & non-MTSS	493	313	669

Panel B: Fama- MacBeth regression results

	(1)	(2)	(3)	(4)
IVOL*d^{MTSS}	-0.37		-0.34	
	(-0.46)		(-0.42)	
IVOL*d^{NMTSS}	-1.82***		-1.64**	
	(-2.85)		(-2.43)	
IVOL*d^{COV}*d^{MTSS}		-0.31		
		(-0.38)		
IVOL*d^{COV}*d^{NMTSS}		-1.61**		
		(-2.51)		
IVOL*d^{NCOV}*d^{MTSS}		0.39		
		(0.13)		
IVOL*d^{NCOV}*d^{NMTSS}		-2.74***		
		(-4.03)		
IVOL*d^{UP}*d^{MTSS}				-0.72
				(-0.77)
IVOL*d^{UP}*d^{NMTSS}				-0.61
				(-0.58)
IVOL*d^{DOWN}*d^{MTSS}				0.17
				(0.19)
IVOL*d^{DOWN}*d^{NMTSS}				-1.88**
				(-2.20)
IVOL*d^{NO}*d^{MTSS}				-1.87**
				(-2.57)
IVOL*d^{NO}*d^{NMTSS}				-1.64***
				(-3.05)
lnMV	-2.67**	-2.66**	-2.65**	-2.62**
	(-2.68)	(-2.69)	(-2.49)	(-2.49)
lnBM	0.52	0.53	0.60	0.54
	(0.52)	(0.54)	(0.58)	(0.53)
MOM	1.07	1.05	1.15	1.14
	(1.35)	(1.34)	(1.38)	(1.40)
MAX5	0.39	0.38	0.32	0.25
	(0.51)	(0.50)	(0.42)	(0.32)
TURN	-0.60	-0.60	-0.44	-0.43
	(-1.10)	(-1.10)	(-0.78)	(-0.76)
Sample	Full	Full	Covered	Covered
Adjusted R^2	0.163	0.165	0.170	0.179

Table 8: Controlling for short-sale constraints and limits-to-arbitrage

The table reports Fama-MacBeth (1973) regressions on Margin Trading and Short-Selling (MTSS) and limit-to-arbitrage proxies. We use firm size in each month t as the weight and run the value-weighted Fama-MacBeth (1973) regressions. d^{MTSS} (d^{NMTSS}) is assigned one if a stock is (is not) in the MTSS program in month t. 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. *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). *COV* is the number of analysts covering a stock in the previous year. *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. T-statistics based on Newey-West (1987) standard errors are reported in parentheses. '*', '**'and '***' indicate that the regression coefficients are significant at the 10%, 5%, and 1% levels, respectively. 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 (Panel C) shows the Fama-MacBeth regression results controlling for short-sale constraints and limits-to-arbitrage proxied by the comprehensive limit-to-arbitrage index (single limits-to-arbitrage proxies). In both Panel B and Panel C, column 1&2 correspond to the full sample and column 3&4 correspond to analyst-covered subsample.

Panel A: Correlation matrix

	IVOL	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
LA											

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

	(1)	(2)	(3)	(4)
$IVOL*d^{MTSS}$	-0.640		-0.640	
	(-0.79)		(-0.77)	
$IVOL*d^{NMTSS}$	-1.76***		-1.54**	
	(-2.87)		(-2.37)	
$IVOL*d^{COV}*d^{MTSS}$		-0.590		
		(-0.72)		
$IVOL*d^{COV}*d^{NMTSS}$		-1.50**		
		(-2.43)		
$IVOL*d^{NCOV}*d^{MTSS}$		0.340		
		(0.12)		
$IVOL*d^{NCOV}*d^{NMTSS}$		-2.83***		
		(-4.35)		
$IVOL*d^{UP}*d^{MTSS}$				-0.940
				(-1.02)
$IVOL*d^{UP}*d^{NMTSS}$				-0.630
				(-0.59)
$IVOL*d^{DOWN}*d^{MTSS}$				-0.140
				(-0.16)
$IVOL*d^{DOWN}*d^{NMTSS}$				-1.68**
				(-2.14)
$IVOL*d^{NO}*d^{MTSS}$				-2.17***
				(-2.93)
$IVOL*d^{NO}*d^{NMTSS}$				-1.62***
				(-2.82)
lnMV	-1.360	-1.320	-1.290	-1.300
	(-1.33)	(-1.31)	(-1.18)	(-1.20)
lnBM	0.0700	0.0800	0.120	0.0800
	(0.07)	(0.08)	(0.11)	(0.08)
MOM	1.210	1.200	1.310	1.310
	(1.46)	(1.44)	(1.48)	(1.51)
MAX5	0.540	0.530	0.510	0.430
	(0.71)	(0.70)	(0.66)	(0.56)
TURN	-0.110	-0.110	0.0500	0.0400
	(-0.20)	(-0.19)	(0.08)	(0.06)
LA	2.35**	2.38**	2.48**	2.42**
	(2.31)	(2.34)	(2.23)	(2.25)
Sample	Full	Full	Covered	Covered
Adj. R^2	0.171	0.173	0.179	0.187

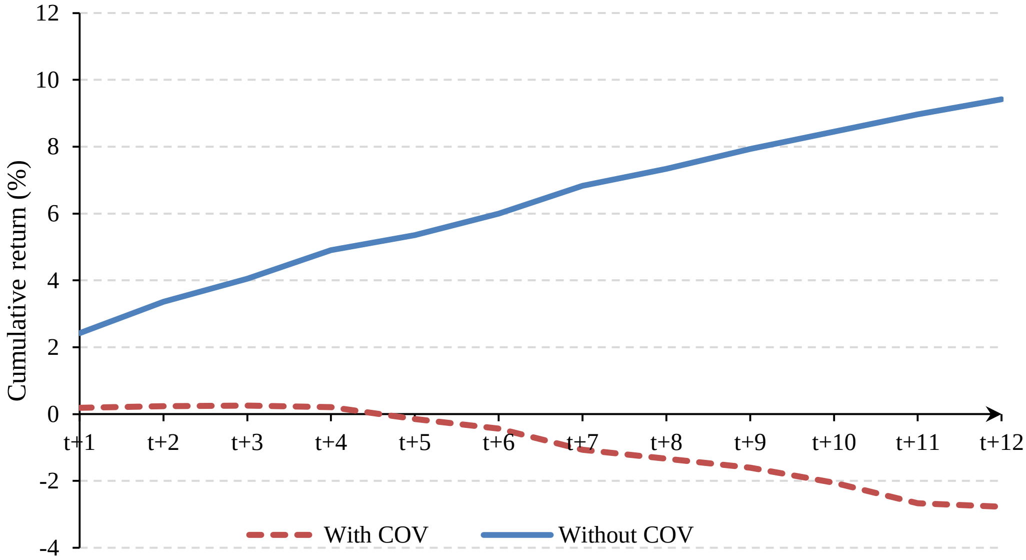
Panel C: Controlling for single limit-to-arbitrage proxies and short-sale constraints

	(1)	(2)	(3)	(4)
IVOL*d^{MTSS}	-0.95		-0.970	
	(-1.20)		(-1.19)	
IVOL*d^{NMTSS}	-1.45*		-1.270	
	(-1.93)		(-1.61)	
IVOL*d^{COV}*d^{MTSS}		-0.890		
		(-1.11)		
IVOL*d^{COV}*d^{NMTSS}		-1.200*		
		(-1.64)		
IVOL*d^{NCOV}*d^{MTSS}		-0.100		
		(-0.04)		
IVOL*d^{NCOV}*d^{NMTSS}		-2.50***		
		(-3.30)		
IVOL*d^{UP}*d^{MTSS}				-1.280
				(-1.33)
IVOL*d^{UP}*d^{NMTSS}				-0.110
				(-0.11)
IVOL*d^{DOWN}*d^{MTSS}				-0.430
				(-0.51)
IVOL*d^{DOWN}*d^{NMTSS}				-1.400*
				(-1.68)
IVOL*d^{NO}*d^{MTSS}				-2.21***
				(-2.84)
IVOL*d^{NO}*d^{NMTSS}				-1.310*
				(-1.64)
lnMV	-2.67**	-2.66**	-2.65**	-2.62**
	(-2.68)	(-2.69)	(-2.49)	(-2.49)
lnBM	0.52	0.53	0.60	0.54
	(0.52)	(0.54)	(0.58)	(0.53)
MOM	1.07	1.05	1.15	1.14
	(1.35)	(1.34)	(1.38)	(1.40)
MAX5	0.39	0.38	0.32	0.25
	(0.51)	(0.50)	(0.42)	(0.32)
TURN	-0.60	-0.60	-0.44	-0.43
	(-1.10)	(-1.10)	(-0.78)	(-0.76)
ILLIQ	1.520	1.520	1.600	1.510
	(1.52)	(1.51)	(1.56)	(1.48)
NLIM	0.040	0.060	0.080	0.100
	(0.10)	(0.17)	(0.21)	(0.27)
VOLUME	-0.230	-0.210	-0.180	-0.210
	(-0.17)	(-0.16)	(-0.13)	(-0.15)
PRICE	-0.99**	-1.00**	-1.02***	-0.98**
	(-2.64)	(-2.67)	(-2.79)	(-2.63)
Sample	Full	Full	Covered	Covered
Adjusted R^2	0.188	0.190	0.196	0.204

Figure 1: Cumulative idiosyncratic volatility spread: covered versus non-covered stocks

Panel A plots average cumulative raw returns (in percent) of value-weighted "Q1-Q5" IVOL spread portfolio. At the end of each month t, we form zero-cost "spread portfolios" by longing the lowest IVOL quintile (Q1) and shorting the highest IVOL quintile (Q5) for both covered stocks and non-covered stocks. Then we add up the raw returns of the spread portfolio of each coverage category, from month t+1 to t+12. Panel B plots average abnormal returns of value-weighted "Q1-Q5" spread portfolio for covered and non-covered stocks. The abnormal returns are adjusted following Daniel et al. (1997, DGTW), controlling for size, value, and momentum effect. The sample period is January 2005 to December 2014.

Panel A: Spreads in cumulative raw returns



Panel B: Spreads in cumulative abnormal returns

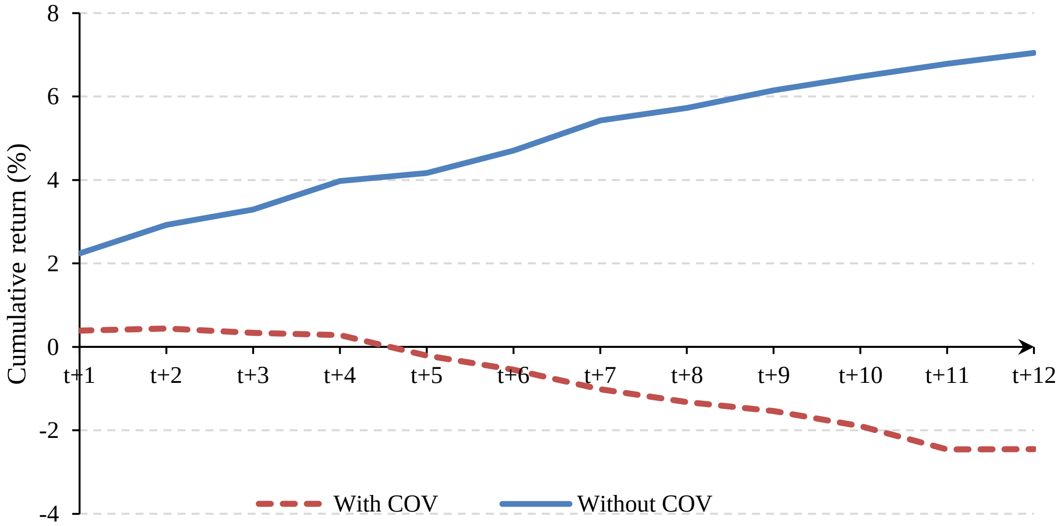
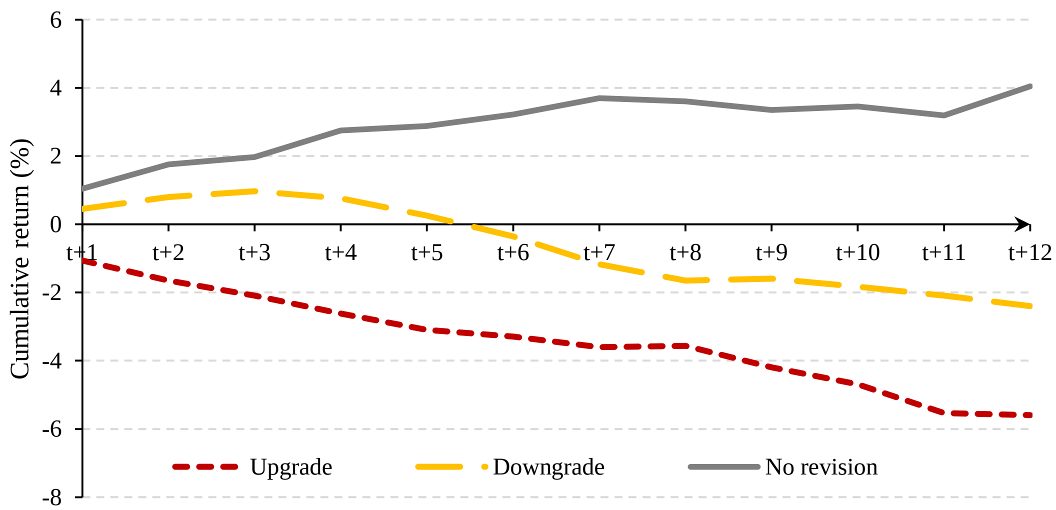


Figure 2: Cumulative idiosyncratic volatility spread of three forecast revision types

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+12 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 January 2005 to December 2014.

Panel A: Spreads in cumulative raw returns



Panel B: Spreads in cumulative abnormal returns