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Is information risk priced? Evidence from abnormal idiosyncratic volatility[☆]

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A B S T R A C T

We propose a new, price-based measure of information risk called abnormal idiosyncratic volatility (*AIV*) that captures information asymmetry faced by uninformed investors. *AIV* is the idiosyncratic volatility prior to information events in excess of normal levels. Using earnings announcements as information events, we show that *AIV* is positively associated with informed return run-ups, abnormal insider trading, short selling, and institutional trading during pre-earnings-announcement periods. We find that stocks with high *AIV* earn economically and statistically larger future returns than stocks with low *AIV*. Taken together, our findings support the notion that information risk is priced.

1. Introduction

Standard asset pricing theory posits that expected asset returns are related to their covariances with systematic factors under the assumption that information is homogeneous for all investors. When information is asymmetric across investors, the question of how asset prices and expected returns are determined is theoretically

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challenging. Different model assumptions lead to different predictions, and technical difficulties hinder a complete analysis.[1] Empirically, the question of whether the risk of information asymmetry is priced in asset returns is far from settled, although many studies have investigated this topic. The primary difficulty is related to the lack of proper measures of information risk. Thus, in this paper, we explore the pricing of information risk by constructing a price-based measure of information risk.

In the previous literature, the most prominent measures of information risk are based on trading quantities.[2] Easley et al. (1996) and (Easley et al., 2002; hereafter EHO) develop a microstructure model and use order flow to estimate the probability of informed trading (*PIN*). Due to difficulties in computing *PIN* under high-frequency trading, Easley et al. (2012) develop a new procedure to overcome flow toxicity, the volume-synchronized probability of informed trading. Instead of using all transactions, Hwang and Qian (2011) construct an information risk measure based on large trades. More recently, Choi et al. (2016) use prior weekly institutional ownership volatility to proxy for information risk. Although these quantity-based measures are shown to be positively related to expected future stock returns, the pricing evidence is also challenged in the literature (Duarte and Young, 2009; hereafter DY; Lai et al., 2014; Chung and Huh, 2016).

We begin with the assumption that information risk is multifaceted; as such, it is unlikely that quantity-based measures can capture information risk in all its aspects (e.g., Odders-White and Ready, 2008; Kim and Stoll, 2014; Brogaard et al., 2016; Back et al., 2018; Duarte et al., 2017). In principle, an informed trading equilibrium incorporates both quantity and price. By inferring informed trading from price variation, we construct an information risk measure called abnormal idiosyncratic volatility (*AIV*), which is the idiosyncratic volatility before an information-intensive event in excess of the idiosyncratic volatility of the normal period. The literature has long recognized that information flow is reflected in idiosyncratic volatility (e.g., Roll, 1988; Morck et al., 2000; Durnev et al., 2004; Ferreira and Laux, 2007; Dang et al., 2015). However, idiosyncratic volatility may reflect other features of firms such as fundamental risk and investors' overreaction to firm-specific information (e.g., Wei and Zhang, 2006; Teoh et al., 2007; Zhang, 2010; Hou et al., 2013). Therefore, *AIV* is employed to tease out unusual price variations caused by trading activities related to information-intensive events.

We estimate *AIV* as the difference in idiosyncratic volatility between pre-earnings-announcement and non-earnings-announcement periods. Earnings announcements are selected in this study as the information-intensive event for several reasons. First, earnings announcements are the most value-relevant information events that firms use to reveal their past profitability and to help investors project their future performance (Beyer et al., 2010). Second, informed trading is pervasive prior to earnings announcements (Krinsky and Lee, 1996; Kim and Verrecchia, 1997; Vega, 2006; Bamber et al., 2011; Brennan et al., 2016; Back et al., 2018). Third, beginning in 1970, the Securities and Exchange Commission has mandated quarterly reporting for all exchange-listed firms in the US. Therefore, estimating *AIV* is feasible for all stocks over the sample period.[3]

Using both annual and quarterly earnings announcements, we estimate *AIV* for stocks listed on the NYSE, Amex, and Nasdaq over the 43-year period from 1972 to 2015. We perform the following analyses. First, because it is well documented in the literature that corporate insiders, short sellers, and institutional traders are informed traders, we link *AIV* to their trading activities to determine whether it captures informed trading. Indeed, we find positive relations between *AIV* and abnormal insider trading, abnormal short selling, and abnormal institutional trading during the pre-earnings-announcement periods. We further show a positive relation between *AIV* and the magnitude of informed return run-ups prior to earnings announcements, which suggests that these investors are truly informed about upcoming earnings announcements for stocks with high *AIV*. We also validate negative *AIV* and show that stocks with negative *AIV* indeed have a lower level of information risk. We finally find that as a measure of information risk, *AIV* may not be as persistent as firm characteristics.

Second, we explore whether the information risk captured by *AIV* is priced. Using portfolio and regression analyses, we find that high-*AIV* firms tend to have high future stock returns. Moreover, the pricing of *AIV* is more pronounced for, but not limited to, small stocks. A trading strategy combining a long position in a high-*AIV* quintile portfolio with a short position in a low-*AIV* quintile portfolio generates a 1.90% risk-adjusted annual return.[4] The spread return increases to 4.08% if the long-short strategy is applied to the smallest size quintile. The pricing of *AIV* is also evidenced in the regression method of

[1] Wang (1993) notes that the role of information asymmetry in the risk premium is indeterminate because the amount of information impounded in an asset price changes with changes in information asymmetry. Easley and O'Hara (2004) demonstrate that information risk is priced because uninformed investors are always on the wrong side of the trade, whereas Hughes et al. (2007) show that the pricing impact of asset-specific private information goes to zero as the number of assets increases. See also Garleanu and Pedersen (2004) and Lambert et al. (2007) for conditions under which information asymmetry affects asset pricing.

[2] There are also alternative measures of information risk based on firm characteristics such as firm size, earnings quality, and analyst coverage. In addition, there is an interesting study by Kelly and Ljungqvist (2012) that uses three natural experiments to test the pricing of information risk.

[3] The disadvantage of focusing solely on earnings announcements is that many other corporate events also contain information about firm value, and excluding these corporate events makes the information risk measure noisier because many of these events are conducted during non-earnings-announcement periods. We view the work documented in this paper as the first step in eventually achieving a full-blown measure of information risk. In spite of this disadvantage, we also note that the results presented in this paper are strong enough to demonstrate that a price-based information risk measure adds value to quantity-based measures of information risk.

[4] We annualize the risk-adjusted return for the ease of comparison with other studies such as momentum by Jegadeesh and Titman (1993) and idiosyncratic volatility anomaly by Ang et al. (2006, 2009). To achieve such return, the portfolio has to be rebalanced monthly.

Fama and MacBeth (1973), with other well-known pricing factors controlled for. The pricing of *AIV* is robust to the exclusion of inactive or penny stocks, different measurement windows of pre-earnings-announcement periods, step-wise tests, alternative *AIV*s based on corporate news events, as well as other specifications.

Finally, we provide additional evidence to illuminate the understanding of the pricing impact of *AIV*. First, because the post-earnings-announcement drift is a well-documented return anomaly and the post-earnings-announcement drift might be related to the measurement of *AIV*, we verify that even though they are somewhat related, the pricing of *AIV* is not driven by the post-earnings-announcement drift. Second, it is tempting to relate the pricing of *AIV* to the idiosyncratic volatility anomaly documented by Ang et al. (2006, 2009); hereafter AHXZ). However, our results show that the pricing of *AIV* is distinct from the idiosyncratic volatility anomaly. The idiosyncratic volatility in both pre- and non-earnings-announcement periods contributes to the pricing of *AIV*. Third, despite the assumption that information risk is multifaceted, *AIV* as the price-based information risk measure may capture the same aspect of information risk proxied by quantity-based measures. We find that *AIV* is still significantly priced with different quantity-based information risk measures as control. Last, we show that the pricing of *AIV* is robust to the control of additional risk and mispricing variables such as stock turnover, short interest ratio, analyst coverage, corporate investment, profitability, accruals, etc.

The contribution of this paper can be understood as follows. First, because theoretical studies regarding whether information risk is priced yield opposite predictions that are derived from their different assumptions, our results provide a specific case in which the risk in information related to earnings announcements is priced, supporting the prediction that information risk is priced in general. Second, the price-based measure we construct is simple yet powerful to capture contemporary, information-related activities and risk premiums for future returns. We acknowledge that the measure we construct may not reflect all aspects of information risk and all information events. We also note that the idea developed in this paper to construct the measure of information risk based on earnings announcements may also be applied to other information events such as merges and acquisitions, product recalls, and patent applications.

The remainder of this paper is organized as follows. Section 2 provides a more in-depth discussion of how our information risk measure, *AIV*, is motivated and describes the construction and summary statistics of the measure. Section 3 shows that the information risk measure, *AIV*, is contemporaneously related to various informed trading activities, but it is only weakly related to alternative information risk measures in the literature. Section 4 presents formal asset pricing tests and shows that the information risk captured by *AIV* is priced. Section 5 further examines whether the pricing of *AIV* derives from information risk. The last section concludes. The Internet Appendix contains tables, referred to as Table IA, of further results that are not reported but briefly discussed in the main text.

2. Measuring information risk

2.1. Quantity- and price-based information risk measures

Quantity-based information risk measures have their pros and cons. Although *PIN* has been widely used in the literature, critics of this measure have also emerged. DY argue that *PIN* is priced not based on its information risk component but on its illiquidity component. Furthermore, Mohanram and Rajgopal (2009) and Lai et al. (2014) challenge the robustness of the return predictability of *PIN* in extended samples. In addition, it is also becoming increasingly difficult to estimate *PIN* because of the ever-growing number of trades and high-frequency algorithmic trading (Kim and Stoll, 2014; Brogaard et al., 2016; Duarte et al., 2017).

Nonpricing evidence regarding other quantity-based information risk measures is also documented in the literature. For the US market, Chung and Huh (2016) show that the pricing effect of the adverse selection costs of trading by Glosten and Harris (1988) and Foster and Viswanathan (1993) is subsumed by the corresponding noninformation costs of trading. For the international markets, Lai et al. (2014) show that the relative trade informativeness measure of Hasbrouck (1991), the percentage price impact measure of Huang and Stoll (1996), the adverse selection component of Huang and Stoll (1997), and the asymmetric information parameter of Madhavan et al. (1997) exhibit no strongly significant pricing effects.

Although informed trading can be discerned from unusual trading quantities, it can also be identified from prices because informed trading is more likely to cause prices to change. In our study, we construct a price-based information risk measure, *AIV*, to be used in the empirical part of the paper. The measure is based on idiosyncratic volatility rather than on the order flow or trading size that characterizes quantity-based information risk measures. It has been recognized in the literature that idiosyncratic volatility is related to firm-specific information impounded in stock prices by informed traders. In an influential paper, Morck et al. (2000) find that the market model R^2 tends to be higher for emerging countries than for developed countries. The intuitive explanation provided by these authors is that more firm-specific information is available to the market in developed countries, whereas the lack of firm-specific information in emerging countries forces investors to infer information for one firm from the price changes of other firms, thereby causing synchronized price changes across firms.

There have been many follow-up studies in the literature (e.g., Durnev et al., 2004; Ferreira and Laux, 2007) that mostly confirm the Morck et al. (2000) findings, particularly in cross-country studies (e.g., Jin and Myers, 2006; Fernandes and Ferrreira, 2008; Fernandes and Ferrreira, 2009; Dang et al., 2015). At the firm level, the issue is much more complicated because idiosyncratic volatility also includes a firm's business and financial risks (e.g., Wei and Zhang, 2006) in addition to risks caused by informed trading. In the empirical part of this paper, we use the difference in idiosyncratic volatilities between a period with a substantial amount of informed trading and a period with no or little informed trading to mitigate the impact of business and financial risks on idiosyncratic volatility.

In the empirical study below, we use the earnings announcement as the event of information release. We calculate the difference in idiosyncratic volatilities between pre-earnings-announcement and non-earnings-announcement periods as a firm's abnormal idiosyncratic volatility, *AIV*. We show that the cross-sectional variation in *AIV* corresponds to much of the contemporaneous information-related trading activities and contains explanatory power for future return differences.

2.2. An empirical measure of information risk

To capture informed trading activity, we use the idiosyncratic volatility of a stock during a period with a high probability of informed trading, and we compare it with idiosyncratic volatility during a normal period. A period prior to an earnings announcement is a natural choice for a period with a high probability of informed trading because private information gathering is more profitable during such a period.[5] There is an abundance of both theoretical arguments and empirical evidence showing that informed trading is pervasive prior to earnings announcements (Krinsky and Lee, 1996; Kim and Verrecchia, 1997; Vega, 2006; Bamber et al., 2011; Brennan et al., 2016; Back et al., 2018).

We measure idiosyncratic volatility relative to the Fama and French (1993) three-factor model (FF-3) using the following regression:

$$R_i = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + \varepsilon_i, \tag{1}$$

where R_i is the daily excess return of stock *i*, *MKT* is the value-weighted market portfolio excess return over the risk-free rate, *SMB* is the size factor, and *HML* is the value factor. The regression is run for each stock and each month using past one-year daily returns to obtain the estimated daily residual, still denoted ε_i for brevity.

For each stock at the end of each month-end, we define the pre-earnings-announcement periods (PEAs) as the five business days before the most recent four earnings announcement days and non-earnings-announcement periods (NEAs) as all the days during the one-year period ending at the month of the last earnings announcement, excluding the 11 business days surrounding each of the four earnings announcement days. For example, consider a firm at the end of December 2014. Suppose the firm made earnings announcement during business hours on March 12, June 11, September 10, and December 10 in 2014, which are all Wednesdays. The PEA consists of March 5–11, June 4–10, September 3–9, and December 3–9 of 2014. The NEA is all business days in 2014, excluding March 5–19, June 4–18, September 4–17, and December 4–17. Note that days during the PEA and NEA for the firm at the end of January and February 2015 are the same as those at the end of December 2014, as the last announcement day is the same.[6]

We compute the annualized idiosyncratic volatility of a stock for pre-earnings-announcement days (IV_{PEA}) and for non-earnings-announcement days (IV_{NEA}) as the log of the annualized standard deviations of the residual from Eq. (1) during these days, assuming that there are 252 trading days in a year. More specifically, we define

$$IV_{PEA} = \ln\sqrt{\frac{252 \times \sum_{j\in PEA} \varepsilon_j^2}{n_{PEA} - 1}},$$

$$IV_{NEA} = \ln\sqrt{\frac{252 \times \sum_{j\in NEA} \varepsilon_j^2}{n_{NEA} - 1}}, \tag{2}$$

where n_{PEA} and n_{NEA} are the number of days in the pre- and non-earnings announcement periods, respectively.

To tease out the idiosyncratic volatility component that is related to information risk surrounding earnings announcements, we use the difference between pre- and non-earnings-announcement periods. We coin the difference in log idiosyncratic volatility as the abnormal idiosyncratic volatility (*AIV*),

$$AIV = IV_{PEA} - IV_{NEA}. \tag{3}$$

AIV is calculated for each firm at the end of each month using the daily data over the past year ending the month of the last earnings announcement. Since almost all stocks make quarterly announcements, *AIV* changes every three months for a given stock, although the changes occur in different months for different stocks. We construct *AIV* to capture information risk related to earnings announcements.

2.3. Data sample and summary statistics

We construct the main data set used in our analysis from Center for Research in Securities Prices (CRSP) and Compustat. We obtain stock and market returns data from CRSP and firm fundamentals and earnings announcement data from Compustat. Our final sample includes all common stocks listed on the NYSE, Amex, and Nasdaq that are covered in CRSP and Compustat. We begin our data with 1972 because Compustat began recording earnings announcement dates in that year. We exclude stocks with prices below one dollar at the end of last June. To accurately calculate idiosyncratic volatility in the pre-earnings-announcement period, we adjust the earnings announcement date to the next trading day if an earnings announcement is made after 4:00 pm. We obtain earnings announcement times from the Institutional

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[5] According to Kim and Verrecchia (1991a,b)), informed investors acquire private information prior to earnings announcement and trade both before and after the earnings are made public. In other words, an anticipated earnings announcement stimulates more private information gathering because the value of private information can be realized immediately after the earnings are announced. Thus, we expect more informed trading to occur in the pre-earnings-announcement period.

[6] We thank the referee for suggesting not to update the NEA days for the two months after the last announcement month because this may cause complications with the idiosyncratic volatility puzzle. Following this suggestion, we also do not update *AIV* for the current month if the last earnings announcement is made within the last five business days of the previous month.

Table 1
Summary statistics.
This table presents the summary statistics of main variables used in the asset pricing test of this study. The main variables are abnormal idiosyncratic volatility (*AIV*), pre-earnings-announcement (log) idiosyncratic volatility (IV_{PEA}), non-earnings-announcement (log) idiosyncratic volatility (IV_{NEA}), monthly excess returns (*R*), market beta (β_{Mkt}), log market capitalization (*Size*), log book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), (Amihud, 2002) illiquidity (*Illiquidity*), past one-month stock return (R_{-1}), past two-month stock returns ($R_{[-3,-2]}$), past three-month stock returns ($R_{[-6,-4]}$), and past six-month stock returns ($R_{[-12,-7]}$). All the variables are defined in Appendix. The summary statistics includes the number of observations, mean, median, standard deviation (STD), the percentiles (5% and 95%), and quartiles (25% and 75%) distribution of the variables. The sample period is from July 1972 to December 2015.

Variable	Observations	Mean	STD	5%	25%	Median	75%	95%
AIV	1,547,696	0.011	0.322	−0.502	−0.185	0.010	0.206	0.529
IV_{PEA}	1,547,696	−0.944	0.568	−1.871	−1.347	−0.949	−0.555	0.015
IV_{NEA}	1,547,696	−0.955	0.513	−1.785	−1.331	−0.962	−0.598	−0.082
R	1,547,696	0.707	12.169	−17.815	−6.213	−0.080	6.507	22.035
β_{Mkt}	1,547,696	1.315	0.329	0.722	1.090	1.300	1.555	1.880
Size	1,547,696	5.076	1.908	2.161	3.645	4.938	6.390	8.455
BM	1,547,696	−0.393	0.792	−1.840	−0.860	−0.315	0.136	0.796
IV_{AHXZ}	1,547,617	0.411	0.273	0.127	0.221	0.336	0.515	0.964
Illiquidity	1,515,731	5.298	15.910	0.004	0.040	0.319	2.390	28.792
R_{-1}	1,540,600	0.011	0.121	−0.173	−0.058	0.003	0.069	0.224
$R_{[-3,-2]}$	1,533,463	0.022	0.171	−0.233	−0.079	0.009	0.105	0.325
$R_{[-6,-4]}$	1,526,331	0.035	0.210	−0.273	−0.092	0.016	0.135	0.412
$R_{[-12,-7]}$	1,508,090	0.077	0.317	−0.356	−0.117	0.037	0.213	0.654

BrokersEstimate System (IBES) and RavenPack database.[7] We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers. Our final sample consists of 1,547,696 firm-month observations spanning from July 1972 to December 2015.

Table 1 reports the descriptive statistics for certain key variables used in the subsequent analysis.[8] *AIV* is our key price-based measure of information risk, defined as $IV_{PEA} - IV_{NEA}$ in Eq. (3). *R* is the monthly stock excess return over one-month T-Bill rate. β_{Mkt} is the market beta of the stock with respect to the CRSP value-weighted index estimated following (Fama and French, 1992). *Size* is the log of market capitalization at the end of last June. *BM* is the log of the book-to-market ratio. Following AHXZ, IV_{AHXZ} is the annualized standard deviation of daily residuals based on the FF-3 model during the previous month. *Illiquidity* is Amihud (2002) illiquidity. We also follow (Brennan et al., 2012) and include four separate past stock returns (R_{-1}, $R_{[-3,-2]}$, $R_{[-6,-4]}$, $R_{[-12,-7]}$) in our asset pricing analysis.

The grand mean (or median) of *AIV* shows that the annualized idiosyncratic volatility during the five-day pre-earnings-announcement period is, on average, 1% higher than that on a non-earnings-announcement day. A proportion of *AIV* observations are negative, and negative *AIV* could be driven by two reasons. First, a higher level of idiosyncratic volatility during the non-earnings announcement period may reflect firms' larger fundamental risk or investors' more extensive noise trading (e.g., Wei and Zhang, 2006; Teoh et al., 2007; Hou et al., 2013).

Second, there are many other corporate events such as mergers and acquisitions (M&As) or product recalls during the non-earnings announcement days, for which idiosyncratic volatility can be large due to the same informational reason as earnings announcements.[9] The length of the pre-announcement period for which informed trading may occur also differs. As such, there is no easy way of cleansing all these corporate events for the sample period we use. We note that the existence of these corporate events and resultant noises would work against our hypothesis because these events may make our *AIV* measure a less accurate proxy for information risk. By comparing the standard deviation of *AIV* with its mean (or median), we also observe a wide variation of *AIV*. Large variation per se helps capture the distinct feature of information risk across firms and over time. But the part caused by noises interfere our inferences.

Fig. 1(a) plots the average absolute residual return from the FF-3 model around earnings announcement days for stocks in the full sample. The bell-shaped pattern reveals a large surprise in stock returns surrounding the announcements. The substantial variation in stock returns indicates information leakage prior to earnings announcements, and that the leaked information is incorporated into stock prices through informed trading (e.g., Vega, 2006; Back et al., 2018). The large variations in post-earnings announcements are consistent with the earnings drift (Kothari, 2001) and investor disagreement (Kondor, 2012), which are well-documented phenomena in the literature. The figure also plots the average stock turnover (number of shares traded deflated by number of shares outstanding). The high trading activity during the pre-earnings-announcement period is consistent with the theoretical prediction of Kim and Verrecchia (1991a,b) that informed investors trade before earnings announcements, which is also evidenced by Ali et al. (2008). Similar to the stock return variation, the higher turnover during and

[7] We adjust the earnings announcement dates for the sample after 2000. We use the date reported in Compustat as the earnings announcement date if the earnings announcement time is not available. The results are unaffected by the earnings announcement date adjustment.

[8] The summary statistics for the rest of the variables used in this study are included in Table IA.1 of the Internet Appendix.

[9] In Section 4.4., we verify this possibility using RavenPack database, which covers a much shorter sample period from 2001 to 2015. The idiosyncratic volatility surrounding some corporate events, such as M&As or bankruptcies, tends to be very large.

Table 2
Informed return run-ups prior to earnings announcements and *AIV*.
This table presents panel regression of the abnormal idiosyncratic volatility (*AIV*) on informed return run-ups prior to earnings announcements with control variables and year fixed effects in the following model.

$$AIV_{it} = a + b_1 Informed_{RunUp,it} + b_2 \beta_{Mkt,it} + b_3 Size_{it} + b_4 BM_{it} + b_5 IV_{AHXZ,it} + b_6 Illiquidity_{it} + b_7 Accruals_{it} + b_8 AQ_{it} + b_9 Analyst_{it} + b_{10} FDisp_{it} + b_{11} FErr_{it}$$

where *AIV* is abnormal idiosyncratic volatility. $Informed_{RunUp}$ is one of the four variables from *SUESign* × *RunUp*, *SUESign* × *RunUpSign*, $SUE_{FC}Sign$ × *RunUp*, or $SUE_{FC}Sign$ × *RunUpSign*. The control variables are market beta (β_{Mkt}), market capitalization (*Size*), book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), Amihud (2002) illiquidity (*Illiquidity*), accruals (*Accruals*), earnings quality (*AQ*), number of analysts following (*Analyst*), analyst dispersion (*FDisp*), analyst forecast errors (*FErr*), and missing analyst indicator ($Missing_{Analyst}$). The *AIV* is multiplied by 100 to scale up the coefficients. The *t*-statistics reported in parentheses are based on robust standard errors adjusted for heteroskedasticity and clustered at both the firm and year level. $\bar{R}^2$ is adjusted R^2. Intercept and year fixed effects are not tabulated. The sample periods are 1972–2015 for models with *SUESign* and 1983–2015 for models with $SUESign_{FC}$.

Variable	M1	M2	M3	M4	M5	M6	M7	M8
SUESign × *RunUp*	**71.359**	**74.548**						
	(6.63)	**(6.59)**						
SUESign × *RunUpSign*			**2.598**	**2.716**				
			(6.99)	**(7.31)**				
$SUESign_{FC}$ × *RunUp*					**46.938**	**49.575**		
					(7.33)	**(7.44)**		
$SUESign_{FC}$ × *RunUpSign*							**1.845**	**1.914**
							(8.12)	**(8.01)**
β_{Mkt}		1.163		1.251		1.341		1.452
		(2.84)		(2.97)		(2.52)		(2.71)
Size		−0.010		−0.063		0.366		0.380
		(−0.07)		(−0.40)		(1.71)		(1.76)
BM		−0.065		−0.064		−0.354		−0.365
		(−0.37)		(−0.37)		(−1.24)		(−1.30)
IV_{AHXZ}		−6.068		−5.830		−7.806		−7.479
		(−5.46)		(−5.47)		(−4.35)		(−4.20)
Illiquidity		0.023		0.021		0.078		0.075
		(2.42)		(2.24)		(3.23)		(3.24)
Accruals		13.345		14.675		8.983		9.554
		(4.11)		(4.21)		(1.52)		(1.63)
AQ		−0.688		−0.082		−1.633		−1.395
		(−0.27)		(−0.03)		(−0.47)		(−0.40)
Analyst		1.203		1.202		0.579		0.554
		(4.75)		(4.68)		(2.33)		(2.24)
FDisp		−0.192		−0.195		−0.025		0.004
		(−1.06)		(−1.07)		(−0.12)		(0.02)
FErr		0.110		0.105		0.140		0.132
		(1.08)		(1.04)		(1.05)		(1.00)
$Missing_{Analyst}$		-0.196		−0.146		0.717		0.725
		(−0.48)		(−0.35)		(1.18)		(1.18)
$\bar{R}^2$	2.5%	3.1%	2.1%	2.5%	2.7%	3.2%	2.4%	2.9%
Firms	2893	2626	2893	2626	2193	2002	2193	2002
Observations	127,272	115,542	127,272	115,542	72,382	66,078	72,382	66,078

after earnings announcements is driven by either informed traders realizing their private information or heterogeneous investors' differential interpretations on earnings announcements (Kim and Verrecchia, 1997; Kandel and Pearson, 1995). Overall, despite the noises contained in the non-earnings-announcement days due to other information events, earnings announcements do represent the most important information events.

3. *AIV* and information risk

In this section, we examine whether *AIV* is related to information risk. We perform a set of tests to evaluate the information risk content of *AIV*. First, we examine the relation between *AIV* and informed return run-ups prior to earnings announcements. Second, we examine the association of *AIV* with abnormal insider trading, short selling, and institutional trading. Third, we verify whether stocks with negative *AIV* indeed have a lower level of information risk. Fourth, we test the persistence of *AIV*. Finally, we summarize the relations between *AIV* and other firm characteristics including alternative measures of information risk.

3.1. AIV *and informed return run-ups prior to earnings announcements*

A higher value of *AIV* may come from a coincidence that noise traders buy shares, and then the stock price increases prior to unexpectedly negative earnings announcements. In this circumstance, stocks with high *AIV* would be misinterpreted as those suffering large information asymmetry. Thus, it is important for us to verify whether certain traders are truly informed about

Table 3
Informed trading and *AIV*.

This table presents panel regression of the abnormal idiosyncratic volatility (*AIV*) on measures of informed trading with control variables and year fixed effects in the following model.

$$AIV_{it} = a + b_1 Informed_{Trading,it} + b_2 Avol_{it} + b_3 \beta_{Mkt,it} + b_4 Size_{it} + b_5 BM_{it} + b_6 IV_{AHXZ,it} + b_7 Illiquidity_{it} + b_8 Accruals_{it} + b_9 AQ_{it} + b_{10} Analyst_{it} + b_{11} FDisp_{it}$$

where *AIV* is abnormal idiosyncratic volatility. In Panel A, $Informed_{Trading}$ is abnormal insider trading (*AIT*), abnormal short selling (*ASS*), or abnormal institutional trading (*AIN*). In Panel B, $Informed_{Trading}$ is one of the three positive part of directional informed return run-ups from $AIT_{Net} \times RunUp$, $ASS_{Net} \times RunUp$, or $AIN_{Net} \times RunUp$. The (untabulated) control variables are abnormal trading volume (*AVol*), market beta (β_{Mkt}), market capitalization (*Size*), book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), Amihud (2002) illiquidity (*Illiquidity*), accruals (*Accruals*), earnings quality (*AQ*), number of analysts following (*Analyst*), analyst dispersion (*FDisp*), analyst forecast errors (*FErr*), and missing analyst indicator ($Missing_{Analyst}$). The *AIV* is multiplied by 100 to scale up the coefficients. The *t*-statistics reported in parentheses are based on robust standard errors adjusted for heteroskedasticity and clustered at both the firm and year level. $\bar{R}^2$ is adjusted R^2. Intercept and year fixed effects are not tabulated. The sample periods are 1996–2015 for models with *AIT* or AIT_{Net}, 2007–2015 for models with *ASS* or ASS_{Net}, and 1999–2015 for models with *AIN* or AIN_{Net}.

Panel A: Informed trading and *AIV*								
Variable	M1	M2	M3	M4	M5	M6	M7	M8
AIT	**0.861**	**1.150**					**3.858**	**3.457**
	(1.91)	**(2.90)**					**(1.97)**	**(3.11)**
ASS			**6.385**	**3.324**			**6.006**	**1.336**
			(8.44)	**(4.86)**			**(2.99)**	**(0.68)**
AIN					**39.200**	**25.275**	**66.905**	**49.118**
					(6.88)	**(5.30)**	**(4.34)**	**(3.78)**
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$\bar{R}^2$	1.7%	7.5%	1.8%	9.1%	3.7%	11.2%	4.7%	14.5%
Firms	432	394	2886	2421	1752	1591	305	280
Observations	8633	7889	25,972	21,791	29,776	27,039	2743	2522

Panel B: Directional informed return run-ups and *AIV*								
Variable	M1	M2	M3	M4	M5	M6	M7	M8
$(AIT_{Net} \times RunUp)^+$	**0.854**	**1.108**					**0.465**	**2.108**
	(1.66)	**(2.39)**					**(0.29)**	**(1.44)**
$(ASS_{Net} \times RunUp)^+$			**5.124**	**5.458**			**2.611**	**4.777**
			(4.82)	**(6.29)**			**(2.90)**	**(3.90)**
$(AIN_{Net} \times RunUp)^+$					**11.761**	**12.513**	**21.970**	**24.522**
					(6.30)	**(6.11)**	**(7.25)**	**(5.32)**
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$\bar{R}^2$	1.7%	7.5%	1.9%	9.4%	2.8%	11.4%	3.2%	15.2%
Firms	430	393	2881	2418	1741	1582	304	279
Observations	8592	7851	25,926	21,766	29,597	26,894	2733	2512

upcoming earnings announcements for stocks with high *AIV*. Specifically, we examine the relation between *AIV* and the magnitude of informed return run-ups prior to earnings announcements.

Presumably, if a return run-up has the same sign as an upcoming earnings announcement surprise, it is indicative of informed trading. If the run-up is small in magnitude or has the opposite sign with the earnings surprise, then naturally no informed trading should be implied. We use the product between earnings surprise and return run-ups to measure the magnitude of informed return run-ups prior to earnings announcements.

In calculation, we follow Livnat and Mendenhall (2006) to define earnings surprise, *SUE*, as the difference between current earnings and last year's earnings, scaled by the stock price. We also calculate an alternative measure of earnings surprise, SUE_{FC}, as the difference between current earnings and the mean of most recent analysts forecast of earnings, scaled by the stock price. SUE_{FC} is a refined measure taking into account the analyst forecast information that advances the market expectation prior to earnings announcements. We denote *SUESign* as the sign of *SUE* and $SUE_{FC}Sign$ as the sign of SUE_{FC}. Return run-up, *RunUp*, is the five-day cumulative abnormal stock return during pre-earnings announcement days. This variable measures the abnormal price change immediately before an earnings announcement. A similar variable is used by Banerjee and Eckard (2001) in the context of M&A announcements for which prices always go up. We denote *RunUpSign* as the sign of *RunUp*. We use the product between *SUESign* (or $SUE_{FC}Sign$) and *RunUp* (or *RunUpSign*) to capture the extent of informed trading.

Table 2 reports the results of regressions of *AIV* on four measures for informed return run-ups based on cross-products outlined above, with and without other control variables. For each of the regressions, *AIV* is found to be positively and significantly related to the variables of informed return run-ups. Using the portfolio approach, Table IA.2 of the Internet Appendix shows similar results that *AIV* is positively associated with informed return run-ups.[10] This set of results provides the first evidence

[10] The relation between *AIV* and informed run-ups appears to be non-monotonic in Panels A1 and A3. The reason is that the absolute value of

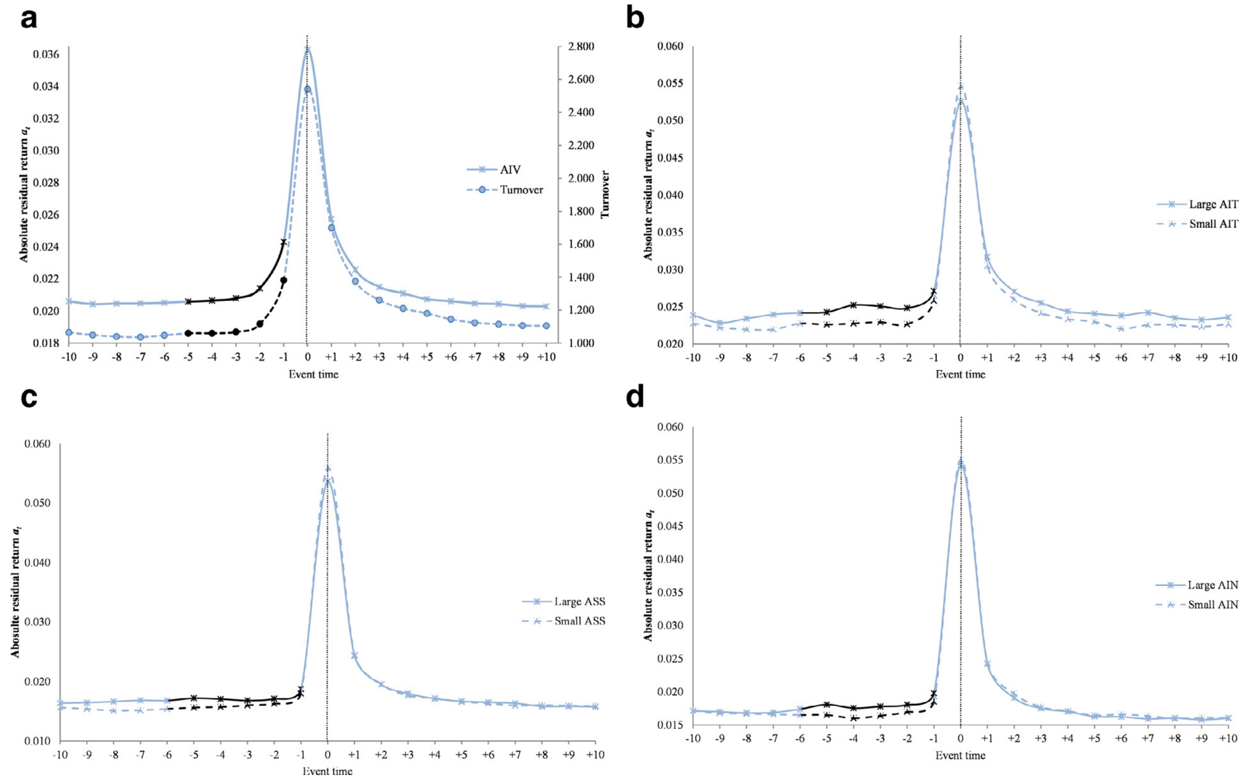

Fig. 1. Price variation and stock turnover around earnings announcements. These figures display average absolute residual return (a_t) for day $t \in [-10, 10]$ around earnings announcements, calculated as the average of daily absolute FF-3 model residuals of day t. (a) further displays average annualized stock turnover around earnings announcements, calculated as the number of shares traded deflated by number of shares outstanding then multiple by 252. (b) displays for the large and small quintile stock portfolios sorted by abnormal insider trading (*AIT*). (c) displays for the large and small quintile stock portfolios sorted by abnormal insider trading (*AIT*). (d) displays for the large and small quintile stock portfolios sorted by abnormal insider trading (*AIT*). The sample period is from July 1972 to December 2015.

that *AIV* is related to informed trading and seems to be a legitimate measure of information risk.

We also include commonly used asset pricing variables in the regressions in Table 2. They are market beta (β_{Mkt}), market capitalization (*Size*), book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), Amihud (2002) illiquidity (*Illiquidity*), accruals (*Accruals*), earnings quality (*AQ*), the number of analysts following (*Analyst*), analyst dispersion (*FDisp*), analyst forecast errors (*FErr*), and missing analyst indicator ($Missing_{Analyst}$). Several notable observations emerge from the table.

First, *AIV* is positively related to β_{Mkt}. It is insignificantly and negatively related to the book-to-market ratio, slightly higher for growth firms. Interestingly, *AIV* does not show a clear relation with market capitalization, *Size*, which is plausibly driven by the fact that the calculation of *AIV* as the difference between IV_{PEA} and IV_{NEA} wash out a majority of firm characteristics. In Table IA.3, we find that large stocks have lower *AIV* if conditional on IV_{NEA}. IV_{NEA} is highly correlated with idiosyncratic volatility, and Bali and Cakici (2008) show that the relation between size and idiosyncratic volatility is negative. Given that *AIV* is the difference between the log of idiosyncratic volatility between pre- and non-earnings-announcement periods, the occasional, positive association between *Size* and *AIV* is partly due to large stocks having a lower value of IV_{NEA}.[11]

Second, the results suggest that stocks with high *AIV* tend to have lower idiosyncratic volatility. This finding is consistent with certain theories. For example, informed traders avoid stocks with high arbitrage risk, as proxied by idiosyncratic volatility (Shleifer and Vishny, 1997). On the other hand, much of the negative association can be mechanical because *AIV* is defined as the difference

RunUp is positively correlated with *AIV*. Therefore, the relation between *RunUp* and *AIV* tends to be strong for either uninformed run-ups (the first quintile portfolio) or informed run-ups (the fifth quintile portfolio). Such relation makes the positive relation between *AIV* and informed run-ups appear less monotonic.

[11] Unconditional on other variables, *AIV* is positively associated with *Size*. Another possible explanation is that large firms have more shares available to be lent to short sellers who contribute to high abnormal idiosyncratic volatility during earnings announcements (Saffi and Sigurdsson, 2011; Massa et al., 2015). Although conventional wisdom suggests that small firms might be characterized by higher information asymmetry between insiders and outsiders, information asymmetry among outside investors may be lower in these firms. The rationale is that outside speculators may not be incentivized to collect private information and trade on small firms, which often feature poor corporate governance that discourages informed trading (e.g., Morck et al., 2000; Durnev et al., 2004; Ferreira and Laux, 2007). This is also partially due to the fact that the AIV used in this paper is derived from earnings related information risk only.

between IV_{PEA} and IV_{NEA}, and IV_{NEA} is positively correlated with IV_{AHXZ}. Because the pricing effect of IV_{AHXZ} remains largely a puzzle, we do not delve further on the subject.

Third, *Illiquidity* is strongly and positively associated with *AIV*. The positive relation between *Illiquidity* and *AIV* is well expected because information risk is a main reason for stock illiquidity. In Table IA.4, we further show that stocks with high abnormal illiquidity proxied by abnormal Amihud's illiquidity or abnormal effective spread have higher *AIV*. *Accruals* and *Analyst* also have significantly positive coefficients, consistent with the information risk interpretation. Other variables such as *AQ* and $Missing_{Analyst}$ are not strongly associated with *AIV*.

3.2. *Insider trading, short selling and institutional trading*

The most important and difficult task that must be undertaken to justify *AIV* as a measure of information risk is to link *AIV* to trading activities by informed traders. In this section, we consider three types of informed traders; namely, corporate insiders, short sellers, and institutional investors.

Corporate insiders: among all types of possible informed traders, corporate insiders have the most direct access to firm-specific information. Although corporate insiders are prohibited by law from trading using material nonpublic information, and insiders in certain firms are disallowed to trade stocks of their firms during a period before corporate event announcements including earnings announcements,[12] corporate insiders nonetheless earn huge trading profits with their private information (e.g., Aboody and Lev, 2000; Piotroski and Roulstone, 2005; Ravina and Sapienza, 2010; Cohen et al., 2012). Therefore, any evidence that stocks characterized by high abnormal insider trading during earnings announcement periods also have large *AIV* would support our hypothesis that *AIV* is related to information risk.

We obtain insider trading data from the Securities and Exchange Commission (SEC) Official Summary of Security Transactions and Holdings in the Thomson Reuters insider filings database. We examine open market purchases and sales by insiders. We aggregate purchases and sales by all corporate insiders of the same firm on the same trading day. For a given stock at the end of each calendar year, we calculate the pre-earnings-announcement insider trading activity (IT_{PEA}) as the annualized daily average proportion of shares traded by insiders in the period from five days to one day prior to the past earnings announcements in that calendar year. Similarly, we compute non-earnings-announcement insider trading activity (IT_{NEA}) as the annualized daily average proportion of shares traded by insiders on all days of the past year, excluding the period from five days before to five days after an earnings announcement. The abnormal insider trading activity (*AIT*) is therefore the difference in insider trading between pre- and non-earnings-announcement periods ($IT_{PEA} - IT_{NEA}$).

The columns marked as M1 and M2 in Panel A of Table 3 report the results of regressions of *AIV* on *AIT* with and without other control variables. The results show that *AIV* are positively and significantly related to *AIT*. The model with control variables even exhibits a stronger relation. While the goodness-of-fit is not large, it reveals that some of the variation in *AIV* is indeed associated with abnormal insider trading prior to earnings announcements for some firms, given that many other firms have restrictions on their insiders to trade before earnings announcements. Among control variables in M2, we add a new control variable, *AVol*, which is abnormal trading volume defined as the difference in the daily average number of million shares traded between pre- and non-earnings-announcement periods. The positive relation between *AVol* and *AIV* indicates that abnormal idiosyncratic volatility ahead of earnings is associated with abnormally high trading volume. The presence of *AVol* does not subsume the significance of *AIT* in explaining *AIV*. Panels A1 and B1 of Table IA.5 further reveal a similar positive association between *AIV* and *AIT* using the portfolio approach.

Fig. 1(b) plots the average absolute residual return from the FF-3 model around earnings announcement days for stocks with large and small quintile stock portfolios sorted by *AIT* separately. Consistent with M1 and M2 of Table 3, stocks in the highest *AIT* quintile have a larger return variation prior to earnings announcements, which leads to a smaller announcement-day surprise relative to stocks in the lowest *AIT* quintile.

Short sellers: following the previous literature, short sellers are also selected as prominent representatives of informed traders. Boehmer et al. (2008) show that short sellers contribute to more than 10% of daily trading volume and are extremely informed. International evidence also shows that short selling is associated with an increase in the speed with which information is incorporated into prices (e.g., Bris et al., 2007; Beber and Pagano, 2013; Saffi and Sigurdsson, 2011; Massa et al., 2015).

We obtain the information on short sales from Markit Securities Finance Analytics. Markit data represents the largest pool of loanable equities in the world, and it includes firms with lending data of 90% of the market capitalization of CRSP firms in the US market. We use the daily open short interest from January 2007 to December 2015. More detailed descriptions of the data can be found in Saffi and Sigurdsson (2011).

For each stock at the end of each calendar year, we calculate the pre-earnings-announcement short selling activity (SS_{PEA}) as the annualized average daily absolute change in the short interest ratio during the period from five days before to one day before earnings announcements during the calendar year. Because both the increase and decrease in short interest convey short sellers' trading information, our measure uses the absolute value of the

[12] Insiders in the US must report specific details for each of their trades. This requirement dates back to the Securities and Exchange Act of 1934 under which the SEC promulgated Rule 10b-5. This regulation requires that certain persons who have material nonpublic information about a firm should disclose that information or abstain from trading. The US Supreme Court clarified that the rule applies to the firm's insiders, namely, its officers and directors, as well as controlling shareholders. With the promulgation of the Sarbanes–Oxley Act of 2002, the SEC adopted new rules and shortened the window for most SEC filings involving insider trading information to two business days after the buy or sell transaction. Prior to this change, the reporting period typically lasted until the 10th day of the month following the insiders' trades.

change in the short interest ratio. The short interest ratio is the number of shares that are currently being shorted divided by the number of shares outstanding. The non-earnings-announcement short selling activity (SS_{NEA}) is the annualized average daily absolute change in the short interest ratio in all days in the same calendar year, excluding the period from five days before to five days after an earnings announcement. Abnormal short selling activity (*ASS*) is therefore the difference in short sales between pre- and non-earnings-announcement periods ($SS_{PEA} - SS_{NEA}$).

Columns M3 and M4 in Panel A of Table 3 report the regressions of *AIV* on *ASS* with and without controls. We show that *AIV* is strongly and positively associated with *ASS*. This finding adds creditability to *AIV* as a measure of information risk. In particular, after controlling for other potentially relevant variables, among which *AVol* explains much of the variation in *AIV, ASS* remains very significant. We conduct a similar analysis using the portfolio approach, and the result presented in Panels A2 and B2 of Table IA.5 further confirm that *AIV* is positively associated with *ASS*.

Fig. 1(c) plots the average absolute residual return from the FF-3 model around earnings announcement days for stocks with large and small quintile stock portfolios sorted separately by *ASS*. Stocks with a larger *ASS* appear to have a larger return variation before earnings announcements, which leads to a smaller announcement-day surprise relative to stocks in the lowest *ASS* quintile.

Institutional investors: our next inquiry involves the relation between *AIV* and institutional trading. Institutional investors are resourceful with respect to collecting information, skillful in analyzing the collected information, and powerful in mobilizing their funds. Puckett and Yan (2011) find that institutional investors earn significant abnormal returns in their trading. Hendershott et al. (2015) find that institutional trading volume predicts both the occurrence and sentiment of news announcements. More specifically, Campbell et al. (2009) show that institutional trades are highly informed regarding near-future earnings announcements. Therefore, institutional trading activity may increase idiosyncratic volatility before earnings announcements.

We obtain daily institutional trading information from the ANcerno data set. ANcerno provides consulting services to help institutional investors monitor their trading costs. The data set covers all the equity transaction histories of its institutional clients for each equity trade over the January 1999 to June 2015 period. The ANcerno data set has been widely used in studying institutional trading activity. A more detailed description of the data can be found in Puckett and Yan (2011) and Jame (2018).

For each stock at the end of each calendar year, we calculate the pre-earnings-announcement institutional trading activity (IN_{PEA}), which is the annualized daily average proportion of shares traded by institutions in the period from five days to one day prior to the past earnings announcements in that calendar year. The non-earnings-announcement institutional trading activity (IN_{NEA}) is the annualized daily average proportion of shares traded by institutions on all days in the same calendar year, excluding the period from five days before to five days after an earnings announcement. The abnormal institutional trading activity (*AIN*) is therefore the difference in institutional trading between pre- and non-earnings-announcement periods ($IN_{PEA} - IN_{NEA}$).

The columns marked as M5 and M6 in Panel A of Table 3 report the regressions of *AIV* on *AIN* with and without other control variables. Again, the results show that *AIV* is positively and significantly associated with *AIN*. The result of the portfolio approach in Panels A3 and B3 of Table IA.5 further confirms this positive association.

Fig. 1(d) plots the average abnormal absolute residual return from the FF-3 model around earnings announcement days for stocks with large and small quintile stock portfolios sorted separately by *AIN*. Stocks with a larger *AIN* appear to have a larger return variation before earnings announcements, although the announcement-day abnormal returns are similar across the two portfolios.

In the columns marked as M7 and M8 in Panel A of Table 3, all the three informed trading variables (*AIT, ASS*, and *AIN*) are included to explain *AIV*. All three variables are also positive and significant. Taken together, our findings provide the consistent evidence that *AIV* is related to information risk induced by informed traders such as corporate insiders, short sellers, and institutional investors prior to earnings announcements.

Further evidence: *AIT, ASS*, and *AIN* captures the magnitude of abnormal trading activities for insiders, short sellers, and institutional investors. It is plausible that these informed traders bet on a wrong direction of future earnings announcements. To address this concern, we first calculate the net insider purchase (AIT_{Net}), the decrease in short interest (ASS_{Net}),[13] and the net purchase by institution investors (AIN_{Net}). Second, we construct the three variables of directional informed trading: $(AIT_{Net} \times RunUp)^+$, $(ASS_{Net} \times RunUp)^+$, and $(AIN_{Net} \times RunUp)^+$. Each of the three variables is defined as the positive part of the product of AIT_{Net} (ASS_{Net} or AIN_{Net}) and *RunUp*. If the value of the product is negative, the variable is set as zero. The three variables measure whether abnormal insider trading, short selling, and institutional trading are in the same direction as the stock return run-up ahead of earnings announcements. The results in Panel B of Table 3 indeed show that *AIV* is positively associated with directional informed trading, where abnormal trading activities are in line with the stock return run-up. This finding is consistent with our interpretation that when insiders, short sellers, and institutional investors have private information, their trading activities drive *AIV* higher.

3.3. *Negative* AIV

In principle, *AIV* as the measure of information risk should be nonnegative. The logic is that if informed traders have little private information, the stock price should experience an insignificant movement prior to

[13] We use the decrease instead of increase in short interest to make the sign of ASS_{Net} consistent with the direction of informed trading. For example, a decrease in short selling or positive ASS_{Net} indicates good news is expected, while an increase in short selling or negative ASS_{Net} indicates bad news is expected. Defined this way, its coefficient should be positive under our hypothesis, like those of other two variables.

earnings announcements. For stocks with a larger degree of information asymmetry, informed traders would trade aggressively and hence result in a substantial price variation prior to earnings announcements. For either case, we expect *AIV* to be greater than zero. However, in Table 1, we observe a proportion of firm-years for which *AIV* is negative. Thus, it is our onus to explain why we obtain negative *AIV* and also to verify whether stocks with negative *AIV* indeed have a lower level of information risk.

Negative *AIV* is caused by several reasons. First, firms may undertake more corporate activities during the non-earnings announcement period than the pre-earnings announcement period. More corporate activities result in a higher fundamental risk, which can be reflected in idiosyncratic volatility. Second, there are many other corporate events such as M&As or product recalls during the non-earnings announcement days, for which idiosyncratic volatility can be large due to the same informational reason as earnings announcements. Third, given the non-earnings announcement period is longer than the pre-earnings announcement period and idiosyncratic volatility is measured based on past realized stock returns, the likelihood of extreme price movement caused by noise trading tends to be higher during the non-earnings announcement period. Taken together, *AIV* tend to have large cross-sectional and time-series variation, and the negative value of *AIV* is plausible.

Next, we verify whether stocks with negative *AIV* as a group indeed have a lower level of information risk. Specifically, we use the sign of *AIV*, denoted as *DAIV*, as the dependent variable. We perform probit regressions to reexamine the relation between *DAIV* and informed trading variables in Table 4. Panel A of Table 4 is the counterpart of Table 2. While the dependent variable and the regression model are different, the signs of the coefficients remain mostly unchanged, and the significance appears even stronger. The sign of *AIV* is found to be positively and significantly related to the variables of informed return run-ups.

Panel B of Table 4 is the counterpart of Table 3. Consistent with the results of *AIV*, stocks with negative *AIV* have a lower level of abnormal insider trading, short selling, and institutional trading. In Table IA.6, we further replicate Tables 2 and 3 using only the subsamples of firms with negative *AIV*. Relative to stocks with slight negative *AIV*, those stocks with very negative *AIV* experience a lower level of informed return run-ups, abnormal insider trading, short selling, and institutional trading.

Overall, the results suggest that stocks with negative *AIV* have a lower level of information risk than those with positive *AIV*. *AIV* indeed measures information risk, though it is not free of noise.

3.4. *Persistence of* AIV

AIV is constructed to capture the risk associated with asymmetric information. The persistence of information risk measures might be different from that of fundamental risk measures for several reasons. First, private information regarding the valuation of a firm is short lived in an efficient market and sometimes occurs in a random fashion. The time distribution of private information depends on many factors such as the industry of a firm, the demand shock to the firm's products, the research and development effort that the firm makes, and the likelihood of innovation failure, etc. Many of these factors tend to be time varying. For example, technology development often takes uneven paces, which create hot issues at different times across different industries.

Second, information risk is generated when informed investors trade on private information in a short-term period. For example, institutional investors such as hedge funds follow the change in a firm's fundamentals and move quickly in and out of the firm's stocks. Given the prohibition of trading on material nonpublic information, insiders must trade discreetly to avoid being caught trading illegally. Similarly, short selling activities become intense only if the stock is regarded as overpriced. As such, information risk measures would be updated quickly.

All these features lend support to the notion that a measure of information risk should be conditional and fast changing and thereby may not be as persistent as other firm characteristics, such as price ratios, size, financial leverage, and the number of analysts following. In short, persistence is not a necessary condition for a measure of information risk.

We confirm in the Internet Appendix that *AIV* is not persistent. In Table IA.7, we conduct the Fama–MacBeth cross-sectional regression approach and regress current *AIV* on past *AIV*. The result shows that the 12-month autoregressive coefficient of *AIV* is 0.067 only, even though the coefficient is statistically significant. Furthermore, the transition matrix of Table IA.8 shows that the current position of a firm belonging to a *AIV* quintile portfolio does not predict to which portfolio the firm would belong 12 months later. To further understand the transition matrix results, Table IA.9 shows that the *AIV* value of portfolio sorted by industry or firm size is relatively more persistent than firm-level *AIV*. In Table IA.10, we show that several other information risk variables documented in the asset pricing literature, namely probability of symmetric order-flow shocks (*PSOS*), *Accruals*, and *FErr*, may not be persistent either.

Because *AIV* is calculated as the difference between IV_{PEA} and IV_{NEA}, we examine the persistence of the two variables individually to understand the source of the lack of persistence in *AIV*. Table IA.11 shows that IV_{NEA} is as persistent as idiosyncratic volatility calculated over the one-year period because they differ only for a total of 44 days (four times 11 days surrounding earnings announcements). IV_{PEA}, however, is relatively less persistent than IV_{NEA}, in a way consistent with the notion we describe above that information risk is time varying and fast changing. Given that IV_{PEA} is correlated with IV_{NEA}, the cancellation of the correlated component between IV_{PEA} and IV_{NEA} makes *AIV* much less persistent.

3.5. *Relations with quantity-based information risk measures*

In this section, we investigate the relations between *AIV* and other information risk measures, especially the quantity-based information risk measures. The purpose is

Table 4
Informed trading and the sign of *AIV*.

This table repeats the analyses in Table 2 and Panel A of Table 3 using probit regression in the following model to examine the relation between informed *RunUp* or informed trading and the sign of *AIV*.

$$DAIV_{it} = a + b_1 Informed_{it} + b_2 \beta_{Mkt,it} + b_3 Size_{it} + b_4 BM_{it} + b_5 IV_{AHXZ,it} + b_6 Illiquidity_{it} + b_7 Accruals_{it} + b_8 AQ_{it} + b_9 Analyst_{it} + b_{10} FDisp_{it} + b_{11} FErr_{it}$$

where *DAIV* is a dummy variable of abnormal idiosyncratic volatility (*AIV*); it takes value of one if *AIV* is greater than zero, and zero otherwise. In Panel A, *Informed* is one of the informed *RunUp* variables from $SUESign \times RunUp$, $SUESign \times RunUpSign$, $SUESign_{FC} \times RunUp$, or $SUESign_{FC} \times RunUpSign$. In Panel B, *Informed* is one of the informed informed trading variables from abnormal insider trading (*AIT*), abnormal short selling (*ASS*), or abnormal institutional trading (*AIN*). The (untabulated) control variables are abnormal trading volume (*AVol*), market beta (β_{Mkt}), market capitalization (*Size*), book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), Amihud (2002) illiquidity (*Illiquidity*), accruals (*Accruals*), earnings quality (*AQ*), number of analysts following (*Analyst*), analyst dispersion (*FDisp*), analyst forecast errors (*FErr*), and missing analyst indicator ($Missing_{Analyst}$). The *t*-statistics reported in parentheses are based on Huber-White standard errors adjusted for heteroskedasticity. $\bar{R}^2$ is adjusted R^2. Intercept and year fixed effects are not tabulated. The sample periods are 1972–2015 for models with *SUESign*, 1983–2015 for models with $SUESign_{FC}$, 1996–2015 for models with *AIT*, 2007–2015 for models with *ASS*, and 1999–2015 for models with *AIN*.

Panel A: Informed *RunUp* and *AIV*

Variable	M1	M2	M3	M4	M5	M6	M7	M8
$SUESign \times RunUp$	**2.132**	**2.250**						
	(21.49)	**(21.47)**						
$SUESign \times RunUpSign$			**0.077**	**0.081**				
			(11.29)	**(11.36)**				
$SUESign_{FC} \times RunUp$					**1.540**	**1.648**		
					(12.63)	**(12.78)**		
$SUESign_{FC} \times RunUpSign$							**0.065**	**0.070**
							(8.01)	**(8.18)**
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$\bar{R}^2$	1.3%	1.5%	1.1%	1.3%	1.5%	1.7%	1.4%	1.6%
Firms	2893	2626	2893	2626	2193	2002	2224	2002
Observations	127,272	115,542	127,272	115,542	72,382	66,078	73,382	66,078

Panel B: Informed trading and *AIV*

Variable	M1	M2	M3	M4	M5	M6	M7	M8
AIT	**0.016**	**0.035**					**0.760**	**0.546**
	(1.09)	**(2.01)**					**(2.80)**	**(2.53)**
ASS			**0.197**	**0.106**			**0.141**	**−0.004**
			(4.91)	**(2.51)**			**(1.26)**	**(−0.04)**
AIN					**1.322**	**0.833**	**2.381**	**1.741**
					(11.24)	**(7.84)**	**(6.62)**	**(4.53)**
AVOL		0.004		0.003		0.003		0.003
		(10.71)		(19.97)		(22.71)		(7.91)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$\bar{R}^2$	1.0%	4.1%	1.1%	4.6%	1.9%	5.2%	2.7%	7.5%
Firms	432	394	2886	2421	1752	1591	305	280
Observations	8633	7889	25,972	21,791	29,776	27,039	2743	2522

to gauge the degree that *AIV* can serve as a new information risk measure. If *AIV* proposed in this study is highly correlated with existing measures of information risk, or if it can be well explained by the combination of other existing information risk measures, then *AIV* may simply be a proxy for a similar type of information risk, and the incremental contribution of *AIV* as a new information risk proxy would be marginal.

We consider several measures of information risk, mostly quantity-based measures. They are the probability of informed trading, PIN_{EHO}, proposed by Easley et al. (2002), PIN_{DY}, a measure proposed by Duarte and Young (2009) with the same name; and the probability of symmetric order-flow shocks, *PSOS*, another measure proposed by Duarte and Young (2009). We also consider *AVol*, used in the previous regressions, abnormal turnover (*ATurn*), and abnormal spread (*ASpread*). The last three variables are defined in a similar way as *AIV*, contrasting their pre-earnings announcement value with their post-earnings announcement value.[14]

We regress *AIV* on each of the six alternative information risk measures, controlling for other firm characteristics and asset pricing variables. The results are reported in Table 5. First, we find that *AIV* is not strongly associated with PIN_{EHO} and PIN_{DY}. Second, other four information risk measures are significant to various degrees in explaining *AIV* with correct signs. However, the explanatory power of these quantity-based information risk measures for *AIV* is not substantially large. Although *AIV* is somewhat related to existing information risk measures, most of the variation in *AIV* is not explained by these variables.

[14] *AVol*, *ATurn*, and *ASpread* are also related to stock market liquidity. Because stock market liquidity is intimately linked with information asymmetry, we consider them here along with other control variables.

Table 5
Relations with quantity-based information risk measures.
This table presents panel regression of the abnormal idiosyncratic volatility (*AIV*) on measures of quantity-based information risk variables with control variables and year fixed effects in the following model.

$$AIV_{it} = a + b_1 PIN_{it} + b_2\beta_{Mkt,it} + b_3 Size_{it} + b_4 BM_{it} + b_5 IV_{AHXZ,it} + b_6 Illiquidity_{it} + b_7 Accruals_{it} + b_8 AQ_{it} + b_9 Analyst_{it} + b_{10} FDisp_{it} + b_{11} FErr_{it}$$

where *AIV* is abnormal idiosyncratic volatility. *PIN* is Easley and O'Hara's PIN (PIN_{EHO}), Duarte and Young's PIN (PIN_{DY}), Duarte and Young's PSOS (*PSOS*), abnormal trading volume (*AVol*), abnormal turnover (*ATurn*), or abnormal effective spread (*ASpread*). The control variables are market beta (β_{Mkt}), market capitalization (*Size*), book-to-market ratio (*BM*), AHXZ's idiosyncratic volatility (IV_{AHXZ}), Amihud (2002) illiquidity (*Illiquidity*), accruals (*Accruals*), earnings quality (*AQ*), number of analysts following (*Analyst*), analyst dispersion (*FDisp*), analyst forecast errors (*FErr*), and missing analyst indicator ($Missing_{Analyst}$). The *AIV* is multiplied by 100 to scale up the coefficients. The *t*-statistics reported in parentheses are based on robust standard errors adjusted for heteroskedasticity and clustered at both the firm and year level. $\bar{R}^2$ is adjusted R^2. Intercept and year fixed effects are not tabulated. The sample period varies according to the availability of quantitative-based information risk variables.

	M1	M2	M3	M4	M5	M6
PIN_{EHO}	**1.812**					
	(0.54)					
PIN_{DY}		**3.513**				
		(1.01)				
PSOS			**5.343**			
			(3.58)			
AVol				**0.111**		
				(9.13)		
ATurn					**17.844**	
					(19.98)	
ASpread						**1.726**
						(2.11)
β_{Mkt}	1.831	1.814	1.874	0.522	−0.497	1.282
	(1.59)	(2.02)	(2.10)	(1.09)	(−1.05)	(1.81)
Size	−0.247	0.453	0.567	−0.471	−0.141	0.277
	(−0.50)	(1.05)	(1.39)	(−3.50)	(−1.04)	(0.82)
BM	−0.342	−0.578	−0.527	0.101	0.449	−0.445
	(−0.83)	(−1.72)	(−1.55)	(0.57)	(2.89)	(−1.51)
IV_{AHXZ}	−2.975	−2.097	−2.073	−6.327	−4.493	−4.785
	(−1.74)	(−1.61)	(−1.59)	(−5.77)	(−4.93)	(−2.73)
Illiquidity	0.001	0.051	0.035	0.011	0.007	0.099
	(0.03)	(1.28)	(0.88)	(1.22)	(0.93)	(2.36)
Accruals	37.599	30.704	30.846	14.493	9.964	23.707
	(3.68)	(3.30)	(3.34)	(3.74)	(3.00)	(2.77)
AQ	2.331	2.660	2.410	−1.375	−2.660	−1.282
	(0.55)	(0.69)	(0.61)	(−0.52)	(−1.07)	(−0.33)
Analyst	0.278	0.305	0.362	0.515	0.193	0.366
	(0.63)	(0.70)	(0.85)	(2.25)	(0.69)	(0.96)
FDisp	−0.128	0.214	0.232	−0.199	−0.169	0.249
	(−0.22)	(0.42)	(0.46)	(−1.13)	(-0.95)	(0.73)
FErr	0.068	0.043	0.035	0.087	0.065	-0.044
	(0.26)	(0.17)	(0.14)	(0.86)	(0.59)	(-0.25)
$Missing_{Analyst}$	−0.752	−0.770	−0.942	−1.520	−1.392	−0.783
	(−0.88)	(−1.07)	(−1.29)	(−3.42)	(−3.21)	(−1.16)
$\bar{R}^2$	1.6%	2.2%	2.2%	5.3%	1.3%	2.7%
Firms	1499	1476	1476	2660	2660	1456
Observations	22,483	32,469	32,469	117,043	117,043	45,122

The overall results suggest that *AIV* is a concrete measure of information risk at the stock level. More importantly, *AIV* is a new measure of information risk that is not closely correlated with commonly used pricing factors or alternate measures of information risk. Our next task is to examine the cross-sectional pricing of *AIV*.

4. Is the earnings-announcement-related information risk priced?

In this section, we employ several steps to test the pricing of *AIV*. First, we look at the distribution of stock returns across portfolios of stocks single-sorted by *AIV* and double-sorted by market capitalization and then by *AIV*. Second, we test whether *AIV* affects cross-sectional expected stock returns using Fama and French (1992) asset pricing framework. Finally, we conduct a variety of robustness tests on the pricing of *AIV* including alternative *AIV*s based on corporate news events.

4.1. Portfolio approach

As the first step in evaluating our hypothesis that the price-based information risk proxied by *AIV* is related to future stock returns, we construct monthly equally weighted portfolios sorted by *AIV*. Panel A of Table 6 reports average monthly returns in excess of the one-month T-Bill rate (R) and Fama–French–Carhart four-factor

Table 6
Monthly excess returns and risk-adjusted portfolio alphas of *AIV* portfolios.
This table reports equally weighted average monthly excess returns (R) and Fama–French–Carhart four-factor risk-adjusted portfolio alphas (R_{Adj}) of stock portfolios sorted on the abnormal idiosyncratic volatility (*AIV*). Panel A shows R and R_{Adj} of single-sorted portfolios formed monthly on prior-month *AIV*. Panel B shows R_{Adj} of double-sorted portfolios sorted monthly first by prior June market capitalization (*Size*) and then by prior-month *AIV*. Panel C shows equally weighted average future monthly excess returns (R) of stock portfolios sorted on the abnormal idiosyncratic volatility (*AIV*). The future values R in 2 months, 3 months, 6 months, 9 months, 12 months, 18 months, and 24 months are reported. The differences in R and R_{Adj} between the high and the low portfolios are also reported, along with t-statistics in parentheses. The t-statistics reported in parentheses are based on Newey–West standard errors. The sample period is from July 1972 to December 2015.

Portfolios	Panel A: Single-sorted portfolios		Panel B: Double-sorted portfolios sort by *Size*, then *AIV*				
	R	R_{Adj}	Small *Size*	2	3	4	Large *Size*
Low *AIV*	0.999	−0.146	−0.319	−0.204	−0.170	0.013	0.060
2	1.124	−0.005	−0.057	−0.115	−0.082	0.060	0.082
3	1.151	0.008	−0.037	−0.045	−0.063	0.010	0.134
4	1.136	−0.025	−0.100	−0.210	0.037	0.023	0.056
High *AIV*	1.137	0.012	0.021	−0.108	0.011	0.150	0.081
High-Low	**0.138**	**0.158**	**0.34**	**0.096**	**0.181**	**0.137**	**0.021**
	(3.19)	**(3.45)**	**(4.09)**	**(1.20)**	**(2.37)**	**(1.89)**	**(0.31)**
Portfolios	Panel C: Month-by-month portfolio returns						
	R_{t+2}	R_{t+3}	R_{t+6}	R_{t+9}	R_{t+12}	R_{t+18}	R_{t+24}
Low *AIV*	1.030	1.079	1.136	1.153	1.183	1.280	1.291
2	1.137	1.153	1.135	1.147	1.210	1.229	1.258
3	1.140	1.138	1.171	1.192	1.271	1.239	1.274
4	1.162	1.141	1.125	1.199	1.231	1.299	1.299
High *AIV*	1.146	1.142	1.198	1.193	1.241	1.340	1.340
High-Low	**0.116**	**0.063**	**0.062**	**0.040**	**0.058**	**0.059**	**0.049**
	(2.47)	**(1.38)**	**(1.37)**	**(0.87)**	**(1.26)**	**(1.27)**	**(1.07)**

risk-adjusted portfolio alphas (R_{Adj}) of single-sorted quintile portfolios formed monthly sorted by *AIV*. Panel B shows the R_{Adj} of double-sorted quintile portfolios sorted monthly first by *Size* measured at prior June and then by prior-month *AIV*. All t-statistics reported in parentheses are based on Newey–West standard errors. The sample period runs from July 1972 to December 2015.

The results of Panel A show a generally increasing, but slightly tent-shaped, relation between *AIV* and future stock returns. From quintile 1 to 3 the relation is monotonically increasing, but reverses slightly and remains flat for quintiles 4 and 5, for raw returns. For risk-adjusted returns, the pattern is also increasing in general but nonmonotonically. The differences in excess and risk-adjusted returns between the high and low *AIV* quintile portfolios are both positive and significant at the 1% level. Most importantly, the return spreads between the high and low *AIV* quintile portfolios are significant economically. A trading strategy combining a long position in a high *AIV* quintile portfolio with a short position in a low *AIV* quintile portfolio generates a 1.66% annualized excess return and a 1.90% annualized (Fama–French–Carhart) risk-adjusted return.

There might be a concern that the positive risk premium for *AIV* is simply a manifestation of return effects related to firm size. To address this potential concern, we employ double-sorted portfolio returns in Panel B to provide robust evidence that the positive relation between *AIV* and future stock returns is not driven by market capitalization. The difference in risk-adjusted returns between high and low *AIV* quintile portfolios is statistically significant in three of the five *Size* quintiles. Furthermore, the return differential is more pronounced in the lowest *Size* quintile portfolio. The long high-*AIV* and short low-*AIV* trading strategy applied in the lowest *Size* quintile portfolio yields 4.08% annualized excess returns. In an unreported analysis, we further conduct a double-sorted portfolio analysis with the book-to-market ratio or Amihud's illiquidity and *AIV*. The positive relation between *AIV* and future stock returns is robust for controlling these firm characteristics.

We have also tried the Fama–French five-factor model and the five-factor plus momentum factor model. We present the result based on the five-factor model in Table IA.12. The risk-adjusted portfolio return result based on the five-factor model is slightly weaker than that of Fama–French–Carhart four-factor models. The result of the five-factor plus momentum factor model is very much similar to that of the five-factor model.

The results of Panel C show that the predictive power of *AIV* on future returns declines over time. The differences in excess returns between the high and low *AIV* quintile portfolios become statistically less significant for future months longer than two months. Despite being statistically insignificant, it is somewhat comfortable that the differences in excess returns remain positive in each of the 24 months after the portfolios are formed. The inability of *AIV* for long-term return prediction is consistent with the low persistence of *AIV* documented in Table IA.7 and Table IA.8. That is, when *AIV* changes over time, its return predictive power naturally declines over long-term horizons. Similarly, in Table IA.13, we show that the differences in future *AIV* between the high and low *AIV* quintile portfolios also decline over time, although the differences remain positive and statistically significant.

Overall, the portfolio results provide the first evidence that the price-based information risk proxied by *AIV* positively affects future stock returns. In the next step, we conduct cross-sectional regression analyses to examine the pricing ability of *AIV* using the Fama–MacBeth methodology.

4.2. Fama–MacBeth approach

In this section, we follow Fama and French (1992) method with cross-sectional return determinants, including market beta, market capitalization, and the book-to-market ratio as control. In addition, following Brennan et al. (2012) and AHXZ, we include idiosyncratic volatility, illiquidity, and past stock returns in our analysis of asset pricing returns. For each month, we run cross-sectional regressions of monthly stock excess returns on return determinants as follows.

$$\begin{aligned} R_{i,t+1} = {} & a + b_1 AIV_{it} + b_2 \beta_{Mkt,it} + b_3 Size_{it} + b_4 BM_{it} \\ & + b_5 IV_{AHXZ,it} + b_6 Illiquidity_{it} + b_7 R_{-1} + b_8 R_{[-3,-2],it} \\ & + b_9 R_{[-6,-4],it} + b_{10} R_{[-12,-7],it} + \varepsilon_{i,t+1}, \end{aligned}$$

where $R_{i,t+1}$ is the monthly excess stock return for firm i at time $t+1$, *AIV* is abnormal idiosyncratic volatility, β_{Mkt} is market beta, *Size* is market capitalization, *BM* is the book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is the past month stock return, $R_{[-3,-2]}$ is the past two-month stock returns, $R_{[-6,-4]}$ is the past three-month stock returns, and $R_{[-12,-7]}$ is the past six-month stock returns. Time-series averages of the estimates are reported in Table 7. All t-statistics reported in parentheses are based on Newey–West standard errors. M1–M2 examine the full sample period from July 1972 to December 2015, M3–M4 examine the period from July 1972 to December 1993, and M5–M6 examine the period from January 1994 to December 2015.

Panel A of Table 7 reveals several notable findings. First, our hypothesis is that uninformed investors demand a risk premium for trading stocks with informed investors prior to earnings announcements, and hence stocks with high information risk measured by *AIV* should compensate for uninformed investors' potential trading losses. We thus expect a positive and significant coefficient of *AIV*. The results support our hypothesis. The coefficients of *AIV* are all positive with t-statistics varying from 2.22 to 4.61. Compared with the result of the portfolio approach, the pricing of *AIV* in our Fama–MacBeth approach appears to be more economically significant.

Second, *AIV* is significantly priced not only in the full sample but also across two subperiods. Notably, the pricing of *AIV* is more pronounced during the second subperiod, which is consistent with the astonishing growth in short selling and institutional trading in recent years.

Third, we find consistent signs and significance levels for the coefficients of other conventional pricing factors, except for *beta, Size*, and $R_{[-3,-2]}$. For example, *BM, Illiquidity*, $R_{[-6,-4]}$, and $R_{[-12,-7]}$ have positive and significant coefficients in all the models. IV_{AHXZ} and R_{-1} are negatively and significantly associated with monthly excess stock returns.

In Panel B of Table 7, we analyze the relation between *AIV* and long-term expected stock returns using the panel regression and cluster standard errors at both the firm and month levels. The result shows that *AIV* has a long-horizon predictive power for future cumulative stock returns. However, in the further tests of long-term monthly returns in Tables IA.14, we find that the predictive power of *AIV* comes mainly from short horizons; the slope coefficients of *AIV* become statistically less significant for future months longer than three months. Nevertheless, the coefficients of *AIV* on future returns remain positive even up to 24 months after *AIV* is computed.

4.3. Robustness issues

In this section, we present robustness checks on the use of *AIV* as an information risk measure. The issues are whether the *AIV* effect is driven by small stocks or inactive stocks, whether the *AIV* measure is sensitive to the window for its construction, and whether *AIV* effect is subject to some microstructure related concerns. The results are reported in Tables IA.15–18.

Results for large stocks: because the risk premium of *AIV* is more significant in the small *Size* quintile portfolio shown in Table 5, it is natural to inquire whether the relation between *AIV* and the cross-section of stock returns is driven by inactive or penny stocks. To address this concern in the sample selection, we examine a subsample of large and actively traded stocks by replicating the Fama–MacBeth regressions of M1 and M2 from Table 7 and report the results in Table IA.15. We include only stocks with a price greater than \$5 at the end of prior June in M1–M2. In M3–M4, we test stocks listed on the NYSE and Amex only because larger firms are listed and traded on the NYSE/Amex and have high trading volumes. We examine stocks with at least 100 shares traded on each trading day over the past one year in M5–M6. All the results confirm our findings regarding the positive risk premium of information risk proxied by *AIV*.

Pre-earnings-announcement window: we define the pre-earnings-announcement window as a five-day period before the earnings announcement in the main tests. We verify that the results are robust to alternative definitions of pre-earnings-announcement windows. In Table IA.16, we examine alternative measurement windows for the pre-earnings-announcement period of *AIV*. Here, $[-10,-1]$ ($[-3,-1]$, $[-10,-1]$ [2,10], $[-5,-1]$ [2,5], and $[-3,-1]$ [2,3]) refer to the alternative measures of *AIV* ($IV_{PEA} - IV_{NEA}$), where IV_{PEA} is calculated as the log annualized standard deviation of daily residuals based on the FF-3 model in days $[-10,-1]$ ($[-3,-1]$, $[-10,-1]$ [2,10], $[-5,-1]$ [2,5], and $[-3,-1]$ [2,3]) prior to quarterly and annual earnings announcements over the preceding year, and IV_{NEA} is defined as the log annualized standard deviation of daily residuals based on the FF-3 model excluding days around announcements $[-10,10]$ ($[-3,3]$, $[-10,10]$, $[-5,5]$, and $[-3,3]$) over the preceding year. The results show that our findings are robust to alternative measurement windows.

Step-wise function: we investigate whether the relation between *AIV* and expected return is step-wise. We introduce a step-wise dummy variable, *DAIV*, which takes the value of one if *AIV* is positive, and zero otherwise. In M1–M2 of Table IA.17, the coefficients of the dummy variable(*DAIV*) are positive and significant. However, the

Table 7
The effect of *AIV* on cross-sectional expected stock returns.

This table shows Fama–MacBeth monthly cross-sectional returns and panel long-term cross-sectional cumulative returns results for the following model.

$R_{i,t+1} = a + b_1 AIV_{it} + b_2 \text{Control}_{it} + \varepsilon_{i,t+1}$,

$R_{i,[t+1,t+m]}/m = a + b_1 AIV_{it} + b_2 \text{Control}_{it} + \varepsilon_{i,t+1}$,

where $R_{i,t+1}$ is the monthly stock excess return of firm i at time $t+1$, $R_{i,[t+1,t+m]}/m$ is the average monthly stock excess return of firm i over the next m months, and *AIV* is abnormal idiosyncratic volatility. The control variables are as follows. β_{Mkt} is market beta, *Size* is market capitalization, *BM* is book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is past one-month stock return, $R_{[-3,-2]}$ is past two-month stock returns, $R_{[-6,-4]}$ is past three-month stock returns, and $R_{[-12,-7]}$ is past six-month stock returns. In Panel A, the Fama–MacBeth regression is used. The t-statistics reported in parentheses are based on Newey–West standard errors. M1–M2 examine a sample period from July 1972 to December 2015, M3–M4 examine a sample period from July 1972 to December 1993, and M5–M6 examine a sample period from January 1994 to December 2015. The panel presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. In Panel B, the panel regression with month fixed effect is used. The t-statistics reported in parentheses are based on robust standard errors adjusted for heteroskedasticity and clustered at both the firm and month level. Month fixed effects and intercept are not tabulated. $\bar{R}^2$ is adjusted R^2, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period is from July 1972 to December 2015.

Panel A: Monthly cross-sectional returns using Fama–MacBeth regression

Variable	full Sample		1972–1993		1994–2015	
	M1	M2	M3	M4	M5	M6
AIV	**0.149**	**0.176**	**0.101**	**0.153**	**0.196**	**0.198**
	(4.38)	**(4.61)**	**(2.22)**	**(2.83)**	**(3.94)**	**(3.68)**
β_{Mkt}	−0.092	0.061	−0.305	−0.083	0.116	0.201
	(−0.35)	(0.29)	(−0.97)	(−0.30)	(0.28)	(0.64)
Size	0.012	−0.041	−0.019	−0.051	0.042	−0.032
	(0.34)	(−1.43)	(−0.39)	(−1.21)	(0.86)	(−0.81)
BM	0.304	0.283	0.386	0.401	0.225	0.167
	(4.60)	(4.54)	(4.25)	(4.34)	(2.36)	(2.06)
IV_{AHXZ}		−1.609		−1.544		−1.672
		(−8.12)		(−6.10)		(−5.49)
Illiquidity		0.015		0.015		0.015
		(4.17)		(2.42)		(3.88)
R_{-1}		−5.436		−7.816		−3.110
		(−11.21)		(−11.07)		(−5.90)
$R_{[-3,-2]}$		0.263		0.075		0.446
		(1.03)		(0.22)		(1.17)
$R_{[-6,-4]}$		0.613		0.781		0.449
		(2.43)		(2.23)		(1.24)
$R_{[-12,-7]}$		0.913		1.421		0.417
		(5.38)		(6.19)		(1.78)
Intercept	0.828	1.199	1.176	1.335	0.489	1.066
	(2.96)	(4.36)	(3.44)	(4.31)	(1.12)	(2.36)
$\bar{R}^2$	3.6%	6.4%	3.9%	7.0%	3.2%	5.9%
Firms	2,965	2,772	2,480	2,195	3,439	3,337
Observations	1,547,696	1,447,235	639,776	566,278	907,920	880,957

Panel B: Long-term cumulative cross-sectional returns using panel regression

Variable	$R_{t,t+1}/2$ M1	$R_{t,t+3}/3$ M2	$R_{t,t+6}/6$ M3	$R_{t,t+9}/9$ M4	$R_{t,t+12}/12$ M5	$R_{t,t+18}/18$ M6	$R_{t,t+24}/24$ M7
AIV	**0.154**	**0.135**	**0.104**	**0.100**	**0.091**	**0.086**	**0.083**
	(3.19)	**(3.15)**	**(3.08)**	**(3.29)**	**(3.27)**	**(3.57)**	**(3.94)**
β_{Mkt}	0.080	0.070	0.067	0.045	0.051	0.068	0.072
	(0.45)	(0.47)	(0.63)	(0.52)	(0.68)	(1.13)	(1.42)
Size	0.019	0.020	0.014	0.011	0.013	0.017	0.017
	(0.71)	(0.94)	(0.93)	(0.88)	(1.17)	(1.93)	(2.12)
BM	0.334	0.321	0.304	0.289	0.273	0.260	0.234
	(5.84)	(6.77)	(8.43)	(9.90)	(10.86)	(12.10)	(12.28)
IV_{AHXZ}	−0.418	−0.373	−0.334	−0.302	−0.300	−0.249	−0.275
	(−0.99)	(−1.25)	(−1.94)	(−2.17)	(-2.60)	(-2.93)	(−4.27)
Illiquidity	0.005	0.005	0.004	0.003	0.002	0.001	0.001
	(2.29)	(2.72)	(3.21)	(2.91)	(2.50)	(1.67)	(1.44)
R_{-1}	−2.114	−1.165	−0.362	−0.039	0.154	−0.057	−0.012
	(−2.86)	(−2.12)	(−1.46)	(−0.18)	(0.87)	(−0.44)	(−0.12)
$R_{[-3,-2]}$	0.365	0.296	0.501	0.389	0.332	0.060	0.040
	(0.73)	(1.01)	(2.79)	(2.16)	(2.24)	(0.57)	(0.49)
$R_{[-6,-4]}$	0.596	0.682	0.456	0.392	0.132	0.022	−0.068
	(1.90)	(2.81)	(3.05)	(2.72)	−(1.20)	(0.27)	(−1.01)

(*continued on next page*)

Table 7
(*continued*)

Panel B: Long-term cumulative cross-sectional returns using panel regression							
Variable	$R_{t,t+1}/2$ M1	$R_{t,t+3}/3$ M2	$R_{t,t+6}/6$ M3	$R_{t,t+9}/9$ M4	$R_{t,t+12}/12$ M5	$R_{t,t+18}/18$ M6	$R_{t,t+24}/24$ M7
$R_{[-12,-7]}$	0.430	0.280	0.009	−0.172	-0.214	-0.172	−0.208
	(1.76)	(1.19)	(0.07)	(−1.96)	(-2.72)	(-3.16)	(−4.05)
$\bar{R}^2$	19.3%	19.8%	18.9%	17.2%	16.0%	14.7%	12.8%
Firms	2,772	2772	2772	2772	2,772	2,772	2772
Observations	1,447,235	1,447,235	1,447,235	1,447,235	1,447,235	1,447,235	1,447,235

significance of *DAIV* disappears if *AIV* is included in M3–M4. This finding suggests that the significant and positive relation between *AIV* and expected return is not step-wise but continuous. We further separate the sample to two parts, $AIV < 0$ and $AIV > 0$. We conduct the Fama–Macbeth regressions separately for the two samples. The result in M5–M8 of Table IA.17 shows that the slope of *AIV* is significantly positive for the $AIV < 0$ subsample and marginally significant for the $AIV > 0$ subsample. This result indicates a nonlinear relation between *AIV* and expected returns, although the nonlinearity is not a step function. Overall, the results suggest that the positive relation between *AIV* and expected returns is not only driven by the sign of *AIV* but also the magnitude of *AIV*.

Other robustness: finally, to avoid the bid-ask bounce and lagged reaction effects found in Jegadeesh and Titman (1993), we skip one month to test the relation between *AIV* and future stock returns. M1 of Table IA.18 skip one month between *AIV* and $R_{i,t+1}$, and we find that *AIV* remains significantly priced. Theoretically, idiosyncratic risk can also be measured by the market model. Therefore, we show the results for an alternative measure of *AIV* that is calculated based on the market model instead of the FF-3 model in M2. In M3, we construct an alternative measure of *AIV* that is calculated based on earnings-announcement dates without adjusting for the time of earnings announcements. Raw *AIV* is calculated without taking the logarithm transformation of idiosyncratic volatility in M4. In M5, we estimate a new version of *AIV* that is adjusted for the nonzero return during the estimation period.[15] In M6, we use a restricted sample with nonmissing information on insider trading, short selling, or institutional trading. We remove a stock-month observation if the stock is not covered in all three databases in the prior two years. The restricted sample has shorter coverage from 1996 to 2015 and has much less sample included. The restricted sample is larger in *Size*, has lower *AIV* and book-to-market ratio, and has higher analyst coverage. The sample is more liquid measured by past turnover or Amihud's price impact.

[15] Specifically, we define IV_{PEA} and IV_{NEA} as follows

$$IV_{PEA} = \ln\sqrt{\frac{252\times\sum_{j\in PEA}(\varepsilon_j-\bar{\varepsilon})^2}{n_{PEA}-1}}, \quad IV_{NEA} = \ln\sqrt{\frac{252\times\sum_{j\in NEA}(\varepsilon_j-\bar{\varepsilon})^2}{n_{NEA}-1}}. \tag{4}$$

4.4. Further evidence from corporate news events

To estimate *AIV*, we calculate the difference in idiosyncratic volatility between pre-earnings-announcement periods and non-earnings-announcement periods. Earnings announcements are selected in this study as the information-intensive event. However, other corporate events that carry valuable information are presumably useful in this regard as well. To verify whether *AIV* is sensitive to the incorporation of other corporate events, we obtain corporate news data from RavenPack News Analytics.

RavenPack is a leading global news database used by practitioners in quantitative and algorithmic trading and also by scholars in accounting and finance research (e.g., Kelley and Tetlock, 2013; Kolasinski et al., 2013; Shroff et al., 2014; Dai et al., 2015; Dang et al., 2015). RavenPack collects and analyzes real-time, firm-level business news from leading news providers (e.g., Dow Jones Newswire, The Wall Street Journal, and Barrons) and other major publishers and web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites.

News events are categorized by "earnings," "dividends," "M&As," "bankruptcy," "product services," and many others, with a total of more than 100 news categories. The sample period of RavenPack is from January 2001 to December 2015. RavenPack constructs the news sentiment score for each news article based on professional algorithms, which were developed and evaluated by effectively combining traditional language analysis, financial expert consensus, and market response methodologies. Specifically, the news sentiment score indicates whether or not, and to what extent, a news story may have a positive, neutral, or negative effect on stock prices. This score is assigned to all relevant firms listed in the news report. The sentiment score ranges from 0 to 100, with a value below (above) 50 indicating the negative (positive) sentiment of a given news. A score of 50 represents a neutral sentiment.

We construct AIV_{News} in the same way as *AIV* by treating news events as earnings announcements. The results for AIV_{News} are reported in Table 8. For the sake of comparison, M1 presents the baseline result using *AIV* with the same sample period as AIV_{News}. In M2 (M3), we focus on significant news events and calculate AIV_{News} by including news articles with $ESS < 40$ or $ESS > 60$ ($ESS < 45$ or $ESS > 55$). In M4, all news events are used in estimating

Table 8
AIV with corporate news events.
This table shows Fama–MacBeth cross-sectional regression results for the following model.

$$R_{i,t+1} = a + b_1 AIV_{News,it} + b_2 \text{Control}_{it} + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the monthly stock excess return of firm i at time $t+1$, and AIV_{News} is abnormal idiosyncratic volatility estimated using firm-specific news events. The control variables are as follows. β_{Mkt} is market beta, *Size* is market capitalization, *BM* is book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is past one-month stock return, $R_{[-3,-2]}$ is past two-month stock returns, $R_{[-6,-4]}$ is past three-month stock returns, and $R_{[-12,-7]}$ is past six-month stock returns. In M1, the baseline result using *AIV* with sample period similar to those of AIV_{News} is presented. In M2, news that have negative and positive event sentiment with *ESS* score smaller than 40 or greater than 60 are used in estimating pre-news idiosyncratic volatility part of AIV_{News}. In M3, news that have negative and positive event sentiment with *ESS* score smaller than 45 or greater than 55 are used in estimating pre-news idiosyncratic volatility part of AIV_{News}. In M4, all news events are used in estimating pre-news idiosyncratic volatility part of AIV_{News}. All news events are used in estimating non-news idiosyncratic volatility part of AIV_{News}. In all cases, earning announcements is used in estimating pre-news and non-news idiosyncratic volatility part of AIV_{News}. The *t*-statistics reported in parentheses are based on Newey–West standard errors. The table presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period is from January 2001 to December 2015.

Variable	Baseline	Negative and positive news		All news
		$ESS < 40$ or $ESS > 60$	$ESS < 45$ or $ESS > 55$	
	M1	M2	M3	M4
AIV_{News}	**0.160**	**0.162**	**0.218**	**0.199**
	(2.92)	**(2.43)**	**(3.45)**	**(3.21)**
β_{Mkt}	0.049	0.064	0.062	0.063
	(0.12)	(0.16)	(0.16)	(0.16)
Size	−0.091	−0.091	−0.092	−0.092
	(−2.25)	(−2.18)	(−2.20)	(−2.21)
BM	0.145	0.157	0.157	0.157
	(1.79)	(1.94)	(1.94)	(1.94)
IV_{AHXZ}	−1.889	−1.943	−1.945	−1.947
	(−5.72)	(−5.90)	(−5.90)	(−5.91)
Illiquidity	0.009	0.009	0.009	0.009
	(2.09)	(2.22)	(2.23)	(2.22)
R_{-1}	−2.606	−2.622	−2.622	−2.620
	(−3.81)	(−3.82)	(−3.82)	(−3.81)
$R_{[-3,-2]}$	−0.003	0.023	0.024	0.023
	(−0.01)	(0.05)	(0.05)	(0.05)
$R_{[-6,-4]}$	−0.089	−0.104	−0.107	−0.107
	(−0.18)	(−0.21)	(−0.22)	(−0.22)
$R_{[-12,-7]}$	0.173	0.148	0.148	0.149
	(0.55)	(0.47)	(0.47)	(0.48)
Intercept	1.647	1.645	1.650	1.650
	(2.97)	(2.94)	(2.95)	(2.95)
$\bar{R}^2$	0.058	0.058	0.058	0.058
Firms	3126	3002	3002	3002
Observations	562,712	540,292	540,307	540,310

AIV_{News}. We note that the distributions of various AIV_{News}s have higher means than *AIV*, with a higher percentage of positive observations.

The results show that AIV_{News} also significantly and positively predicts future stock returns. The magnitudes of the slope coefficients in the three regressions appear similar. The statistical significance, however, increases with the value of $|ESS - 50|$ (i.e., the value relevance of the news). The results confirm that our idea of using abnormal idiosyncratic volatility to construct a price-based information risk measure applies to a broad spectrum of corporate events as well.

5. Alternative explanations

Our *AIV* measure is motivated as a price-based measure of information risk, and it is found to be positively related to future stock returns. However, there might be alternative explanations of the result. In this section, we examine several alternative explanations and perform tests to ensure that the pricing of *AIV* is further robust to various specifications.

5.1. The post-earnings-announcement drift

A well-known phenomenon of the post-earnings-announcement drift has been documented in the literature. Because our *AIV* measure is based on price variations surrounding earnings announcements, a natural question is whether the *AIV* effect on future stock returns is driven by the post-earnings-announcement drift. In Section 3, we show that *AIV* is positively associated with the product of earnings surprise, *SUE*, and pre-announcement stock price run-ups, *RunUp*. Because the post-earnings announcement drift is a continuation of *SUE* and *RunUp*, we use the two variables as proxies for the expected post-earnings announcement drift. In particular, we examine whether the effect of *AIV* on expected returns is subsumed by either *SUE* or *RunUp*.

Table 9
AIV and the post-earnings announcement drift.

This table provides Fama–MacBeth cross-sectional regressions of future one-month return, $R_{i,t+1}$ on on AIV_{it}, pre-announcement return run-up (*RunUp*), earnings surprises (*SUE*), and *AIV* adjusted for the pre-announcement return run-up and surprise (AIV_{Adj}), along with other control variables.

$$R_{i,t+1} = a + b_1 AIV_{it} + b_2 PEAD_{it} + b_3 \text{Control}_{it} + \varepsilon_{i,t+1},$$

$$R_{i,t+1} = a + b_1 AIV_{adj,it} + \text{Control}_{it} + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the monthly stock excess return of firm *i* at time $t+1$, *AIV* is abnormal idiosyncratic volatility, $AIV_{adj} = AIV/|CAR(d1, d2)|$where $CAR(d1, d_2)$ is the cumulative abnormal return over the $(d+d1, d+d2)$ period, *d* refers to announcement day, and *d*1 and *d*2 are measured in days. *PEAD* is the expected post-earnings announcement drift, proxied by the pre-announcement return run-up, or *SUE* or their combination, The control variables are as follows. β_{Mkt} is market beta, *Size* is market capitalization, *BM* is book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is past one-month stock return, $R_{[-3,-2]}$ is past two-month stock returns, $R_{[-6,-4]}$ is past three-month stock returns, and $R_{[-12,-7]}$ is past six-month stock returns. The *t*-statistics reported in parentheses are based on Newey–West standard errors. The table presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period is from July 1972 to December 2015.

Variable	*RunUp* and *SUE* as controls			$\frac{AIV}{\lvert CAR(0,1)\rvert}$	$\frac{AIV}{\lvert CAR(-1,1)\rvert}$	$\frac{AIV}{\lvert CAR(0,5)\rvert}$	$\frac{AIV}{\lvert CAR(-5,5)\rvert}$
	M1	M2	M3	M4	M5	M6	M7
AIV	**0.104**	**0.168**	**0.112**				
	(2.68)	**(3.65)**	**(2.21)**				
RunUp	3.488		3.110				
	(12.33)		(11.53)				
SUE		6.828	6.493				
		(8.35)	(8.56)				
AIV_{Adj}				**0.003**	**0.004**	**0.003**	**0.004**
				(3.90)	**(5.24)**	**(3.90)**	**(5.24)**
β_{Mkt}	0.049	0.075	0.055	0.059	0.059	0.059	0.059
	(0.24)	(0.36)	(0.26)	(0.29)	(0.29)	(0.29)	(0.29)
Size	−0.039	−0.046	−0.045	−0.041	−0.042	−0.041	−0.042
	(−1.34)	(−1.60)	(−1.55)	(−1.42)	(−1.44)	(−1.42)	(−1.44)
BM	0.285	0.276	0.276	0.284	0.284	0.284	0.284
	(4.57)	(4.39)	(4.41)	(4.55)	(4.55)	(4.55)	(4.55)
IV_{AHXZ}	−1.607	−1.448	−1.449	−1.605	−1.605	−1.605	−1.605
	(−8.14)	(−7.26)	(−7.26)	(−8.10)	(−8.11)	(−8.10)	(−8.11)
Illiquidity	0.014	0.014	0.013	0.015	0.015	0.015	0.015
	(4.01)	(3.48)	(3.41)	(4.16)	(4.13)	(4.16)	(4.13)
R_{-1}	−5.694	−5.753	−5.949	−5.431	−5.428	−5.431	−5.428
	(−11.59)	(−11.47)	(−11.84)	(−11.19)	(−11.19)	(−11.19)	(v11.19)
$R_{[-3,-2]}$	−0.009	0.019	−0.204	0.262	0.261	0.262	0.261
	(−0.03)	(0.07)	(−0.77)	(1.03)	(1.03)	(1.03)	(1.03)
$R_{[-6,-4]}$	0.548	0.380	0.333	0.610	0.610	0.610	0.610
	(2.17)	(1.51)	(1.32)	(2.42)	(2.42)	(2.42)	(2.42)
$R_{[-12,-7]}$	0.897	0.743	0.736	0.913	0.912	0.913	0.912
	(5.31)	(4.55)	(4.53)	(5.38)	(5.37)	(5.38)	(5.37)
Intercept	1.207	1.173	1.200	1.202	1.206	1.202	1.206
	(4.40)	(4.15)	(4.30)	(4.37)	(4.40)	(4.37)	(4.40)
$\bar{R}^2$	6.5%	6.7%	6.8%	6.4%	6.4%	6.4%	6.4%
Firms	2772	2700	2700	2772	2772	2772	2772
Observations	1,446,837	1,406,623	1,406,527	1,446,734	1,446,734	1,446,734	1,446,734

The results of Table 9 show that both the coefficients of *RunUp* and *SUE* are significantly positive in predicting future returns. Yet, the coefficient of *AIV*, though slightly weakened, remains significantly positive. This finding suggests that the positive relation between *AIV* and future stock returns is not driven by the post-earnings-announcement drift.

In addition to controlling *RunUp* and *SUE*, we also scale *AIV* by the absolute value of the cumulative abnormal return as $AIV_{Adj} = AIV/|CAR(d1, d2)|$, where *CAR*(*d*1, *d*2) is the cumulative abnormal return over the (*d*1, *d*2) (e.g., (0,1), (−1,1), (0,5), and (−5, 5)) period including the earnings announcement day. The absolute value of the cumulative abnormal return measures the magnitude of the post-earnings announcement drift up to day *d*2. The rationale behind this construction is that, if *AIV* is positively correlated with the post-earnings announcement drift, AIV_{Adj} should be less of concern because the effect of the post-earnings announcement drift is cancelled out between the numerator and the denominator.

Columns M4 to M7 in Table 9 indeed show that AIV_{Adj} is positively correlated with future stock returns. While relative to the baseline regression the coefficient becomes smaller due to the scaling of AIV_{Adj}, the significance remains strong. Therefore, the result tends not to support the possibility that the pricing of *AIV* is driven by the post-earnings announcement drift.

5.2. The idiosyncratic volatility anomaly

The positive relation between *AIV* and future stock returns is robust after controlling for many firm characteristics, including the previous month's idiosyncratic volatility, IV_{AHXZ}, used by AHXZ, as shown in Tables 6–9. Because *AIV* is the difference in the log of idiosyncratic volatility (of the past year) between pre- and non-earnings-announcement periods, the concern that the *AIV* effect on future returns might reflect the IV_{AHXZ} anomaly remains valid. After all, the idiosyncratic volatility in the non-earnings-announcement period of the past year is cross-sectionally and positively correlated with idiosyncratic volatility in the past month, and *AIV* is significantly and negatively associated with IV_{AHXZ}, as shown in Tables 2–4, although the goodness-of-fit is poor together with other explanatory variables. To quell such concerns, we provide additional evidence in Table 10, which shows that the *AIV* effect can be distinguished from the IV_{AHXZ} anomaly.

Panel A of Table 10 reports the average Fama–French–Carhart risk-adjusted future returns, R_{Adj}, on five-by-five portfolios sorted first by IV_{AHXZ} and then by *AIV*. The results show that in each of the IV_{AHXZ} quintiles, average future returns increase with *AIV*, although not monotonically. The difference in average R_{Adj} between the high and low *AIV* portfolios is significantly positive for three out of five IV_{AHXZ} quintiles.

Panel B of Table 10 reports the average Fama–French–Carhart risk-adjusted future returns, R_{Adj}, on five-by-five portfolios sorted first by IV_{NEA} and then by IV_{PEA}. The average future returns increase with IV_{PEA} in all but the highest IV_{NEA} quintiles and again not monotonically. The difference in average R_{Adj} between the high and low *AIV* portfolios is positive for the second and third IV_{NEA} quintiles. The results provide preliminary evidence that the pricing of *AIV* is not driven by the IV_{AHXZ} anomaly, and, to a certain extent, that IV_{PEA} contributes to the pricing of *AIV*.

Panel C of Table 10 reports Fama–MacBeth regressions of future returns on IV_{PEA} and IV_{NEA} separately with other control variables, including IV_{AHXZ}. The results in M1 and M2 show that neither IV_{PEA} nor IV_{NEA} has a significant effect on future returns when used alone. When IV_{PEA} and IV_{NEA} are both used in the regression M3, the signs are consistent with that of *AIV*. In other words, the future stock return is expected to be high if IV_{PEA} is high when IV_{NEA} is controlled. This is exactly the reason for how we define *AIV*. These results show that the difference between IV_{PEA} and IV_{NEA} matters most in predicting future stock returns.

To further mitigate the impact of IV_{AHXZ} on our *AIV*, we construct AIV_{Orth} as the residual of *AIV* regressed on IV_{AHXZ} and IV_{AHXZ}'s top quintile dummy, which is obtained when we sort stocks by IV_{AHXZ}. The regression in M4 using AIV_{Orth} clearly shows that, net of the IV_{AHXZ} effect, *AIV* has its own effect on future returns.

Overall, the results from Table 10 indicate that the *AIV* effect on future stock returns is distinct from the IV_{AHXZ} anomaly.

5.3. Quantity-based information risk measures

Despite the assumption that information risk is multifaceted, *AIV*, the price-based information risk measure, may capture the same aspect of information risk as quantity-based measures. To address this concern, we need to show that *AIV* is still positively related to future stock returns after controlling for conventional quantity-based information risk measures. For example, Easley et al. (2002) show that PIN_{EHO} reflects information risk implied from order flows and systematically priced by investors, but we do not include PIN_{EHO} in our main analysis. To exclude this alternative interpretation, Table 11 includes PIN_{EHO} and the related variables, such as PIN_{DY} and *PSOS*, as additional control variables.

The results show that *AIV* is significantly priced across all the models from M1 to M4 after controlling for alternative measures of information risk.[16] Moreover, the *t*-statistics of *AIV* are all significant in these models. Consistent with Easley et al. (2002) and Duarte and Young (2009), PIN_{EHO} and PIN_{DY} are positively related to monthly excess stock returns in untabulated results with only β_{Mkt}, *Size*, and *BM* as controls. The coefficients of PIN_{EHO} and PIN_{DY} become insignificant in the full specification with the inclusion of IV_{AHXZ}, *Illiquidity*, R_{-1}, $R_{[-3,-2]}$, $R_{[-6,-4]}$, and $R_{[-12,-7]}$.

Furthermore, we construct quantity-based information risk measures using abnormal stock trading volume and turnover prior to earnings announcements and compare them with *AIV*. Specifically, abnormal trading volume (*AVol*) and abnormal turnover (*ATurn*) are defined in a similar way in which we construct *AIV*.[17] M5–M6 reports Fama–MacBeth regressions of future returns on *AVol* and *ATurn*. The results show that *AVol* has no prediction power on future stock returns, and *ATurn* is marginally associated with future returns. Importantly, *AIV* survives in the pricing competition with these quantity-based information risk measures.

Finally, we calculate abnormal effective spread (*ASprd*) as the difference in daily average proportional effective spread between pre- and non-earnings-announcement periods. M7 reports the Fama–MacBeth regression of future returns on *ASprd*. The coefficient of *ASprd* is not significant, while the pricing of *AIV* remains robust.

5.4. Additional risk and mispricing measures

As a final checkup, we examine whether the pricing of *AIV* is robust to the control of additional variables, which are used in the literature to measure either risk, related to stock liquidity, default risk, and information environment or mispricing. Specifically, the variables we choose include the past one-year stock turnover (*Turnover*), short interest ratio (*Short*), missing short interest indicator ($Missing_{Short}$), the number of analysts following (*Analyst*), analyst forecast dispersion (*FDisp*), analyst forecast errors (*FErr*), missing analyst indicator ($Missing_{Analyst}$), corporate investment (*CapEx*), gross profitability (*GPA*), Ohlson (1980) distress score (*Oscore*), accruals (*Accruals*), and earnings quality (*AQ*).

Table 12 reports the results by including the above control variables sequentially. First, we show that *AIV* remains positively and significantly associated with future stock returns. This finding suggests that *AIV* as a return predictor

[16] PIN_{EHO} is available from 1984–1998, and PIN_{DY} and *PSOS* are available from 1984 to 2005. Also, PIN_{EHO}, PIN_{DY}, and *PSOS* are only available for NYSE stocks.

[17] *AVol* and *ATurn* are derived from CRSP and are available from 1972 to 2015.

Table 10
The idiosyncratic volatility anomaly.

Panel A of this table shows R_{Adj} of double-sorted portfolios sorted monthly first by prior-month AHXZ's idiosyncratic volatility (IV_{AHXZ}) and then by prior-month *AIV*. Panel B shows R_{Adj} of double-sorted portfolios sorted monthly first by prior-month non-earnings-announcement idiosyncratic volatility (IV_{NEA}) and then by prior-month pre-earnings-announcement idiosyncratic volatility (IV_{PEA}). The differences in R_{Adj} between the high and the low portfolios are also reported along with *t*-statistics in parentheses. The *t*-statistics reported in parentheses are based on Newey–West standard errors. Panel C shows Fama–MacBeth cross-sectional regression results for the following model.

$$R_{i,t+1} = a + b_1 IV_{PEA,it} + b_2 IV_{NEA,it} + b_3 \text{Control}_{it} + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the monthly stock excess return of firm *i* at time $t+1$, IV_{PEA} is pre-earnings-announcement idiosyncratic volatility, and IV_{NEA} is non-earnings-announcement idiosyncratic volatility. The control variables are as follows. β_{Mkt} is market beta, *Size* is market capitalization, *BM* is book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is past one-month stock return, $R_{[-3,-2]}$ is past two-month stock returns, $R_{[-6,-4]}$ is past three-month stock returns, and $R_{[-12,-7]}$ is past six-month stock returns. The *t*-statistics reported in parentheses are based on Newey–West standard errors. M4 examines the effect of *AIV* that is orthogonal to the IV_{AHXZ} (AIV_{Orth}) on cross-sectional expected stock returns. The table presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period is from July 1972 to December 2015.

Panel A: Double-sorted portfolios, sort by IV_{AHXZ}, then *AIV*

Portfolios	Low IV_{AHXZ}	2	3	4	High IV_{AHXZ}
Low *AIV*	0.069	0.005	0.106	−0.107	−0.869
2	0.113	0.184	0.102	0.108	−0.576
3	0.068	0.193	0.226	0.184	−0.585
4	0.075	0.214	0.268	−0.039	−0.682
High *AIV*	0.147	0.174	0.256	0.121	−0.531
High-Low	**0.077**	**0.169*****	**0.150****	**0.228****	**0.338*****
	(1.51)	**(2.80)**	**(2.10)**	**(2.25)**	**(3.52)**

Panel B: Double-sorted portfolios, sort by IV_{NEA}, then IV_{PEA}

Portfolios	Low IV_{NEA}	2	3	4	High IV_{NEA}
Low IV_{PEA}	0.135	0.074	−0.050	−0.097	−0.401
2	0.209	0.173	0.057	0.114	−0.389
3	0.140	0.098	0.131	−0.012	−0.433
4	0.157	0.118	0.140	−0.160	−0.573
High IV_{PEA}	0.161	0.169	0.135	−0.055	−0.622
High-Low	**0.026**	**0.095**	**0.185****	**0.042**	**-0.221**
	−0.36	**(1.64)**	**(2.22)**	**(0.43)**	**(−1.41)**

Panel C: Regression approach

Variable	M1	M2	M3	M4
PEA	**−0.008**		**0.126**	
	(−0.08)		**(2.69)**	
NEA		**−0.242**	**−0.344**	
		(−1.46)	**(−2.31)**	
AIV_{Orth}				**0.171**
				(4.51)
β_{Mkt}	0.064	0.147	0.138	0.061
	(0.35)	(0.89)	(0.84)	(0.29)
Size	−0.040	−0.059	−0.058	−0.041
	(−1.38)	(−1.97)	(−1.93)	(−1.43)
BM	0.283	0.267	0.267	0.283
	(4.62)	(4.44)	(4.45)	(4.54)
IV_{AHXZ}	−1.530	−1.319	−1.340	−1.604
	(−9.98)	(−10.70)	(−10.99)	(−8.09)
Illiquidity	0.015	0.017	0.017	0.015
	(4.12)	(4.64)	(4.61)	(4.17)
R_{-1}	−5.469	−5.533	−5.537	−5.436
	(−11.33)	(−11.53)	(−11.52)	(−11.21)
$R_{[-3,-2]}$	0.264	0.283	0.282	0.263
	(1.04)	(1.11)	(1.11)	(1.03)
$R_{[-6,-4]}$	0.647	0.703	0.706	0.613
	(2.63)	(2.91)	(2.93)	(2.43)
$R_{[-12,-7]}$	0.921	0.931	0.932	0.913
	(5.63)	(5.85)	(5.87)	(5.38)
Intercept	1.130	0.794	0.831	1.198
	(4.25)	(2.67)	(2.75)	(4.36)
$\bar{R}^2$	6.6%	6.8%	6.9%	6.4%
Firms	2772	2772	2772	2772
Observations	1,447,235	1,447,235	1,447,235	1,447,235

Table 11
Quantity-based information risk measures.
This table provides Fama–MacBeth cross-sectional regression results with quantity-based information risk variables that include Easley and O'Hara's PIN (PIN_{EHO}), Duarte and Young's PIN (PIN_{DY}), Duarte and Young's PSOS (*PSOS*), abnormal trading volume (*AVol*), abnormal turnover (*ATurn*), and abnormal effective spread (*ASpread*) over the following baseline model.

$$R_{i,t+1} = a + b_1 AIV_{it} + b_2 PIN_{it} + b_3 \mathrm{Control}_{it} + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the monthly stock excess return of firm i at time $t+1$, and *AIV* is abnormal idiosyncratic volatility. The control variables are as follows. β_{Mkt} is market beta, *Size* is market capitalization, *BM* is book-to-market ratio, IV_{AHXZ} is AHXZ's idiosyncratic volatility, *Illiquidity* is Amihud (2002) illiquidity, R_{-1} is past one-month stock return, $R_{[-3,-2]}$ is past two-month stock returns, $R_{[-6,-4]}$ is past three-month stock returns, and $R_{[-12,-7]}$ is past six-month stock returns. The *t*-statistics reported in parentheses are based on Newey–West standard errors. The table presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period varies according to the availability of quantity-based information risk variables.

Variable	M1	M2	M3	M4	M5	M6	M7
AIV	**0.189**	**0.249**	**0.253**	**0.251**	**0.184**	**0.133**	**0.196**
	(2.96)	**(4.49)**	**(4.54)**	**(4.52)**	**(4.64)**	**(3.34)**	**(3.71)**
PIN_{EHO}	**0.103**						
	(0.21)						
PIN_{DY}		**0.649**		**0.683**			
		(1.77)		**(1.92)**			
PSOS			**−0.039**	**−0.054**			
			(−0.16)	**(−0.23)**			
AVol					**−0.007**		
					−(1.19)		
ATurn						**0.100**	
						(1.80)	
ASpread							**0.003**
							(0.02)
β_{Mkt}	−0.234	−0.026	−0.024	−0.020	0.062	0.051	−0.025
	(−0.79)	(−0.10)	(−0.09)	(−0.08)	(0.30)	(0.25)	(−0.11)
Size	0.039	0.029	0.014	0.031	−0.040	−0.042	−0.003
	(0.99)	(0.75)	(0.38)	(0.80)	−(1.38)	(−1.46)	(−0.11)
BM	0.233	0.223	0.220	0.220	0.283	0.285	0.190
	(2.90)	(3.07)	(3.07)	(3.07)	(4.56)	(4.58)	(3.32)
IV_{AHXZ}	−1.818	−1.407	−1.458	−1.396	−1.607	−1.605	−1.767
	(−5.14)	(−4.33)	(−4.41)	(−4.29)	(−8.13)	(−8.10)	(−6.46)
Illiquidity	0.019	0.019	0.021	0.019	0.015	0.015	0.043
	(1.96)	(2.02)	(2.14)	(1.94)	(4.23)	(4.18)	(3.52)
R_{-1}	−4.113	−3.755	−3.773	−3.784	−5.434	−5.439	−3.035
	(−6.67)	(−7.22)	(−7.26)	(−7.27)	(−11.20)	(−11.21)	(−6.35)
$R_{[-3,-2]}$	0.350	0.389	0.374	0.369	0.261	0.261	0.338
	(0.89)	(1.13)	(1.08)	(1.07)	(1.03)	(1.03)	(1.07)
$R_{[-6,-4]}$	0.640	0.798	0.802	0.794	0.608	0.606	0.274
	(1.52)	(2.48)	(2.50)	(2.47)	(2.41)	(2.41)	(0.80)
$R_{[-12,-7]}$	1.227	0.895	0.914	0.901	0.914	0.911	0.670
	(6.02)	(4.27)	(4.37)	(4.34)	(5.39)	(5.38)	(3.18)
Intercept	0.962	0.699	0.933	0.688	1.190	1.212	1.056
	(2.56)	(1.81)	(2.26)	(1.61)	(4.38)	(4.43)	(3.45)
$\bar{R}^2$	6.0%	6.5%	6.5%	6.5%	6.5%	6.5%	0.065
Firms	1470	1460	1460	1460	2772	2772	1477
Observations	264,566	385,532	385,532	385,532	1,447,223	1,447,223	565,778

is not a direct proxy for any of these control variables. Second, most of these additional control variables have coefficients that maintain the same sign as in the original works. For example, Brennan et al. (2012) and Chordia et al. (2001) find that *Turnover* is negatively associated with expected returns. Akbas et al. (2017) and Desai et al. (2002) show that prior-month short interest ratio is negatively associated with expected returns. Fama and French (2006) find that after controlling book-to-market ratio (*BM*), higher rates of investment (*CapEx*) imply lower expected returns, and more profitable (*GPA*) firms have higher expected returns. Dichev (1998) finds that firms with high bankruptcy risk proxied by *Oscore* earn lower returns. Sloan (1996) shows that the current level of *Accruals* is negatively related to expected returns. Core et al. (2008) find that the *AQ* is negatively, but insignificantly, related to expected return.[18] In the unreported result, we include prior-month average bid-ask spread or abnormal bid-ask spread as a control variable in the asset pricing test. The return predictability of *AIV* is not affected by the inclusion of bid-ask spread. These findings suggest that *AIV* contains its own unique feature when horse racing with other information risk measures.

[18] Francis et al. (2005) propose that the AQ factor constructed from the AQ mimicking portfolio is a priced factor, but Core et al. (2008) find no evidence that AQ is a priced risk factor.

Table 12
AIV with additional risk or mispricing variables.
This table repeats Fama-MacBeth regression in M2 of Table 6 with additional variables in the following model.

$$R_{i,t+1} = a + b_1 AIV_{it} + b_2 Turnover_{it} + b_3 Short_{it} + b_4 Missing_{Short,it} + b_5 Analyst_{it} + b_6 FDisp_{it} + b_7 FErr_{it} + b_8 Missing_{Analyst,it} + b_9 CapEx_{it} + b_{10} GPA_{it}$$
$$+ b_{11} Oscore_{it} + b_{12} Accruals_{it} + b_{13} AQ_{it} + b_{14} \mathrm{Control}_{it} + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the monthly stock excess return of firm i at time $t+1$, *AIV* is abnormal idiosyncratic volatility, *Turnover* is past one year stock turnover, *Short* is past one month short interest ratio, $Missing_{Short}$ is missing short interest ratio indicator, *Analyst* is number of analysts following, *FDisp* is analyst dispersion, *FErr* is analyst forecast errors, $Missing_{Analyst}$ is missing analyst indicator, *CapEx* is investment, *GPA* is gross profitability, *Oscore* is Ohlson (1980) distress score, *Accruals* is accruals, and *AQ* is earnings quality. All other control variables are defined in Appendix. The t-statistics reported in parentheses are based on Newey–West standard errors. The table presents time-series averages of the estimated slope coefficients from the above regression. $\bar{R}^2$ is the time-series average of adjusted R^2 in the cross-sectional regression, and Firms denotes the time-series average of the number of firms in the cross-sectional regression. The sample period is from May 1998 to December 2015 for M2, from January 1983 to December 2015 for M3, and from July 1972 to December 2015 for all other models.

Variable	M1	M2	M3	M4	M5	M6
AIV	**0.165**	**0.154**	**0.179**	**0.138**	**0.170**	**0.120**
	(4.41)	**(2.65)**	**(4.18)**	**(3.55)**	**(3.69)**	**(2.61)**
Turnover	−0.273					−0.213
	(−3.06)					(−1.84)
Short		−4.359				−1.537
		(−3.84)				(−3.45)
$Missing_{Short}$		0.106				−0.024
		(0.23)				−(0.14)
Analyst			0.190			0.163
			(3.82)			(4.25)
FDisp			0.030			0.022
			(0.79)			(0.74)
FErr			−0.068			−0.029
			(−2.99)			(−1.69)
$Missing_{Analyst}$			−0.075			−0.031
			(v0.97)			(−0.51)
CapEx				−0.614		−0.428
				(−7.34)		(−5.05)
GPA				0.311		0.322
				(2.27)		(2.37)
Oscore				−0.048		−0.034
				(−3.31)		(−2.42)
Accruals					−2.576	−2.732
					(−7.56)	(−7.69)
AQ					−3.455	−2.995
					(−3.18)	(v2.83)
β_{Mkt}	0.206	0.225	−0.048	0.038	0.042	0.106
	(1.10)	(0.62)	(−0.21)	(0.18)	(0.21)	(0.61)
Size	−0.018	−0.017	−0.112	−0.051	−0.073	−0.119
	(−0.64)	(−0.37)	(−3.11)	(−1.82)	(−2.58)	(−3.87)
BM	0.257	0.102	0.212	0.242	0.207	0.160
	(4.32)	(1.14)	(3.29)	(3.77)	(3.27)	(2.61)
IV_{AHXZ}	−1.387	−1.680	−1.722	−1.461	−1.472	−1.182
	(−7.78)	(−4.89)	(−7.82)	(−7.86)	(−7.61)	(−7.24)
Illiquidity	0.011	0.012	0.014	0.015	0.016	0.012
	(3.13)	(2.75)	(4.53)	(4.08)	(4.42)	(3.50)
R_{-1}	−5.515	−2.684	−3.835	−5.549	−5.480	−5.723
	(−11.46	(−4.36)	(−8.94)	(−11.33	(−11.57	(−12.13
$R_{[-3,-2]}$	0.312	0.296	0.388	0.171	0.214	0.199
	(1.26)	(0.66)	(1.37)	(0.68)	(0.78)	(0.75)
$R_{[-6,-4]}$	0.687	0.254	0.510	0.576	0.680	0.710
	(2.75)	(0.59)	(1.87)	(2.34)	(2.59)	(2.81)
$R_{[-12,-7]}$	0.988	0.303	0.724	0.774	0.832	0.841
	(5.90)	(1.07)	(4.21)	(4.67)	(4.89)	(5.25)
Intercept	0.993	0.840	1.438	1.142	1.509	1.353
	(3.99)	(1.44)	(4.34)	(4.22)	(5.43)	(5.06)
$\bar{R}^2$	6.9%	6.7%	5.8%	6.8%	6.6%	7.7%
Firms	2772	3264	3156	2466	2417	2270
Observations	1,447,212	692,051	1,230,802	1,287,497	1,261,774	1,185,161

6. Conclusion

In this paper, we examine whether the risk due to information asymmetry is compensated for in expected stock returns. We note that the theoretical models in the literature result in opposite predictions based on their different assumptions and that the previous empirical studies encounter issues related to robustness and computational difficulties. We also take a stand that information risk is multifaceted and cannot be represented with a single measure.

We develop a price-based information risk measure based on a firm's idiosyncratic volatility differential between pre- and non-earnings-announcement periods. The price-based information risk measure we construct, *AIV*, has variations both across firms and over time. *AIV* is related to not only informed return run-ups but also insider trading, short selling, and institutional trading activities. The higher *AIV* firm-years are associated with higher informed return run-ups and abnormal insider trading, short selling, and institutional trading activities prior to earnings announcements. Moreover, *AIV* is unrelated to alternative information risk measures used in the literature.

The information risk captured by *AIV* is positively associated with expected stock returns. Furthermore, the *AIV* effect is distinct from quantity-based information risk measures and not a reflection of the idiosyncratic volatility anomaly, the post-earnings-announcement drift, and alternative risk and mispricing factors.

Overall, these results support the general notion that information risk is priced.

Appendix Variable definition

Variable	Acronym	Description	Source
Panel A: Information risk measures			
Abnormal idiosyncratic volatility	*AIV*	$IV_{PEA} - IV_{NEA}$, difference in idiosyncratic volatility between pre-earnings-announcement and non-earnings-announcement periods	CRSP & Compustat
Pre-earnings-announcement idiosyncratic volatility	IV_{PEA}	Log of annualized standard deviation of daily residuals based on the Fama–French three-factor model in five days $[-5, -1]$ prior quarter and annual earnings announcements over the preceding one year	CRSP & Compustat
Non-earnings-announcement idiosyncratic volatility	IV_{NEA}	Log of annualized standard deviation of daily residuals based on the Fama–French three-factor model excluding days around earnings announcement $[-5,5]$ over the preceding one year	CRSP & Compustat
News events abnormal idiosyncratic volatility	AIV_{News}	Difference in idiosyncratic volatility between pre-news and non-news periods over the preceding one year where pre-news is five days $[-5, -1]$ prior news and earnings announcements, and non-news is days excluding days around news and earnings announcements $[-5,5]$	CRSP, Compustat, & RavenPack
Orthogonalized abnormal idiosyncratic volatility	AIV_{Orth}	Residual from running monthly cross-sectional regression of the following model, $AIV_{it} = a + b_1 IV_{AHXZ} + b_2 TopIV_{AHXZ} + \varepsilon_{it}$, where $TopIV_{AHXZ}$ is an indicator variable that takes a value of one if IV_{AHXZ} is on the top quartile cross-sectionally and zero otherwise	CRSP & Compustat
Panel B: Asset pricing test variables			
Monthly excess returns	*R*	Monthly stock returns in excess of risk-free rate (in percentage)	CRSP
Monthly risk-adjusted returns	R_{Adj}	Monthly risk-adjusted returns based on the Fama–French three-factor model	CRSP
Market beta	β_{Mkt}	Market beta of the stock with respect to the CRSP value-weighted index estimated following Fama and French (1992)	CRSP
Market capitalization	*Size*	Log of the market capitalization of firm in million dollars	CRSP
Book-to-market ratio	*BM*	Log of the book-to-market equity ratio	CRSP & Compustat
AHXZ's idiosyncratic volatility	IV_{AHXZ}	Annulized standard deviation of daily residuals based on the Fama–French three-factor model following AHXZ during previous month (in percentage)	CRSP
Amihud (2002) illiquidity	*Illiquidity*	Annual mean of the daily absolute stock returns divided by dollar trading volume following Amihud (2002); this estimate is multiplied by 10^6	CRSP
Past one-month stock return	R_{-1}	Stock returns in the past one month (in percentage)	CRSP
Past two-month stock returns	$R_{[-3,-2]}$	Cumulative stock returns over two months ending at the beginning of the previous month (in percentage)	CRSP
Past three-month stock returns	$R_{[-6,-4]}$	Cumulative stock returns over three months ending three months ago (in percentage)	CRSP
Past six-month stock returns	$R_{[-12,-7]}$	Cumulative stock returns over six months ending six months ago (in percentage)	CRSP
Panel C: Informed return run-ups and informed trading variables			
Earnings surprises	*SUE*	Unexpected earnings calculated as most recent announced earnings minus earnings one year before, scaled by stock price following rolling seasonal random walk model in Livnat and Mendenhall (2006)	Compustat
	SUESign	The sign of *SUE*	
Updated earnings surprise	SUE_{FC}	Unexpected earnings calculated as most recent announced earnings minus average earnings forecast made by analysts prior fiscal year end, scaled by stock price	Compustat & IBES
	$SUE_{FC}Sign$	The sign of SUE_{FC}	
Pre-announcement return run-up	*RunUp*	Cumulative abnormal return in five days prior earnings announcement [-5,-1], abnormal return is calculated as raw return minus market return	CRSP & Compustat

Variable	Acronym	Description	Source
	RunUpSign	The sign of *RunUp*	
Abnormal insider trading	*AIT*	Difference in insider trading between pre-earnings-announcement [-5,-1] and non-earnings-announcement periods (days excluding [-5,5]). Trading is measured as annualized daily proportion of shares traded.	Thomson Reuters Insider
Abnormal short selling	*ASS*	Difference in absolute change in open short interest between pre-earnings-announcement [-5,-1] and non-earnings-announcement periods (days excluding [-5,5]). Open short interest is measured as annualized daily proportion of shares in open short interest.	Markit Security Finance Analytics
Abnormal institutional trading	*AIN*	Difference in institutional trading between pre-earnings-announcement [-5,-1] and non-earnings-announcement periods (days excluding [-5,5]). Trading is measured as annualized daily proportion of shares traded	ANcerno
Abnormal net insider trading	AIT_{Net}	Similar to *AIT* with net insider trading. Net insider trading is measured as insider purchase minus insider sales of stocks.	Thomson Reuters Insider
Abnormal net short selling	ASS_{Net}	Similar to *ASS* with net short selling. Net short selling is measured as change in open short interest. The sign is adjusted such that an increase in open short interest takes negative sign while a decrease takes positive sign.	Markit Security Finance Analytics
Abnormal net institutional trading	AIN_{Net}	Similar to *AIN* with net institution trading. Net institution trading is measured as institution purchase minus institution sales of stocks.	ANcerno
Panel D: Information environment and other variables			
Accruals	*Accruals*	Total accruals defined as changes in current assets minus changes in current liabilities minus changes in cash plus changes in current debt in current liabilities scaled by total assets following Sloan (1996)	Compustat
Earnings quality	*AQ*	Standard deviation of prior five-year residual accruals obtained by regressing total accruals on past, current, and future cash flows, and revenue growth for each year and industry group scaled by average total assets, following Francis et al. (2005)	CRSP & Compustat
Number of analysts following	*Analyst*	Log of one plus the number of financial analysts following a firm	IBES
Analyst dispersion	*FDisp*	Standard deviation of analyst forecasts scaled by mean of analyst forecasts	IBES
Analyst forecast errors	*FErr*	Absolute value of the difference between announced earnings and mean of forecast earnings scaled by mean of analyst forecasts	IBES
Missing analyst indicator	$Missing_{Analyst}$	Indicator variable that takes value of one if the number of analyst following is less than two and zero otherwise	IBES
Past one year turnover	*Turnover*	Number of shares traded in the past twelve months scaled by the average number of shares outstanding	CRSP
Short interest ratio	*Short*	Number of shares being shorted in the previous month scaled by number of shares outstanding	Compustat
Missing *Short* indicator	$Missing_{Short}$	Indicator variable that takes value of one if the Short interest ratio is missing	Compustat
Investment	*CapEx*	Capital expenditure measured by annual change in total assets scaled by lagged total assets	Compustat
Gross profitability	*GPA*	Gross profit deflated by total assets following Novy-Marx (2013), gross profit is revenue minus cost of goods sold	Compustat
Distress score	*Oscore*	Bankruptcy score from a nine-factor linear combination of coefficient-weighted ratios following Ohlson (1980)	CRSP & Compustat
EHO's PIN	PIN_{EHO}	Probability of informed trading estimated following Easley et al. (2002)	Hvidkjaer's website
DY's PIN	PIN_{DY}	Probability of informed trading estimated following Duarte and Young (2009)	Duarte's website
DY's PSOS	*PSOS*	Probability of symmetric order-flow shocks estimated following Duarte and Young (2009)	Duarte's website
Abnormal trading volume	*AVol*	Difference in annualized daily average number of million shares traded between pre-earnings-announcement and non-earnings-announcement periods	CRSP & Compustat
Abnormal turnover	*ATurn*	Difference in annualized daily average shares turnover between pre-earnings-announcement and non-earnings-announcement periods; turnover is numbers of shares traded over total number of shares outstanding	CRSP & Compustat
Abnormal effective spread	*ASpread*	Difference in daily average proportional effective spread between pre-earnings-announcement [-5,-1] and non-earnings-announcement periods (days excluding [-5,5]). Proportional effective spread is measured as $2\|P_t - P_M\|/P_t$ where P_t is the transacted price, and P_M is the prevailing mid-quote.	TAQ

References

Aboody, D., Lev, B., 2000. Information asymmetry, r&d, and insider gains. J. Financ. 55, 2747–2766.

Akbas, F., Boehmer, E., Erturk, B., Sorescu, S., 2017. Short interest, returns, and unfavorable fundamental information. Financ. Manag. 46, 455–486.

Ali, A., Klasa, S., Li, O., 2008. Institutional stakeholdings and better-informed traders at earnings announcements. J. Account. Econ. 46, 47–61.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Financ. 61, 259–299.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further u.s. evidence. J. Financ. Econ. 91, 1–23.

Back, K., Crotty, K., Li, T., 2018. Identifying information asymmetry in securities markets. Rev. Financ. Stud. 31, 2277–2325.

Bali, T., Cakici, N., 2008. Idiosyncratic volatility and the cross-section of expected returns. J. Financ. Quant. Anal. 43, 29–58.

Bamber, L., Barron, O., Stevens, D., 2011. Trading volume around earnings announcements and other financial reports: theory, research design, empirical evidence, and directions for future research. Contemp. Account. Res. 28, 431–471.

Banerjee, A., Eckard, E.W., 2001. Why regulate insider trading? evidence from the first great merger wave (1897–1903). Am. Econ. Rev. 91, 1329–1349.

Beber, A., Pagano, M., 2013. Short-selling bans around the world: evidence from the 2007–09 crisis. J. Financ. 68, 343–381.

Beyer, A., Cohen, D., Lys, T., Walther, B., 2010. The financial reporting environment: review of the recent literature. J. Account. Econ. 50, 296–343.

Boehmer, E., Jones, C., Zhang, X., 2008. Which shorts are informed? J. Financ. 63, 491–527.

Brennan, M., Chordia, T., Subrahmanyam, A., Tong, Q., 2012. Sell-order liquidity and the cross-section of expected stock returns. J. Financ. Econ. 105, 523–541.

Brennan, M., Huh, S.W., Subrahmanyam, A., 2016. Asymmetric effects of informed trading on the cost of equity capital. Manag. Sci. 62, 2460–2480.

Bris, A., Goetzmann, W., Zhu, N., 2007. Efficiency and the bear: short sales and markets around the world. Journal of Finance 62, 1029–1079.

Brogaard, J., Hendershott, T., Riordan, R., 2016. Price discovery without trading: evidence from limit orders.

Campbell, J., Ramadorai, T., Schwartz, A., 2009. Caught on tape: institutional trading, stock returns, and earnings announcements. J. Financ. Econ. 92, 66–91.

Choi, J., Jin, L., Yan, H., 2016. Informed trading and the cost of capital.

Chordia, T., Subrahmanyam, A., Anshuman, V.R., 2001. Trading activity and expected stock returns. J. Financ. Econ. 59, 3–32.

Chung, K., Huh, S., 2016. The noninformation cost of trading and its relative importance in asset pricing. Rev. Asset Pric. Stud. 6, 261–302.

Cohen, L., Malloy, C.J., Pomorski, L., 2012. Decoding inside information. J. Financ. 67, 1009–1043.

Core, J.E., Guay, W.R., Verdi, R., 2008. Is accruals quality a priced risk factor? J. Account. Econ. 46, 2–22.

Dai, L., Parwada, J.T., Zhang, B., 2015. The governance effect of the media's news dissemination role: evidence from insider trading. J. Account. Res. 53, 331–366.

Dang, T., Moshirian, F., Zhang, B., 2015. Commonality in news around the world. J. Financ. Econ. 116, 82–110.

Desai, H., Ramesh, K., Thiagarajan, S.R., Balacahandran, B.V., 2002. An investigation of the informational role of short interest in the nasdaq market. J. Financ. 57, 2263–2287.

Dichev, I., 1998. Is the risk of bankruptcy a systematic risk? J. Financ. 53, 1131–1147.

Duarte, J., Hu, E., Young, L., 2017. What Does the PIN Model Identify as Private Information?.

Duarte, J., Young, L., 2009. Why is PIN priced? J. Financ. Econ. 91, 119–138.

Durnev, A., Morck, R., Yeung, B., 2004. Value-enhancing capital budgeting and firm-specific stock return variation. J. Financ. 59, 65–105.

Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns? J. Financ. 57, 2185–2221.

Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J., 1996. Liquidity, information, and infrequently traded stocks. J. Financ. 51, 1405–1436.

Easley, D., O'Hara, M., 2004. Information and the cost of capital. J. Financ. 59, 1553–1583.

Easley, D., Lopez de Prado, M.M., O'Hara, M., 2012. Flow toxicity and liquidity in a high-frequency world. Rev. Financ. Stud. 25, 1457–1493.

Fama, E., French, K., 1992. The cross-section of expected stock returns. J. Financ. 47, 427–465.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.

Fama, E., French, K., 2006. Profitability, investment and average returns. J. Financ. Econ. 82, 192–518.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636.

Fernandes, N., Ferrreira, M., 2008. Does international cross-listing improve the information environment? J. Financ. Econ. 88, 216–244.

Fernandes, N., Ferrreira, M., 2009. Insider trading laws and stock price informativeness. Rev. Financ. Stud. 22, 1845–1887.

Ferreira, M., Laux, P., 2007. Corporate governance, idiosyncratic risk, and information flow. J. Financ. 62, 951–989.

Foster, D., Viswanathan, S., 1993. Variations in trading volume, return volatility, and trading costs: evidence on recent price formation models. J. Financ. 48, 187–211.

Francis, J., LaFond, R., Olsson, P., Schipper, K., 2005. The market pricing of accruals quality. J. Account. Econ. 39, 295–327.

Garleanu, N., Pedersen, P., 2004. Adverse selection and the required return. Rev. Financ. Stud. 17, 643–665.

Glosten, L., Harris, L., 1988. Estimating the components of the bid-ask spread. J. Financ. Econ. 21, 123–142.

Hasbrouck, J., 1991. The summary informativeness of stock trades: an econometric analysis. Rev. Financ. Stud. 4, 571–595.

Hendershott, T., Livdan, D., Schurhoff, N., 2015. Are institutions informed about news? J. Financ. Econ. 117, 249–287.

Hou, K., Peng, L., Xiong, W., 2013. Is r^2 A Measure of Market Inefficiency?.

Huang, R., Stoll, H., 1996. Dealer versus auction markets: a paired comparison of execution costs on nasdaq and the NYSE. J. Financ. Econ. 41, 313–357.

Huang, R., Stoll, H., 1997. The components of the bid-ask spread: a general approach. Rev. Financ. Stud. 10, 995–1034.

Hughes, J.S., Liu, J., Liu, J., 2007. Information asymmetry, diversification, and cost of capital. Account. Rev. 82, 705–729.

Hwang, C.Y., Qian, X., 2011. Price Discovery Function of Large Trades and the Cross-section of Expected Stock Returns.

Jame, R., 2018. Liquidity provision and the cross section of hedge fund returns. Manag. Sci. 64, 2973–3468.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. 48, 65–91.

Jin, L., Myers, S.C., 2006. r^2 around the world: new theory and new tests. J. Financ. Econ. 79, 257–292.

Kandel, E., Pearson, N., 1995. Differential interpretation of public signals and trade in speculative markets. J. Polit. Econ. 103, 831–872.

Kelley, E.K., Tetlock, P.C., 2013. How wise are crowds? insights from retail orders and stock returns. J. Financ. 68, 1229–1265.

Kelly, B., Ljungqvist, A., 2012. Testing asymmetric-information asset pricing models. Rev. Financ. Stud. 25, 1366–1413.

Kim, O., Verrecchia, R., 1991a. Trading volume and price reactions to public announcements. J. Account. Res. 29, 302–321.

Kim, O., Verrecchia, R., 1991b. Market reactions to anticipated announcements. J. Financ. Econ. 30, 273–309.

Kim, O., Verrecchia, R., 1997. Pre-announcement and event-period private information. J. Account. Econ. 24, 395–419.

Kim, S.T., Stoll, H.R., 2014. Are trading imbalances indicative of private information? J. Financ. Mark. 20, 151–174.

Kolasinski, A.C., Reed, A.V., Ringgenberg, M.C., 2013. A multiple lender approach to understanding supply and search in the equity lending market. J. Financ. 68, 559–595.

Kondor, P., 2012. The more we know about the fundamental, the less we agree on the price. Rev. Econ. Stud. 79, 1175–1207.

Kothari, S., 2001. Capital markets research in accounting. J. Account. Econ. 31, 105–231.

Krinsky, I., Lee, J., 1996. Earnings announcements and the components of the bid-ask spread. J. Financ. 51, 1523–1535.

Lai, S., Ng, L., Zhang, B., 2014. Does PIN affect equity prices around the world? J. Financ. Econ. 114, 178–195.

Lambert, R., Leuz, C., Verrecchia, R., 2007. Accounting information, disclosure, and the cost of capital. J. Account. Res. 45, 385–420.

Livnat, J., Mendenhall, R., 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. J. Account. Res. 44, 177–205.

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? a transaction-level analysis of NYSE stocks. Rev. Financ. Stud. 10, 1035–1064.

Massa, M., Zhang, B., Zhang, H., 2015. The invisible hand of short selling: does short selling disciplines earnings management? Rev. Financ. Stud. 28, 1701–1736.

Mohanram, P., Rajgopal, S., 2009. Is PIN priced risk? J. Account. Econ. 47, 226–243.

Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? J. Financ. Econ. 58, 215–260.

Novy-Marx, R., 2013. The other side of value: the gross profitability premium. J. Financ. Econ. 108, 1–28.

Odders-White, E.R., Ready, M.J., 2008. The probability and magnitude of information events. J. Financ. Econ. 87, 227–248.

Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res. 18, 109–131.

Piotroski, J.D., Roulstone, D.T., 2005. Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? J. Account. Econ. 39, 55–81.

Puckett, A., Yan, X., 2011. The interim trading skills of institutional investors. J. Financ. 66, 601–633.

Ravina, E., Sapienza, P., 2010. What do independent directors know? evidence from their trading. Rev. Financ. Stud. 23, 962–1003.

Roll, R., 1988. r^2. J. Financ. 43, 541–566.

Saffi, P., Sigurdsson, K., 2011. Price efficiency and short selling. Rev. Financ. Stud. 24, 821–852.

Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. J. Financ. 52, 35–55.

Shroff, N., Verdi, S., Yu, G., 2014. Information environment and the investment decisions of multinationals corporations. Account. Rev. 89, 759–790.

Sloan, R., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Account. Rev. 71, 289–315.

Teoh, S.H., Yang, Y., Zhang, Y., 2007. R-square: Noise or Firm-specific Information?.

Vega, C., 2006. Stock price reaction to public and private information. J. Financ. Econ. 82, 103–133.

Wang, J., 1993. A model of intertemporal asset prices under asymmetric information. Rev. Econ. Stud. 60, 249–282.

Wei, S., Zhang, C., 2006. Why did individual stocks become more volatile? J. Bus. 79, 259–292.

Zhang, C., 2010. A reexamination of the causes of time-varying stock return volatilities. J. Financ. Quant. Anal. 45, 663–684.