Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

Price nonsynchronicity, idiosyncratic risk, and expected stock returns in China

Huaigang Long, Adam Zaremba & Yuexiang Jiang

To cite this article: Huaigang Long, Adam Zaremba & Yuexiang Jiang (2020) Price nonsynchronicity, idiosyncratic risk, and expected stock returns in China, Economic Research-Ekonomska Istraživanja, 33:1, 160-181, DOI: 10.1080/1331677X.2019.1710229

To link to this article: https://doi.org/10.1080/1331677X.2019.1710229

Published online: 27 Feb 2020.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2020, VOL. 33, NO. 1, 160–181
https://doi.org/10.1080/1331677X.2019.1710229

Price nonsynchronicity, idiosyncratic risk, and expected stock returns in China

Huaigang Long[a], Adam Zaremba[b,c] and Yuexiang Jiang[a]

[a]School of Economics, Zhejiang University, Hangzhou, China; [b]Dubai Business School, University of Dubai, Dubai, United Arab Emirates; [c]Department of Investment and Capital Markets, Poznań University of Economics and Business, Poznań, Poland

ABSTRACT
We are the first to examine the pricing of relative idiosyncratic risk, or price nonsynchronicity, in the Chinese equity market. Using several tests, we investigate returns on more than 2700 companies in the period 1998 to 2018. Contrary to the U.S. evidence, price nonsynchronicity negatively predicts future returns in the cross-section. A value-weighted strategy going long (short) the quintile of least (most) synchronised stocks produces a negative monthly six-factor model alpha of −0.61%. Also, we demonstrate that the effect is driven by the low-idiosyncratic volatility anomaly. Once the absolute idiosyncratic risk is taken into account, the nonsynchronicity becomes irrelevant for future returns.

ARTICLE HISTORY
Received 31 August 2019
Accepted 23 December 2019

KEYWORDS
Nonsynchronicity; synchronicity; idiosyncratic risk; idiosyncratic volatility; return predictability; low-risk anomaly

JEL CODES
G10; G11; G12; G14

1. Introduction

Finance literature usually proxies firm-specific return variation with one of two measures: absolute idiosyncratic volatility or relative idiosyncratic volatility (Nguyen, Lan, & Treepongkaruna, 2018). Absolute idiosyncratic volatility (*IVOL*) is derived as a regression residual from an asset-pricing model, most frequently the Fama-French (2013) three-factor model (see, e.g., Ang, Hodrick, Xing, & Zhang, 2006, 2009). The relative idiosyncratic volatility—or price nonsynchronicity (*NS*)—is represented by logarithmic transformation of the R^2 coefficient from a factor model regression (Aabo, Pantzalis, & Park, 2017).[1]

Conventional finance theory indicates that firm-specific return variation should not be priced in equilibrium when investors hold a diversified portfolio in a complete frictionless market. Nonetheless, Ang, Hodrick, et al. (2006) demonstrate a negative relationship between risk-specific risk and future returns. Subsequently, future studies confirmed the results with evidence from different research samples and offered several economic mechanisms linking stock-specific risk with future returns (see Blitz, van Vliet, and Baltussen (2019) or Zaremba and Shemer (2018) for a comprehensive

CONTACT Adam Zaremba adam.zaremba@ue.poznan.pl; azaremba@ud.ac.ae

review). In the vast majority of these articles, the stock-specific return variation was measured with absolute idiosyncratic volatility rather than with relative idiosyncratic volatility. Hence, while the negative relationship between *IVOL* and future stock return is broadly acknowledged and has been a frequently researched phenomenon in international stock markets, the evidence for *NS* is very limited.[2] The major aim of this paper is to help to fill this gap. A preponderance of studies investigate the relationship between *NS* and firms' information efficiency, governance environment, capital allocation, and economy growth rates etc., but its role for pricing of stocks is largely an unexplored field.[3] And importantly, the U.S. evidence shows the two measures—*IVOL* and R^2—although conceptually similar, are not interchangeable (Li, Rajgopal, & Venkatachalam, 2014). In this study, not only are we the first to establish the role of price nonsynchronicity for future returns outside the United States—in China; we also aim at demonstrating the source of this relationship.

Existing evidence on the cross-sectional correlation between stock price nonsynchronicity and expected returns is limited solely to the United States. Nguyen et al. (2018) document that, contrary to *IVOL*, *NS* positively predicts future performance in the cross-section. They indicate that *NS* is an independent return predictor providing incremental information about expected returns, not contained by *IVOL*, and Chang and Luo (2010) deliver similar evidence. Nguyen et al. (2018) argue that the positive association between *NS* and future payoffs is predominantly driven by systematic risks across firms that are negatively related to future performance and dominate the impact of idiosyncratic components. Furthermore, a couple of asset pricing studies which employed return predictive variables closely linked to nonsynchronicity find supportive evidence on the link between *NS* and expected returns: Leung and Tam (2018) employ the elastic-net estimator, a machine learning method, to prove that the most synchronised assets underperform; Asness, Frazzini, Gormsen, and Pedersen (2016) research the role of a simple correlation coefficient and find that equities that have a low return correlation with the market portfolio underperform.

In contrast to the earlier studies, we concentrate on Chinese equities, finding them appealing from several perspectives. First, the Chinese stock market has experienced rapid growth during the last two decades. As of January 2019, the total market value of Chinese listed companies surpassed the threshold of USD 10 trillion (WFE, 2019), second only to the United States. China—officially the largest economy around the globe in terms of GDP at purchasing power parity (PPP)—has definitely become a crucial destination for international equity investors.

Second, we believe that due to its characteristics the Chinese stock market constitutes a unique playing field for researching the effect of nonsynchronicity. Asness et al. (2016) and Frazzini and Pedersen (2014) claim that short selling and leverage constraints along with limited investors of rationality are among the factors that lead to the negative pricing of systematic risk in assets market. Since Nguyen et al. (2018) accentuated the role of exposure to systematic risks in the development of the nonsynchronicity anomaly, this may prove a vital issue. Notably, in China any leverage opportunities are very limited, the short sale became available only recently, and the trading floor is dominated by unsophisticated individual investors. Moreover, according to Weigert (2016), the premium for bearing certain types of idiosyncratic risk, like tail risk, is smaller in nations with low income per capita, collectivistic cultures, and limited risk aversion. Importantly, China is not only a large but also a still-growing economy with per capita income far below the level of Western Europe or North America. It is also scored as having one of the lowest individualism and lowest uncertainty avoidance ranks in the world (Hofstede Insights, 2018). In consequence, even some risks that bear a positive premium in developed markets—like the tail risk (Huang, Liu, Rhee, & Wu, 2012)—might be negatively priced in China (Long, Jiang, & Zhu, 2018).

In this study, we aim to contribute in two ways. First, the cross-sectional relationship between price nonsynchronicity and future returns has not been examined in China; we are the first to do so. To this end, we investigate the performance of over 2700 Chinese firms in the years 1998 to 2018. We apply time-series and cross-sectional tests and control for a battery of established return predictors. Contrary to the evidence from the U.S. market, we find that nonsynchronicity is negatively linked to future returns in the cross-section. An equal-weighted (value-weighted) zero-investment strategy going long the firms with the highest nonsynchronicity and simultaneously shorting the with the most synchronised companies produces a *negative* Fama-French six-factor model alpha (Fama & French, 2018) amounting to −0.49% (−0.61%) per month with a corresponding t-statistic of −2.83 (−2.57).

Second, we check the source of the negative relationship between nonsynchronicity and future returns in China. In particular, we are interested in determining whether it is explained by some other return predictor. Hence, we apply three different tests: cross-sectional regressions, time-series spanning tests, and examination of portfolios from dependent bivariate sorts. We document that the nonsynchronicity effect is driven entirely by the role of absolute idiosyncratic volatility: once we control for idiosyncratic volatility, the role of nonsynchronicity becomes irrelevant. In the time-series spanning test and two-way sorted portfolios, absolute idiosyncratic volatility subsumes nonsynchronicity, but nonsynchronicity does not subsume idiosyncratic volatility. Thus, we conclude that the nonsynchronicity effect in China is not an anomaly per se, but rather another manifestation of the well-established low idiosyncratic risk anomaly. Summing up, contrary to U.S. evidence (Li et al., 2014; Nguyen et al., 2018), the roles of nonsynchronicity and idiosyncratic volatility are very similar.

The remainder of the paper proceeds as follows. Section 2 contains a literature review. Section 3 outlines our data and return predictive variables. Section 4 discusses our research methods. Section 5 contains the presentation and discussion of the results. Finally, Section 6 concludes the study.

2. Literature review

Stock price nonsynchronicity (or firm-specific price variation), the opposite of price synchronicity, measures the portion of a firm's stock return variation that is unexplained by market and industry returns (Durnev, Morck, Yeung, & Zarowin, 2003). Stock price nonsynchronicity is usually expressed via the relationship between idiosyncratic volatility to total or systematic volatility (Chan, Hameed, & Kang, 2013).

Morck, Yeung, and Yu (2000) are the first to suggest using the R^2 coefficient from the Capital Asset Pricing Model to estimate stock price synchronicity. Following their paper, the literature on synchronicity proliferated, focusing on several different aspects including measurement, generation mechanism, determinants, and economic implications.

Regarding measurement, many studies use the logarithmic transformation of the R^2 coefficient from a factor pricing model to capture stock price synchronicity (Chan & Hameed, 2006; Durnev et al., 2003; Gul, Kim, & Qiu, 2010). A higher R^2 value suggests stronger co-movement between the individual stock price and the market. Some papers also use stock idiosyncratic volatility to proxy nonsynchronicity (Rajgopal & Venkatachalam, 2011); however, many others argue that idiosyncratic volatility captures separate economic phenomena and it is not necessarily interchangeable with the R^2 coefficient (Ang, Hodrick, et al., 2006, Ang et al., 2009; Li et al., 2014).

What is the underlying meaning (or generation mechanism) of the coefficient R^2? Roll (1988)'s seminal study in this area implies that R^2 may reflect either private information or occasional noise trading. This forms two major views on the issue: the informational efficiency view and the irrational behaviour view. The first approach is represented, for instance, by Morck et al. (2000). By comparing a sample of forty countries, they find that higher firm-specific returns variation (lower R^2) is associated with stronger public investor property rights. In countries that provide public investors with poorer protection from corporate insiders, problems such as corporate income shifting could make firm-specific information less useful to risk arbitrageurs. Hence, this may impede the market value of firm-specific information into stock prices, reducing firm-specific stock price variation and increasing stock return synchronicity. Jin and Myers (2006) argue that investor protection cannot fully explain the difference of R^2 among countries, and opaque information can significantly increase R^2. They provide evidence to support this view by examining stock returns from forty stock markets between 1990 and 2001. Kim, Zhang, Li, and Tian (2014) demonstrate a significant relation between press freedom and lower stock price synchronicity in a sample of firms from fifty countries. Similarly, using a unique global news data set across forty-one countries from 2000 to 2009, Dang, Moshirian, and Zhang (2015) demonstrate that news is most often positively associated with both stock return co-movement and stock liquidity commonality. This finding supports the information-efficiency view, that lower price synchronicity is caused by greater capitalisation of firm-specific information (Morck et al., 2000). In a different study, Kim and Shi (2012) investigate if and how a voluntary adoption of International Financial Reporting Standards (IFRS) influences the extent to which firm-specific information is capitalised into stock prices. Their findings also support the information efficiency view on cross-country R^2 variation.

The second strain of literature, associating investors irrationality with R^2 variation, is supported by findings of a variety of studies (Bartram, Brown, & Stulz, 2012; Dasgupta, Gan, & Gao, 2010; Devos, Hao, Prevost, & Wongchoti, 2015; Li et al., 2014). The authors of these studies argue that firm-specific return variation is caused by noise trading, psychological biases, and irrational sentiment in the market. According to the information efficiency view, if the market environment is informationally efficient, the R^2 coefficients would be low. However, some empirical findings are inconsistent with this idea. For example, Li et al. (2014) empirically show that R^2 is negatively related with some information environment proxies such as bid-ask spreads, price delay, and illiquidity. Chan and Chan (2014) find a significantly negative relationship between stock return synchronicity and seasoned equity offerings (SEO) discounts, which is also incompatible with the information-efficiency view. In addition, Alves, Peasnell, and Taylor (2010) expand the data set from Jin and Myers (2006) to forty countries over twenty years, demonstrating that the R^2 coefficient as a measure of firm-specific information quality is sometimes difficult to reconcile with an informational explanation. Barberis, Shleifer, and Wurgler (2005) use additions to the S&P 500 to distinguish between the two views on return co-movement. They provide evidence that a stock's beta increases after inclusion in an index even if its fundamental value does not change. In consequence, their findings are in line with the friction- or sentiment-based view on co-movement or R^2.

Greenwood (2008) obtains similar results by researching the co-movement of stocks in Nikkei index. Other studies show that investors' attention, sentiment, and learning leads to dynamic changes of the R^2 coefficient (Hou, Peng, & Xiong, 2013; Kumar & Charles, 2006; Peng & Xiong, 2006; Peng, Xiong, & Bollerslev, 2007).

A separate strain of research concentrates on the determinants of the R^2 coefficient. Such possible determinants include corporate governance variables (Gul et al., 2010; Li, Brockman, & Zurbruegg, 2015), institutional systems and laws (Fernandes & Ferreira, 2009; Morck et al., 2000), culture (Eun, Wang, & Xiao, 2015), information opaqueness (Hutton, Marcus, & Tehranian, 2009; Jin & Myers, 2006; Peterson, Schmardebeck, & Wilks, 2015), securities analysts (Chan & Hameed, 2006; Crawford, Roulstone, & So, 2012; Piotroski & Roulstone, 2004), and investors types (An & Zhang, 2013; Gul et al., 2010).

Many articles also focus on the economic consequences of the R^2 variation. For example, Wurgler (2000) shows that the efficiency of capital allocation is negatively correlated with firm-specific information in domestic stock returns (i.e., R^2). Durnev et al. (2003) suggest that a higher R^2 signals more information-laden stock prices and therefore more efficient stock markets and more efficient corporate investment (Durnev, Morck, & Yeung, 2004). Defond and Hung (2004) examine data on the CEO turnover in thirty-three countries and a link between R^2 and corporate governance. Chen, Goldstein, and Jiang (2007) show that price nonsynchronicity has a strong positive effect on the sensitivity of corporate investment to stock price. A low R^2 indicates high informational efficiency of a stock market, facilitating Schumpeterian creative destruction and boosting economic growth (Chun, Kim, Morck, & Yeung, 2008; Morck, Yeung, & Yu, 2013). Finally, some authors also argue that stocks with high R^2 values are more likely to crash (Hutton et al., 2009; Jin & Myers, 2006).

This summary indicates that that literature is relatively rich on the generation mechanism, determinants, and economic consequences of R^2. Nevertheless, very little attention has been paid to the pricing effect of R^2. As far as we are concerned, only two working papers show evidence of a cross-sectional correlation between stock price nonsynchronicity and expected returns in the stock markets of the United

States (Chang & Luo, 2010; Nguyen et al., 2018). Interestingly, the Chinese stock market appears to be different from the U.S. market. For example, as argued by Morck et al. (2013), Chinese stocks display, on average, R^2 values more than twice as high as U.S. equities. Although many studies also focus on R^2 in China, these is no literature that studies the pricing effect of R^2 (cf., Gul et al., 2010; Hu, Zhao, & Zhang, 2019; Li et al., 2015; Xu, Chan, Jiang, & Yi, 2013; Zhang, Li, Shen, & Teglio, 2016). Thus, this paper will help to close this gap and investigate the pricing effect of stock price nonsynchronicity.

3. Data and variables

We base our research on all Chinese A-share companies with information available in CSMAR (China Securities Market and Accounting Research). Our study period for monthly returns is February 1998 to October 2018, however, we also use earlier data going back to January 1997 when necessary to derive the return predictive signals, like. We consider all the companies available, including both currently listed and delisted ones to avoid survivorship bias. We focus on common equities only, dropping other investment vehicles such as exchange-traded funds. All the companies taken into account are listed in Chinese yuan (RMB). To mitigate practical problems with thinly-traded micro-caps, we exclude the 10% of the smallest companies each month. We also eliminate all zero-return firm-month observations, as in Daske, Hail, Leuz, and Verdi (2008). Our final sample comprises 2787 individual companies. The exact number of firms changes through time; the time-series average amounts to 1227.

Our crucial return predictive variable is stock nonsynchronicity, abbreviated *NS*. We compute it closely following Morck et al. (2000), Chen, Goldstein, and Jiang (2006), and Nguyen et al. (2018). Hence, we define the nonsynchronicity for security i as the logistic transformation of the inverse coefficient of determination, R^2:

$$NS = \ln\left(\frac{1-R_i^2}{R_i^2}\right). \tag{1}$$

Notably, since R^2 depends on the standard deviation of the error term of stock i, $\sigma^2_{\varepsilon,i}$, and the total volatility of stock returns, $\sigma^2_{r,i}$, so that $R_i^2 = 1 - \frac{\sigma^2_{\varepsilon,i}}{\sigma^2_{r,i}}$, a simple modification reveals the close relationship between the idiosyncratic volatility and price synchronicity:

$$NS = \ln\left(\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_{r,i} - \sigma^2_{\varepsilon,i}}\right). \tag{2}$$

Hence, the measure of synchronicity may be regarded as an unsophisticated modification of the absolute idiosyncratic volatility. Thus, an increase in the idiosyncratic risk should go hand-in-hand with increasing nonsynchronicity; the two variables should be closely correlated.

Numerous asset pricing studies of stock returns derive idiosyncratic risk and R^2 from the three-factor model of Fama and French (1993)[4]:

$$R_{i,t} = \beta_{MKT,i}MKT_T + \beta_{SMB,i}SMB_T + \beta_{HML,i}HML_T + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the excess return on stock i in month t, $\varepsilon_{i,t}$ is the error term, and $\beta_{MKT,i}$, $\beta_{SMB,i}$, and $\beta_{HML,i}$ are estimated measures of exposure to the market risk (*MKT*), small-minus-big (*SMB*), and high-minus-low (*HML*) factors, respectively. *MKT* is the excess return on the market portfolio, and *SMB* and *HML* represent the returns on zero-investment portfolios going long (short) stocks with low (high) market value and high (low) book-to-market ratio, respectively.

Hence, as in Nguyen et al. (2018), we use one trailing year of daily returns and we employ the risk decomposition based on the Fama-French model:

$$\begin{aligned}\sigma^2_{r,i} = {} & \beta^2_{MKT,i}\sigma^2_{MKT} + \beta^2_{SMB,i}\sigma^2_{SMB} + \beta^2_{HML,i}\sigma^2_{HML} + 2\beta_{MKT,i}\beta_{SMB,i}\rho_{MKT,SMB} \\ & + 2\beta_{MKT,i}\beta_{HML,i}\rho_{MKT,HML} + 2\beta_{SMB,i}\beta_{HML,i}\rho_{SMB,HML} + \sigma^2_{r,i},\end{aligned} \tag{4}$$

where $\sigma^2_{r,i}$, σ^2_{MKT}, σ^2_{SMB}, σ^2_{HML}, $\sigma^2_{r,i}$ represent the variance of the excess returns on stock i, the factor returns, and the error term, respectively. Finally, $\rho_{MKT,SMB}$, $\rho_{MKT,SMB}$, and $\rho_{MKT,SMB}$ denote the Pearson's pairwise correlation coefficients between returns on different factors.[5] To assure the quality of our data, all the factor returns are obtained directly from the CSMAR database.

In addition to *NS*, we also employ a battery of control variables. *BETA* is the stock market beta from the capital asset pricing model (CAPM) (Sharpe, 1964), derived from the past 12-months of daily returns. *MV* is the natural logarithm of the market value of the company at the end of the previous month. *BM* denotes the natural logarithm of book-to-market ratio based on accounting data from June of the previous year, as in Fama and French (1993). Frazzini and Pedersen (2014), Banz (1981), and Rosenberg, Reid, and Lanstein (1985) were among the first to demonstrate the roles of beta, market value, and book-to-market ratio for future returns. *VAR* represents value-at-risk based on a 5% breakpoint estimated from the trailing (one-year) daily returns following Bali and Cakici (2004). *TURN* is the turnover rate, i.e., the number of shares traded in the previous month divided by the number of shares outstanding (Datar, Naik, & Radcliffe, 1998). *AMIH* is the Amihud illiquidity measure calculated as in Amihud (2002). Absolute idiosyncratic volatility, *IVOL* is consistent with the measurement approach in equations (1)–(4). It is obtained from the three-factor Fama-French model (Fama & French, 1993) derived as in Ang, Chen, and Xing (2006), based on one year of daily data. *COSKEW* and *COKURT* represent systematic skewness and kurtosis, respectively, while *ISKEW* and *IKURT* denote idiosyncratic skewness and kurtosis. *BDOWN* and *BUP* are downside and upside betas. *BDOWN*, *BUP*, as well as *COSKEW*, *COKURT*, *ISKEW*, and *IKURT* are computed as in Ang, Chen, et al. (2006). *TAIL* represents the security's tail risk computed as in Long et al. (2018). Finally, *MAX* and *MIN* denote maximum and minimum daily returns from the last month, as in Bali, Cakici, and Whitelaw (2011).

The basic statistical properties of the considered variables are reported in Table 1. The exhibit also presents the correlation coefficients with *NS*. Importantly, some of the variables are strongly correlated with nonsynchronicity; in particular, observe the strong link with idiosyncratic volatility. The Pearson's and Spearman's correlation coefficients amount to 0.52 and 0.64, respectively, and both are highly significant.

4. Methods

We begin our examinations with a simple overview of the cross-sectional relationship between nonsynchronicity and future returns in the Chinese equity market. To this end, we check the performance of univariate portfolios formed on *NS*. Each month we rank all securities in our sort on *NS* into quintiles, and we build equal-weighted and value-weighted portfolios. We are interested in seeing whether there is some pattern in the cross-section of portfolio payoffs linked to nonsynchronicity. Furthermore, as a simple assessment of monotonicity, we also compute returns on a long-short zero-investment strategy going long the quintile of securities with the highest *NS*, simultaneously shorting the ones with the lowest *NS*. Importantly, although the performance of such a portfolio provides an intuitive overview of the cross-sectional pattern in returns, any actual investment implications should be taken with caution. During a large part of our study period short selling was hardly available in China, so the practical implementation of such a strategy could pose a substantial challenge.

We evaluate the return on the one-way sorted portfolios using the Fama-French six-factor model (Fama & French, 2018):

$$R_t = \alpha_{FF6} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \varepsilon_t, \tag{5}$$

where R_t denotes the excess returns for month t on a tested portfolio; MKT_t, SMB_t, HML_t, UMD_t, RMW_t, and CMA_t are the monthly returns on the market, small-minus-big, high-minus-low, up-minus-down, robust-minus-weak, and conservative-minus-aggressive factor portfolios, respectively; ε_t denotes the error term; and α_{FF6}, β_{MKT}, β_{SMB}, β_{HML}, β_{UMD}, β_{RMW}, and β_{CMA} are the model's estimated parameters. We obtain all the factor returns from the CSMAR database. Notably, the six-factor model of Fama and French (2018) nests a few earlier popular factor models, including the CAPM (Sharpe, 1964), the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the five-factor model of Fama and French (2015). Importantly, additional robustness checks (available upon demand) demonstrate that, qualitatively, our results also hold with the application of these nested models.

To further confirm our results, we supplement our computations with two additional tests. The first is the GRS test (Gibbons, Ross, & Shanken, 1989). this test checks the hypothesis that all the factor-model alphas in the cross-section of portfolio returns are simultaneously equal to each other and to zero. The second check is the simulation-based test of monotonic relationship (MR) originating from Patton and Timmermann (2010). This test aims at detecting a monotonic relationship in the

Table 1. Descriptive statistics of the examined variables.

	R	NS	BETA	MV	BM	BDOWN	BUP	REV	MOM	TAIL
Mean	0.009	0.369	1.116	12.323	1.069	1.195	0.993	0.013	0.255	0.146
St. dev.	0.149	0.759	0.277	49.530	1.684	0.433	0.367	0.272	1.277	0.416
Skewnes	2.883	0.689	−1.595	19.502	27.942	−17.964	−1.497	224.673	108.088	0.460
Kurtosis	78.925	2.501	65.856	500.131	2054.020	2480.593	100.401	88,908.595	25,109.759	7.410
Minimum	−0.851	−2.323	−13.386	0.395	0.000	−62.434	−13.532	−0.782	−0.910	−1.631
1st quartile	−0.073	−0.135	0.964	2.511	0.403	0.980	0.797	−0.074	−0.235	−0.083
Median	−0.002	0.338	1.126	4.733	0.692	1.205	0.994	−0.002	0.004	0.154
3rd quartile	0.077	0.814	1.278	9.510	1.236	1.409	1.191	0.079	0.428	0.376
Maximum	7.796	8.140	5.272	2168.137	143.803	19.841	13.285	110.408	343.758	7.817
$\rho_{Pearson}$	−0.02***	—	−0.57***	−0.06*	−0.21***	−0.42***	−0.43***	0.07***	0.39***	0.00
	(−3.76)	(–)	(−7.74)	(−1.77)	(−7.66)	(−6.63)	(−6.87)	(7.72)	(10.42)	(0.00)
$\rho_{Spearman}$	−0.36***	—	−0.51***	0.04	−0.28***	−0.43***	−0.36***	0.03***	0.35***	0.01
	(−5.91)	(—)	(−9.73)	(0.62)	(−7.91)	(−10.56)	(−8.65)	(4.39)	(12.23)	(0.36)
	AMIH	TURN	IVOL	VAR	COSKEW	COKURT	ISKEW	IKURT	MAX	MIN
Mean	0.184	28.540	0.022	0.047	−0.013	0.013	0.859	4.916	0.105	−0.087
St. dev.	3.362	30.949	0.021	0.020	0.029	0.007	1.042	11.702	0.322	0.020
Skewnes	294.855	2.613	35.821	1.229	0.734	1.935	5.310	14.080	41.899	−2.671
Kurtosis	105,526.822	11.150	1665.975	0.869	0.929	5.733	64.961	234.762	2047.027	72.397
Minimum	0.000	0.001	0.001	0.001	−0.121	−0.017	−10.985	−1.346	0.009	−0.730
1st quartile	0.016	8.415	0.016	0.034	−0.033	0.009	0.413	1.840	0.093	−0.100
Median	0.041	18.174	0.021	0.042	−0.017	0.012	0.821	3.183	0.100	−0.099
3rd quartile	0.125	37.339	0.026	0.053	0.005	0.015	1.229	5.273	0.100	−0.075
Maximum	1360.423	529.784	1.304	0.100	0.200	0.093	15.586	242.270	20.684	−0.003
$\rho_{Pearson}$	0.06***	0.11***	0.52***	0.05	0.19	−0.71***	0.07	0.17	0.18**	0.00
	(3.45)	(3.15)	(21.84)	(0.31)	(1.28)	(−22.11)	(0.33)	(0.94)	(2.07)	(−0.05)
$\rho_{Spearman}$	−0.06	0.10**	0.64***	0.08	0.21	−0.69***	−0.07	−0.11*	0.10	0.00
	(−1.45)	(2.31)	(16.82)	(0.62)	(1.58)	(−17.60)	(−1.46)	(−1.82)	(0.88)	(0.01)

Note. The table reports the descriptive statistics of the variables from the study: the monthly return (*R*), nonsynchronicity (NS), market beta (BETA), market value (MV, expressed in billion RMB), book-to-market ratio (BM), downside beta (BDOWN), upside beta (BUP), short-term reversal (REV), momentum (MOM), tail risk (TAIL), Amihud illiquidity measure (AMIH), turnover ratio (TURN), idiosyncratic volatility (IVOL), value-at-risk (VAR), systematic skewness (COSKEW), systematic kurtosis (COKURT), idiosyncratic skewness (ISKEW), idiosyncratic kurtosis (IKURT), maximum daily return (MAX), and minimum daily return (MIN). $\rho_{Pearson}$ and $\rho_{Spearman}$ indicate average pairwise coefficients of correlation with NS calculated according to the Pearson and Spearman methods, respectively.

cross-section of returns linked to some underlying variable used for sorting the stocks.

In addition to establishing the baseline pricing relationships in Chinese stocks, this study aspires to determine whether nonsynchronicity contains incremental information about future returns that is not captured by other established return predictors. In other words, does nonsynchronicity provide some unique insights into asset pricing, or is it just another manifestation of, e.g., absolute idiosyncratic volatility. To check this, we employ three separate tests: 1) cross-sectional regressions, 2) time-series spanning tests, and 3) examination of portfolios from bivariate dependent sorts.

Starting with the cross-sectional tests, we apply the stock-level regressions following Fama and MacBeth (1973):

$$R_{i,\,t+1} = \beta_{0,\,t} + \beta_{NS,\,t} NS_{i,\,t} + \sum_{j=1}^{J} \beta_{j,\,t} K_{i,\,t} + \varepsilon_{i,\,t}, \tag{4}$$

where $R_{i,t+1}$ is the excess return on stock i in month $t+1$, $NS_{i,t}$ denotes stock nonsynchronicity for stock i in month t, $K_{i,t}$ represent different additional return predictors (control variables), and $\beta_{0,t}$, $\beta_{NS,t}$ and $\beta_{j,t}$ are regression coefficients. The target of this exercise is to see whether *NS* forecasts future payoffs in the cross-section even after controlling for other variables.[6]

Second, we perform the time-series spanning tests dating back to Huberman and Kandel (1987). In general, we rely on the implementation of Blitz, Hanauer, and Vidojevic (2017). In a nutshell, we build ad hoc factor portfolios in the style of Fama and French (1993) from double-sorts into two size-based subsets and three nonsynchronicity-based subsets, applying identical breakpoints and weighting schemes as Fama and French (1993). The portfolios go long (short) a diversified pool of firms with high (low) *NS*. We also build analogous ad hoc factor portfolios based on the return predictors outlined in Section 3. Finally, we regress the nonsynchronicity factor returns on the six Fama-French factors (Fama & French, 2018) and the remaining ad hoc factors. We want to check whether the long-short nonsynchronicity strategy produces significant alphas after controlling for the other factors. If so, it would indicate that the *NS* factor substantially augments the efficient frontier of the universe of other factor strategies.

Third, as suggested by Bali, Engle, and Murray (2016), we build portfolios from double-dependent sorts on *NS* and other variables. To this end, in the first pass, we first rank the companies on each alternative return-predicting variable and split them into quintiles. In the second pass, within each of these quintiles, we sort the securities into five quintiles based on their nonsynchronicity. Hence, this second 'generation' of portfolios captures the role of *NS* after having already controlled for the other variables at the first stage. Subsequently, we calculate the average *NS* portfolio returns across the quintiles of the control predictors. Finally, to extract the abnormal returns, we evaluate the portfolios' performance with the six-factor model of Fama and French (2018) presented in equation (5).

5. Results

Let us begin with an overview of the general cross-sectional pattern linking stock returns to nonsynchronicity in China. Table 2 reports the performance of equal-weighted (Panel A) and value-weighted (Panel B) portfolios from one-way sorts on *NS*. Contrary to the findings of Nguyen et al. (2018) and Chang and Luo (2010) we observe a negative relationship between *NS* and future returns: a higher *NS* corresponds to a lower subsequent return. When we consider the raw returns, the effect is more pronounced for the value-weighted portfolios, where the average return on the zero-investment strategy going long (short) the stocks with the highest (lowest) *NS* equals −0.50% (t-stat = −2.57). Also, the MR test detects a significant cross-sectional pattern with a p-value of 2.83%. On the other hand, the mean return on the value-weighted long-short portfolio amounts to only an insignificant −0.28% (t-stat = −1.05). The weaker effect in capitalization-weighted portfolios may stem from the fact that, as for many behavioural anomalies, the effect is stronger among small firms (Hong, Lim, & Stein, 2000).

The abnormal returns on the long-short portfolios are not explained by the six factors from the Fama and French (2018) model. Although the zero-investment strategies exhibit some exposure to market, size, profitability, and investment factors, their abnormal returns remain solid and significant amounting to −0.49% (t-stat = 2.83) and −0.61% (t-stat = −2.57) for the equal-weighted and value-weighted portfolios, respectively. The cross-sectional pattern is also confirmed by the outcomes of the GRS and MR tests applied to the six-factor model-adjusted payoffs. Summing up, contrary to the prevailing evidence from the U.S. equity market, the Chinese companies tend to display a strong and *negative* relationship between nonsynchronicity and future returns in the cross-section.

We now continue our investigations by checking whether the *NS* effect is explained by other established return-predictive variables. We start with the results of the cross-sectional regressions summarised in Table 3.[7] In simple regressions—when *NS* is the only predictor considered (specification (1))—the prognostic power of *NS* is strong and significant. The negative coefficient −0.31 (t-stat = −3.29) confirms our finding from one-way sorted portfolios (Table 2). The relationship also remains significant after accounting for the role of *BETA*, *MV*, and *BM*, that is, the return predictors that underlie the three-factor model used to derive the *NS* variable (specification (2)).

Importantly, the role of *NS* in forecasting future payoffs remains strong and reliable even when we control for all the other control variables considered in specifications (3)–(17). This includes absolute idiosyncratic volatility (specification (10)), where the *IVOL* coefficient becomes essentially insignificant once we account for *NS*. Finally, even when we control for all the considered control variables simultaneously (specification (17)), the coefficient on *NS* remains negative and significant (t-stat = −3.25).

To sum up, the results of the cross-sectional regressions shown in Table 3 confirm the strong predictive abilities of *NS*, even after controlling for other variables, including the standard absolute idiosyncratic volatility. Nonetheless, one of the Achilles heels of Fama-MacBeth regressions (Fama & MacBeth, 1973) is that they may lead to

Table 2. Performance of portfolios from one-way sorts on stock price nonsynchronicity (NS).

	Panel A: Equal-weighted portfolios								Panel B: Value-weighted portfolios							
	Low	2	3	4	High	H-L	GRS	MR	Low	2	3	4	High	H-L	GRS	MR
Basic statistical properties																
$\bar{R}$	1.32**	1.28**	1.02*	0.95*	0.82	−0.50**		2.83**	0.77*	0.90*	0.72	0.67	0.49	−0.28		39.46
	(2.50)	(2.30)	(1.90)	(1.78)	(1.54)	(−2.56)			(1.68)	(1.73)	(1.50)	(1.39)	(1.03)	(−1.05)		
Vol	9.79	10.04	9.77	9.64	9.40	3.13			8.49	9.13	8.90	8.89	8.29	4.95		
Skew	0.36	0.33	0.21	0.24	0.24	0.09			0.06	0.26	0.08	0.13	0.11	−0.47		
Kurt	1.41	1.35	0.99	1.36	1.33	0.91			1.86	2.07	0.96	1.66	1.67	2.43		
Evaluation with the six-factor model																
α_{FF6}	0.29**	0.18	−0.06	−0.17	−0.20	−0.49***	1.33**	1.33**	0.36***	0.19	−0.06	−0.15	−0.25	−0.61**	0.02***	0.02***
	(2.34)	(1.55)	(−0.45)	(−1.21)	(−1.16)	(−2.83)			(2.85)	(1.47)	(−0.39)	(−1.08)	(−1.47)	(−2.57)		
β_{MKT}	1.00***	1.04***	1.02***	1.02***	0.96***	−0.04			1.02***	1.08***	1.02***	1.02***	0.91***	−0.11**		
	(31.11)	(38.42)	(40.91)	(35.95)	(38.61)	(−1.38)			(26.95)	(38.29)	(41.64)	(42.53)	(40.07)	(−2.45)		
β_{SMB}	0.58***	0.60***	0.56***	0.60***	0.53***	−0.04			−0.14*	0.11	0.18**	0.20***	0.15**	0.29***		
	(5.40)	(6.80)	(7.34)	(8.89)	(7.45)	(−0.57)			(−1.71)	(1.38)	(2.51)	(3.12)	(2.35)	(2.94)		
β_{HML}	0.14	0.01	−0.02	−0.07	−0.28***	−0.42***			0.31***	0.03	0.06	−0.11**	−0.32***	−0.63***		
	(1.16)	(0.14)	(−0.35)	(−1.25)	(−4.30)	(−4.41)			(4.28)	(0.47)	(0.71)	(−2.15)	(−4.94)	(−6.65)		
β_{UMD}	−0.17***	−0.09***	−0.03	0.02	0.06	0.23***			−0.20***	−0.08**	0.02	0.10***	0.19***	0.39***		
	(−4.42)	(−2.81)	(−0.87)	(0.68)	(1.64)	(5.49)			(−5.69)	(−2.45)	(0.79)	(2.73)	(5.06)	(6.66)		
β_{RMW}	−0.39**	−0.37***	−0.36***	−0.20*	−0.18*	0.20*			−0.06	−0.10	−0.34***	−0.18	−0.12	−0.06		
	(−2.57)	(−2.76)	(−2.81)	(−1.65)	(−1.71)	(1.80)			(−0.57)	(−0.90)	(−2.66)	(−1.61)	(−1.05)	(−0.41)		
β_{CMA}	0.10	0.13	0.07	0.18	0.25**	0.15			−0.01	0.17	−0.05	0.14	0.22*	0.24		
	(0.84)	(1.13)	(0.49)	(1.29)	(1.98)	(1.35)			(−0.13)	(1.52)	(−0.31)	(1.22)	(1.86)	(1.63)		
R^2	92.90	94.29	93.89	93.95	92.43	34.55			92.61	93.69	93.01	92.25	89.94	53.32		

Note. The table exhibits the returns on univariate portfolios from single sorts on nonsynchronicity (NS). The High (Low) portfolio comprises the quintile of companies with the highest (lowest) NS, and H-L denotes the zero-investment strategy going long (short) the High (Low) portfolio. $\bar{R}$ is the mean monthly excess return, Vol is the standard deviation, Skew is skewness, and Kurt is kurtosis. α_{FF6} represents the intercept from the six-factor model of Fama and French (2018), β_{MKT}, β_{SMB}, β_{HML}, β_{UMD}, β_{RMW}, and β_{CMA} are measures of exposure to the MKT, SMB, HML, UMD, RMW, and CMA risk factors, respectively, and R^2 is the time-series coefficient of determination. GRS and MR are p-values from the test of alpha equality of Gibbons et al. (1989) and the test of the monotonic relationship by Patton and Timmermann (2010), respectively. The numbers in parentheses are bootstrap (for $\bar{R}$) and Newey and West (1987) adjusted (for regression coefficients) *t*-statistics. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively. $\bar{R}$, Vol, Skew, Kurt, α_{FF6}, R^2, GRS, and MR are presented as percentages. The asterisks ***, **, and * denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Results of cross-sectional Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
NS	−0.31***	−0.65***	−0.68***	−0.66***	−0.61***	−0.78***	−0.65***	−0.64***	−0.26**	−0.78***	−0.66***	−0.68***	−0.79***	−0.67***	−0.70***	−0.69***	−0.66***	−0.66***
	(−3.29)	(−5.93)	(−6.26)	(−5.93)	(−5.50)	(−6.98)	(−5.99)	(−5.99)	(−2.24)	(−3.84)	(−5.29)	(−6.65)	(−6.27)	(−5.35)	(−5.68)	(−5.85)	(−5.97)	(−3.25)
BETA		−1.53***	−1.73***	−1.39***	−1.55***	−1.64***	−1.52***	−1.35***	−0.31	−1.73***	−1.54***	−1.55***	−1.50***	−1.55***	−1.59***	−1.58***	−1.57***	−0.58
MV		−0.52***	−0.52***	−0.50***	−0.46***	−0.59***	−0.52***	−0.43***	−0.70***	−0.50***	−0.52***	−0.53***	−0.51***	−0.51***	−0.51***	−0.52***	−0.52***	−0.66***
BM		0.18	0.17	0.18*	0.20*	0.20*	0.18*	0.19*	0.25**	0.17	0.18*	0.16	0.20*	0.17	0.17	0.17	0.17	0.28***
BDOWN			0.15															0.05
BUP				−0.22														0.12
REV					−2.73***													−1.37*
MOM						0.73***												0.95***
TAIL							−0.09											0.04
AMIH								1.32***										0.39
TURN									−0.05***									−0.05***
IVOL										5.89								−16.06
VAR											−2.65							7.21
COSKEW												2.70						−8.15
COKURT													−44.68					−69.04
ISKEW														−0.08				−0.07
IKURT															−0.01			0.01
MAX																0.44		−1.60
MIN																	−3.87	−4.76
$\bar{R}^2$	1.01	6.68	7.07	7.18	7.99	7.65	6.82	7.92	8.00	7.38	7.68	7.12	7.44	7.00	7.00	7.04	6.98	14.25

Note. The table reports the average coefficients (multiplied by 100) of the cross-sectional regressions following Fama and MacBeth (1987). The dependent variables are monthly stock-level excess returns, and the independent variables are the nonsynchronicity (NS), stock market beta (BETA), market value (MV), book-to-market ratio (BM), downside beta (BDOWN), upside beta (BUP), momentum (MOM), short-term reversal (REV), idiosyncratic tail risk (TAIL), Amihud illiquidity measure (AMIH), turnover ratio (TURN), idiosyncratic volatility (IVOL), value-at-risk (VAR), systematic skewness (COSKEW), systematic kurtosis (COKURT), idiosyncratic skewness (ISKEW), idiosyncratic kurtosis (IKURT), maximum daily return (MAX), and minimum daily return (MIN). $\bar{R}^2$ is the average cross-sectional coefficient of determination expressed as a percentage. The numbers in parentheses are Newey-West (1987) adjusted *t*-statistics. The asterisks ***, **, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

unreliable conclusions when return predictors are strongly correlated in the cross-section. In fact, as was demonstrated in Table 1, this is precisely the case in our sample: the correlation between *IVOL* and *NS* may serve as an example. Hence, we proceed with two further tests.

The results of the times-series spanning test, shown in Table 4, depict a slightly different picture. Indeed, the ad hoc factor portfolios produce significant negative alphas not only after controlling for all the Fama-French six-factor model (Fama & French, 2018) factors but also after considering *almost* all the other return predictive variables. *Almost*, because there is one notable exception: absolute idiosyncratic volatility (specification (15)). In this case, the *NS* long-short strategy no longer produces reliable alphas. The portfolio displays strong loading on the *IVOL* factor and an intercept of only −0.15% with a corresponding *t*-statistic of −1.33. In other words, the *NS* effect appears to be fully explained by the role of *IVOL*.

To additionally confirm the findings from the factor spanning test, we now carry on with the examination of portfolios from two-way dependent sorts. The results revealed in Table 5 are consistent with the findings in Table 4. On the one hand, the long-short *NS* portfolios deliver significant negative alphas in almost all the settings, i.e., after the initial sorting on almost all the control variables. Moreover, this refers to both equal-weighted and value-weighted portfolios. Nonetheless, there is one noteworthy exception: the bivariate portfolios formed on *NS* and *IVOL*. In this case, both in the equal-weighting and value-weighting approaches, the long-short nonsynchronicity strategies no longer produce any significant intercepts.

The time-series spanning tests and the performance of the bivariate portfolios point to a uniform and consistent conclusion: the *NS* effect is fully subsumed by *IVOL*. In other words, in the horserace between nonsynchronicity and absolute idiosyncratic volatility, it is the nonsynchronicity that prevails. This might suggest that—unlike the earlier evidence from the U.S. suggests—nonsynchronicity is not a separate asset pricing factor, but rather just an imperfect manifestation of the idiosyncratic risk anomaly of Ang, Hodrick, et al. (2006). To assess this, we proceed with one more additional check. Namely, we reverse the time-series spanning test and the double-dependent sorts in Tables 4 and 5, and we ask an inverted question: does nonsynchronicity explain the role of idiosyncratic volatility. To answer this, in the mean-variance spanning test we regress the performance of the ad hoc *IVOL* portfolio on the performance of the Fama-French six factors (Fama & French, 2018) and the *NS* portfolio. Analogously, in the bivariate sort, we first rank the stocks on *NS*, and subsequently on *IVOL*. We aim to see whether absolute idiosyncratic volatility reliably predicts the returns in the cross-section, even after controlling for the influence of *NS*. The outcomes are reported in Table 6.

Panel A of Table 6 demonstrates the results of the time-series spanning test. Although the *IVOL* portfolio exhibits remarkable exposure to *NS*, it continues to produce significant alphas even after controlling for it. In other words, nonsynchronicity does not subsume the power of idiosyncratic volatility. Furthermore, Panel B, which concentrates on the portfolios from two-way sorts, leads to consistent conclusions. The long-short portfolios formed on *IVOL* after controlling for *NS* continue to produce significant raw and risk-adjusted returns. The six-factor model alpha on the

Table 4. Time-series spanning tests of nonsynchronicity portfolios.

	α	MKT	SMB	HML	UMD	RMW	CMA	BETA	MV	BM	BDOWN	BUP	REV	MOM	TAIL	AMIH	R^2
(1)	−0.30***	−0.01	−0.06	−0.09*	0.06	0.04	0.06***										9.38
	(−2.76)	(−0.48)	(−1.62)	(−1.95)	(1.13)	(0.60)	(3.20)										
(2)	−0.33***	0.01	−0.08**	−0.09*	−0.01	−0.03	0.04**	−0.31***									21.48
	(−3.49)	(0.70)	(−2.06)	(−1.95)	(−0.13)	(−0.44)	(2.22)	(−5.75)									
(3)	−0.28**	−0.01	−0.05	−0.08**	0.06	0.05	0.05***		0.05								9.26
	(−2.45)	(−0.54)	(−1.35)	(−1.97)	(1.12)	(0.71)	(3.17)		(0.62)								
(4)	−0.29***	−0.01	−0.07*	−0.06	0.06	0.07	0.05***			−0.11							10.14
	(−2.63)	(−0.42)	(−1.69)	(−1.58)	(1.11)	(0.85)	(2.96)			(−1.21)							
(5)	−0.33***	0.01	−0.07**	−0.09**	−0.02	0.00	0.03*				−0.48***						33.54
	(−3.95)	(0.76)	(−2.13)	(−2.06)	(−0.30)	(−0.07)	(1.90)				(−8.69)						
(6)	−0.27***	0.00	−0.09**	−0.09*	0.04	−0.01	0.03*					−0.30***					19.05
	(−2.68)	(0.22)	(−2.52)	(−1.87)	(0.76)	(−0.13)	(1.88)					(−3.75)					
(7)	−0.22**	−0.01	−0.06	−0.09*	0.07	0.05	0.05***						0.10				10.77
	(−1.99)	(−0.39)	(−1.52)	(−1.90)	(1.24)	(0.77)	(2.80)						(1.60)				
(8)	−0.26**	−0.01	−0.04	−0.05	0.05	0.09	−0.02							0.35***			21.97
	(−2.38)	(−0.94)	(−1.20)	(−1.32)	(0.97)	(1.48)	(−0.82)							(3.75)			
(9)	−0.32***	−0.01	−0.05	−0.07	0.05	0.04	0.06***								−0.18		10.53
	(−2.94)	(−0.53)	(−1.40)	(−1.48)	(0.91)	(0.51)	(3.23)								(−1.22)		
(10)	−0.35***	0.00	−0.07*	−0.09**	0.06	0.04	0.06***									0.07	9.60
	(−2.68)	(−0.26)	(−1.82)	(−2.13)	(1.15)	(0.57)	(3.52)									(0.77)	
	α	MKT	SMB	HML	UMD	RMW	CMA	TURN	IVOL	VAR	COSKEW	COKURT	ISKEW	IKURT	MAX	MIN	R^2
(11)	−0.39***	0.00	−0.06*	−0.08**	0.04	0.02	0.07***	−0.09									10.27
	(−3.63)	(−0.26)	(−1.70)	(−1.99)	(0.81)	(0.33)	(3.77)	(−1.44)									
(12)	−0.15	−0.02	−0.04	−0.02	0.15***	0.13**	0.03		0.44***								32.83
	(−1.33)	(−1.33)	(−1.12)	(−0.43)	(3.22)	(2.11)	(1.59)		(5.45)								
(13)	−0.34***	0.00	−0.05	−0.09**	0.02	0.02	0.05***			−0.14*							11.34
	(−3.59)	(−0.26)	(−1.29)	(−1.99)	(0.41)	(0.31)	(2.89)			(−1.67)							
(14)	−0.32***	−0.01	−0.05	−0.08**	0.05	0.07	0.04**				0.30***						19.50
	(−3.23)	(−0.94)	(−1.26)	(−1.96)	(1.08)	(0.94)	(2.12)				(3.99)						
(15)	−0.13	0.00	−0.09**	−0.05	0.12***	0.08	0.02					−0.51***					42.59
	(−1.26)	(0.20)	(−2.56)	(−1.30)	(2.86)	(1.52)	(0.97)					(−5.12)					
(16)	−0.30***	−0.01	−0.06*	−0.08*	0.07	0.04	0.05***						−0.06				9.32
	(−2.79)	(−0.46)	(−1.67)	(−1.73)	(1.20)	(0.56)	(2.78)						(−0.66)				
(17)	−0.28***	−0.01	−0.06*	−0.07	0.07	0.05	0.05***							−0.15			11.13
	(−2.61)	(−0.44)	(−1.72)	(−1.48)	(1.09)	(0.66)	(2.60)							(−1.58)			
(18)	−0.28**	−0.01	−0.06	−0.09*	0.07	0.04	0.06***								0.05		9.16
	(−2.32)	(−0.50)	(−1.64)	(−1.91)	(1.18)	(0.60)	(3.25)								(0.42)		
(19)	−0.33***	−0.01	−0.06	−0.11**	0.01	0.03	0.06***									0.25***	14.85
	(−3.04)	(−0.33)	(−1.61)	(−2.25)	(0.28)	(0.42)	(3.18)									(3.17)	

Note. The table displays the estimated coefficients from the time-series spanning tests. The dependent variables are the returns on long-short ad hoc factor portfolios from rankings on nonsynchronicity (NS). The independent variables are returns on the six-factor portfolios from the model of Fama and French (2018), as well as other ad hoc long-short factor portfolios from sorts on additional market predictors: stock market beta (BETA), market value (MV), book-to-market ratio (BM), downside beta (BDOWN), upside beta (BUP), momentum (MOM), short-term reversal (REV), tail risk (TAIL), Amihud illiquidity measure (AMIH), turnover ratio (TURN), idiosyncratic volatility (IVOL), value-at-risk (VAR), systematic skewness (COSKEW), systematic kurtosis (COKURT), idiosyncratic skewness (ISKEW), idiosyncratic kurtosis (IKURT), maximum daily return (MAX), and minimum daily return (MIN). α denotes the intercept (alpha) of the regression and R^2 represents the time-series coefficient of determination, both expressed as percentages. The values in brackets are Newey-West (1987) adjusted *t*-statistics. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Performance of portfolios from two-way dependent sorts.

	Panel A: Equal-weighted portfolios						Panel B: Value-weighted portfolios					
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
BETA	0.36***	0.24*	0.02	−0.07	−0.48***	−0.84***	0.26**	0.11	−0.13	−0.10	−0.50***	−0.76***
	(2.72)	(1.84)	(0.15)	(−0.53)	(−3.08)	(−6.02)	(2.17)	(0.92)	(−0.78)	(−0.65)	(−3.02)	(−3.99)
MV	0.30**	0.15	0.00	−0.16	−0.22	−0.52***	0.36***	0.21	0.02	−0.18	−0.20	−0.56***
	(2.39)	(1.20)	(0.02)	(−1.19)	(−1.22)	(−3.19)	(3.34)	(1.62)	(0.14)	(−1.27)	(−1.10)	(−3.45)
BM	0.24*	0.17	−0.08	−0.05	−0.21	−0.45***	0.15	0.04	−0.02	−0.08	−0.22	−0.37*
	(1.86)	(1.38)	(−0.63)	(−0.33)	(−1.19)	(−2.79)	(1.24)	(0.31)	(−0.14)	(−0.48)	(−1.23)	(−1.72)
BDOWN	0.27**	0.16	0.08	−0.07	−0.36**	−0.63***	0.23*	0.05	−0.11	−0.12	−0.44***	−0.66***
	(2.01)	(1.26)	(0.57)	(−0.46)	(−2.16)	(−4.16)	(1.83)	(0.39)	(−0.68)	(−0.73)	(−2.61)	(−3.55)
BUP	0.33**	0.07	0.09	−0.07	−0.35**	−0.68***	0.32**	0.08	0.15	−0.13	−0.38**	−0.70***
	(2.51)	(0.56)	(0.73)	(−0.45)	(−2.32)	(−5.22)	(2.52)	(0.57)	(1.06)	(−0.78)	(−2.50)	(−3.96)
REV	0.27**	0.12	0.00	−0.17	−0.15	−0.42***	0.44***	0.21	0.05	−0.16	−0.14	−0.58***
	(2.05)	(0.92)	(0.03)	(−1.29)	(−0.86)	(−2.62)	(3.25)	(1.59)	(0.40)	(−1.13)	(−0.89)	(−2.82)
MOM	0.23*	0.07	0.05	−0.05	−0.22	−0.46**	0.14	0.08	−0.04	−0.08	−0.26	−0.40*
	(1.68)	(0.55)	(0.33)	(−0.41)	(−1.22)	(−2.50)	(1.07)	(0.64)	(−0.24)	(−0.56)	(−1.52)	(−1.91)
TAIL	0.28**	0.17	−0.05	−0.10	−0.23	−0.52***	0.30**	0.32**	−0.12	−0.09	−0.22	−0.52**
	(2.12)	(1.40)	(−0.40)	(−0.65)	(−1.39)	(−3.28)	(2.11)	(2.26)	(−0.84)	(−0.55)	(−1.13)	(−2.36)
AMIH	0.31**	0.10	0.05	−0.12	−0.27	−0.58***	0.42***	0.19	0.15	0.00	−0.20	−0.62***
	(2.36)	(0.77)	(0.41)	(−0.78)	(−1.61)	(−3.61)	(3.70)	(1.45)	(1.11)	(−0.01)	(−1.15)	(−3.29)
TURN	0.19	0.14	0.02	−0.05	−0.21	−0.40**	0.01	0.01	−0.14	−0.22	−0.37*	−0.38*
	(1.43)	(1.12)	(0.18)	(−0.34)	(−1.18)	(−2.32)	(0.08)	(0.04)	(−0.76)	(−1.29)	(−1.82)	(−1.82)
IVOL	−0.09	0.04	0.03	0.07	0.03	0.12	−0.26	−0.16	0.02	0.00	−0.05	0.21
	(−0.53)	(0.30)	(0.22)	(0.51)	(0.16)	(0.56)	(−1.39)	(−1.01)	(0.14)	(−0.02)	(−0.26)	(0.81)
VAR	0.20	0.20	−0.03	−0.03	−0.27	−0.47***	0.10	0.13	−0.15	−0.11	−0.45***	−0.55***
	(1.52)	(1.62)	(−0.24)	(−0.21)	(−1.48)	(−2.62)	(0.63)	(0.94)	(−1.04)	(−0.69)	(−2.87)	(−2.74)
COSKEW	0.25*	0.05	0.08	−0.11	−0.20	−0.45***	0.22*	0.01	0.00	−0.14	−0.24	−0.46**
	(1.84)	(0.40)	(0.60)	(−0.76)	(−1.17)	(−2.81)	(1.70)	(0.09)	(−0.03)	(−0.77)	(−1.38)	(−2.46)
COKURT	0.12	0.06	0.03	−0.02	−0.11	−0.23	0.41***	0.09	0.06	−0.03	−0.23	−0.64***
	(0.88)	(0.41)	(0.20)	(−0.14)	(−0.72)	(−1.60)	(2.72)	(0.58)	(0.39)	(−0.15)	(−1.55)	(−3.11)
ISKEW	0.30**	0.17	−0.01	−0.16	−0.21	−0.51***	0.32**	0.14	−0.04	−0.15	−0.27	−0.60**
	(2.22)	(1.20)	(−0.12)	(−1.14)	(−1.18)	(−2.88)	(2.17)	(0.97)	(−0.26)	(−1.10)	(−1.59)	(−2.55)
IKURT	0.29**	0.10	−0.01	−0.06	−0.24	−0.53***	0.33**	0.11	−0.04	−0.08	−0.26	−0.60***
	(2.08)	(0.81)	(−0.11)	(−0.47)	(−1.44)	(−3.47)	(2.25)	(0.79)	(−0.23)	(−0.58)	(−1.63)	(−2.77)
MAX	0.22	0.16	0.05	−0.10	−0.26	−0.47***	0.17	0.16	−0.05	−0.17	−0.35**	−0.52**
	(1.64)	(1.22)	(0.36)	(−0.69)	(−1.41)	(−2.63)	(1.28)	(1.07)	(−0.29)	(−1.18)	(−1.98)	(−2.32)
MIN	0.25*	0.20*	−0.02	−0.07	−0.29*	−0.55***	0.21	0.07	−0.07	−0.14	−0.36**	−0.58**
	(1.91)	(1.74)	(−0.12)	(−0.41)	(−1.70)	(−3.41)	(1.33)	(0.53)	(−0.47)	(−0.85)	(−2.00)	(−2.41)

Note. The table reports alphas (expressed as percentages) from the six-factor model of Fama and French (2018) on portfolios from dependent double sorts. In the first step, the companies are sorted into quintile portfolios based on the control variables indicated in the first column. Subsequently, in the second pass, the firms in each portfolio are sorted into quintiles based on nonsynchronicity (NS), forming 25 bivariate equal-weighted (Panel A) or value-weighted (Panel B) portfolios. Finally, we compute average equal-weighted returns on the five portfolios from sorts on NS across the quintiles from rankings on the control variables. The control variables include: stock market beta (BETA), market value (MV), book-to-market ratio (BM), downside beta (BDOWN), upside beta (BUP), momentum (MOM), short-term reversal (REV), tail risk (TAIL), Amihud illiquidity measure (AMIH), turnover ratio (TURN), idiosyncratic volatility (IVOL), value-at-risk (VAR), systematic skewness (COSKEW), systematic kurtosis (COKURT), idiosyncratic skewness (ISKEW), idiosyncratic kurtosis (IKURT), maximum daily return (MAX), and minimum daily return (MIN). The High (Low) portfolio contains the firms with the highest (lowest) NS, and H-L denotes the zero-investment strategy going long (short) the High (Low) portfolio. The numbers in parentheses are Newey-West (1987) adjusted *t*-statistics. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Does nonsynchronicity subsume absolute idiosyncratic volatility?

Panel A: Time-series spanning tests

α	MKT	SMB	HML	UMD	RMW	CMA	NS	R^2
−0.17*	0.03**	−0.02	−0.11**	0.03	−0.24***	−0.23***	0.59***	40.56
(−1.92)	(1.98)	(−0.35)	(−2.29)	(1.48)	(−3.25)	(−3.10)	(6.47)	

Panel B: Bivariate sorts

	Low	2	3	4	High	H-L
Equal-weighted portfolios						
R	1.36*	1.20	1.20	1.01	0.61	−0.75***
	(1.87)	(1.62)	(1.57)	(1.32)	(0.80)	(−3.14)
α_{FF6}	0.46***	0.17	0.07	−0.16	−0.51***	−0.97***
	(2.93)	(1.18)	(0.56)	(−1.21)	(−2.89)	(−4.42)
Valu-weighted portfolios						
R	1.01	0.86	0.88	0.66	0.15	−0.86***
	(1.58)	(1.25)	(1.18)	(0.91)	(0.21)	(−2.84)
α_{FF6}	0.50***	0.05	0.02	−0.26	−0.75***	−1.24***
	(3.60)	(0.34)	(0.14)	(−1.41)	(−3.81)	(−4.89)

Note. The table displays the results of the tests aimed at examining whether idiosyncratic risk (IVOL) subsumes nonsynchronicity (NS). Panel A reports the estimated coefficients from the time-series spanning tests. The dependent variables are the returns on long-short ad hoc factor portfolios from rankings on idiosyncratic volatility (IVOL). The independent variables are returns on the six-factor portfolios from the model of Fama and French (2018) and an ad hoc long-short factor portfolio from sorts on nonsynchronicity. Panel B exhibits mean excess returns (R) and six-factor model alphas on portfolios from dependent double sorts. In the first step, the companies are sorted into quintile portfolios based on their NS; in the second stage, the firms in each portfolio are sorted into quintiles based on IVOL, forming 25 bivariate equal-weighted or value-weighted portfolios. Finally, we compute average equal-weighted returns on the five portfolios from sorts on IVOL across the quintiles from rankings on NS. The High (Low) portfolio contains the firms with the highest (lowest) NS, and H-L denotes the zero-investment strategy going long (short) the High (Low) portfolio. The numbers in parentheses bootstrap (for mean returns) and Newey-West (1987) adjusted (for alphas) t-statistics. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

equal-weighted (value-weighted) long-short portfolio amounts to −0.97% (−1.24%) with a corresponding t-statistic of −4.42 (−4.89). The pattern is striking and significant.

Summing up, the findings in Tables 4–6 demonstrate that *IVOL* subsumes the effect of *NS*, but *NS* cannot subsume the effect of *IVOL*. Clearly, absolute idiosyncratic volatility is the superior return predictor in this comparison.

6. Concluding remarks

This study examines the relationship between stock price nonsynchronicity and expected returns in the Chinese equity market. We find a strong negative relationship: the companies with the highest nonsynchronicity underperform the firms with the lowest nonsynchronicity. The phenomenon is robust and withstands a broad range of control variables.

Our findings differ from the evidence from the United States, where nonsynchronicity is positively correlated with future equity performance. Nguyen et al. (2018) indicate this is because the measure is dominated by the link to systematic risks that negatively correlate with expected returns. On the other hand, we find the nonsynchronicity effect in China is dominated by the role of absolute idiosyncratic volatility. In other words, rather than being an anomaly per se, nonsynchronicity is a manifestation of the low-idiosyncratic risk anomaly. Once we control for the role idiosyncratic risk, the influence on nonsynchronicity is no longer relevant.

Our study not only provides new insights into asset pricing in the Chinese stock market but also bears certain practical implications. *NS* is strongly related to future returns, so forming quantitative strategies based on this variable might be seemingly enticing from an investors' perspective. However, we demonstrate that such an approach is fully subsumed by a well-established low-risk strategy based on absolute idiosyncratic volatility. The quantitatively-oriented managers with a Chinese mandate might be better off simply sticking to the classic signal based on absolute idiosyncratic risk rather than focusing on nonsynchronicity.

Future studies on the topics in this paper could extend them into other international—developed and emerging—markets. Furthermore, it would be interesting to see whether similar pricing relationships hold in other asset classes where the low-risk anomaly has been documented, such as commodities and corporate bonds, for example.

Notes

1. Some of the first studies which proxied firm-specific return variation with R^2 included Roll (1988), Morck et al. (2000), and Durnev et al. (2004).
2. For reviews of the studies on the role of idiosyncratic risk, see, e.g., Blitz et al. (2019), Zaremba (2016), Zaremba and Shemer (2016, 2018), or Szczygielski, Mikutowski, and Zaremba, (2019).
3. See, e.g., Morck et al. (2000); Jin and Myers (2006); Wurgler (2000); Chun et al. (2008).
4. See, e.g., for idiosyncratic risk: Ang, Chen, et al. (2006) and Dasgupta et al. (2010); for R^2: Ferreira, Ferreira, and Raposo (2011) and Kan and Gong (2018).
5. For robustness, we also test several alternative specifications of nonsynchronicity and the related idiosyncratic risk measures including 1) derivation from different factor pricing models: CAPM (Sharpe, 1964), Carhart (1997), and Fama and French (2015), 2) modifying the estimation period to 6, 18, and 24 months, and 3) altering the return interval to weekly or monthly. The results are qualitatively similar for all these specifications.
6. To assure the robustness of our conclusions, we implement the Fama-MacBeth regressions using the Fama-French adjusted three-factor model (Fama & French, 1993), as in Avramov, Kaplanski, and Subrahmanyam, (2018), among others. The test yields no qualitative difference in the results.
7. For brevity, we report the t-statistic only for the *NS* coefficients.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This paper is a part of the project no. 2016/23/B/HS4/00731 of the National Science Centre of Poland. This project is also funded by the China Postdoctoral Science Foundation (No. 2018M640543).

ORCID

Huaigang Long http://orcid.org/0000-0002-9608-9200
Adam Zaremba http://orcid.org/0000-0001-5879-9431

References

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *Review of Financial Studies*, *19*(4), 1191–1239. doi:10.1093/rfs/hhj035

Crawford, S. S., Roulstone, D. T., & So, E. C. (2012). Analyst initiations of coverage and stock return synchronicity. *The Accounting Review*, *87*(5), 1527–1553. doi:10.2308/accr-50186

Li, S., Brockman, P., & Zurbruegg, R. (2015). Cross-listing, firm-specific information, and corporate governance: Evidence from Chinese A-shares and H-shares. *Journal of Corporate Finance*, *32*, 347–362. doi:10.1016/j.jcorpfin.2014.10.008

Aabo, T., Pantzalis, C., & Park, J. C. (2017). Idiosyncratic volatility: An indicator of noise trading? *Journal of Banking & Finance*, *75*, 136–151. doi:10.1016/j.jbankfin.2016.11.003

Alves, P., Peasnell, K., & Taylor, P. (2010). The use of the R^2 as a measure of firm-specific information: A cross-country critique. *Journal of Business Finance & Accounting*, *37*(1–2), 1–26. doi:10.1111/j.1468-5957.2009.02181.x

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56. doi:10.1016/S1386-4181(01)00024-6

An, H., & Zhang, T. (2013). Stock price synchronicity, crash risk, and institutional investors. *Journal of Corporate Finance*, *21*, 1–15. doi:10.1016/j.jcorpfin.2013.01.001

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *61*(1), 259–299. doi:10.1111/j.1540-6261.2006.00836.x

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics*, *91*(1), 1–23. doi:10.1016/j.jfineco.2007.12.005

Asness, C. S., Frazzini, A., Gormsen, N. J., & Pedersen, L. H. (2016). Betting against correlation: Testing theories of the low-risk effect. *SSRN*. Retrieved from https://ssrn.com/abstract=2913508. doi:10.2139/ssrn.2913508

Avramov, D., Kaplanski, G., & Subrahmanyam, A. (2018). Stock return predictability: New evidence from moving averages of prices and firm fundamentals. *SSRN*. Retrieved from https://ssrn.com/abstract=3111334. doi:10.2139/ssrn.3111334

Bali, T. G., & Cakici, N. (2004). Value at risk and expected stock returns. *Financial Analysts Journal*, *60*(2), 57–73. doi:10.2469/faj.v60.n2.2610

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), 427–446. doi:10.1016/j.jfineco.2010.08.014

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18. doi:10.1016/0304-405X(81)90018-0

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283–317. doi:10.1016/j.jfineco.2004.04.003

Bartram, S. M., Brown, G., & Stulz, R. M. (2012). Why are U.S. stocks more volatile? *The Journal of Finance*, *67*(4), 1329–1370. doi:10.1111/j.1540-6261.2012.01749.x

Blitz, D., Hanauer, M. X., & Vidojevic, M. (2017). The idiosyncratic momentum anomaly. Working paper. *SSRN*. Retrieved from https://ssrn.com/abstract=2947044

Blitz, D., van Vliet, P., & Baltussen, G. (2019). The volatility effect revisited. *SSRN*. Retrieved from https://ssrn.com/abstract=3442749

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. doi:10.1111/j.1540-6261.1997.tb03808.x

Chan, K., & Chan, Y. (2014). Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offerings. *Journal of Financial Economics*, *114*(1), 36–53. doi:10.1016/j.jfineco.2014.07.002

Chan, K., & Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics*, *80*(1), 115–147. doi:10.1016/j.jfineco.2005.03.010

Chan, K., Hameed, A., & Kang, W. (2013). Stock price synchronicity and liquidity. *Journal of Financial Markets*, *16*(3), 414–438. doi:10.1016/j.finmar.2012.09.007

Chang, E. C. C., & Luo, Y. (2010). R-squared, noise, and stock returns. *SSRN*. Retrieved from https://ssrn.com/abstract=1572508. doi:10.2139/ssrn.1572508
Chen, Q., Goldstein, I., & Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies*, *20*(3), 619–650. doi:10.1093/rfs/hhl024
Chun, H., Kim, J., Morck, R., & Yeung, B. (2008). Creative destruction and firm-specific performance heterogeneity. *Journal of Financial Economics*, *89*(1), 109–135. doi:10.1016/j.jfineco.2007.06.005
Dang, T. L., Moshirian, F., & Zhang, B. (2015). Commonality in news around the world. *Journal of Financial Economics*, *116*(1), 82–110. doi:10.1016/j.jfineco.2014.11.007
Dasgupta, S., Gan, J., & Gao, N. (2010). Transparency, price informativeness, and stock return synchronicity: Theory and evidence. *Journal of Financial and Quantitative Analysis*, *45*(5), 1189–1220. doi:10.1017/S0022109010000505
Daske, H., Hail, L., Leuz, C., & Verdi, R. (2008). Mandatory IFRS reporting around the world: Evidence on the economic consequences. *Journal of Accounting Research*, *46*(5), 1085–1142. doi:10.1111/j.1475-679X.2008.00306.x
Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, *1*(2), 203–219. doi:10.1016/S1386-4181(97)00004-9
Defond, M. L., & Hung, M. (2004). Investor protection and corporate governance: Evidence from worldwide CEO turnover. *Journal of Accounting Research*, *42*(2), 269–312. doi:10.1111/j.1475-679X.2004.00138.x
Devos, E., Hao, W., Prevost, A. K., & Wongchoti, U. (2015). Stock return synchronicity and the market response to analyst recommendation revisions. *Journal of Banking & Finance*, *58*, 376–389. doi:10.1016/j.jbankfin.2015.04.021
Durnev, A., Morck, R., & Yeung, B. (2004). Value-enhancing capital budgeting and firm-specific stock return variation. *The Journal of Finance*, *59*(1), 65–105. doi:10.1111/j.1540-6261.2004.00627.x
Durnev, A., Morck, R., Yeung, B., & Zarowin, P. (2003). Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research*, *41*(5), 797–836. doi:10.1046/j.1475-679X.2003.00124.x
Eun, C. S., Wang, L., & Xiao, S. C. (2015). Culture and R^2. *Journal of Financial Economics*, *115*(2), 283–303. doi:10.1016/j.jfineco.2014.09.003
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. doi:10.1016/0304-405X(93)90023-5
Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. doi:10.1016/j.jfineco.2014.10.010
Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, *128*(2), 234–253. doi:10.1016/j.jfineco.2018.02.012
Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636. doi:10.1086/260061
Fernandes, N., & Ferreira, M. A. (2009). Insider trading laws and stock price informativeness. *Review of Financial Studies*, *22*(5), 1845–1887. doi:10.1093/rfs/hhn066
Ferreira, D., Ferreira, M. A., & Raposo, C. C. (2011). Board structure and price informativeness. *Journal of Financial Economics*, *99*(3), 523–545. doi:10.1016/j.jfineco.2010.10.007
Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25. doi:10.1016/j.jfineco.2013.10.005
Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica*, *57*(5), 1121–1152. doi:10.2307/1913625
Greenwood, R. (2008). Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights. *Review of Financial Studies*, *21*(3), 1153–1186. doi:10.1093/rfs/hhm052
Gul, F. A., Kim, J., & Qiu, A. A. (2010). Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from china. *Journal of Financial Economics*, *95*(3), 425–442. doi:10.1016/j.jfineco.2009.11.005

Hofstede Insights. (2018). Country comparison tool. Retrieved from https://www.hofstede-insights.com/product/compare-countries/
Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*(1), 265–295. doi:10.1111/0022-1082.00206
Hou, K., Peng, L., & Xiong, W. (2013). Is R^2 a measure of market inefficiency. Ohio State University, City University of New York, Princeton University, and National Bureau of Economic Research. Retrieved from https://wxiong.mycpanel.princeton.edu/papers/R2.pdf
Hu, Y., Zhao, T., & Zhang, L. (2019). Does low price synchronicity mean more informativeness in stock prices? Empirical evidence on information integration speed in the Chinese stock market. *Emerging Markets Finance and Trade*, *55*(5), 1014–1033. doi:10.1080/1540496X.2018.1528973
Huang, W., Liu, Q., Rhee, S. G., & Wu, F. (2012). Extreme downside risk and expected stock returns. *Journal of Banking & Finance*, *36*(5), 1492–1502. doi:10.1016/j.jbankfin.2011.12.014
Huberman, G., & Kandel, S. (1987). Mean-variance spanning. *The Journal of Finance*, *42*(4), 873–888. doi:10.1111/j.1540-6261.1987.tb03917.x
Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R^2, and crash risk. *Journal of Financial Economics*, *94*(1), 67–86. doi:10.1016/j.jfineco.2008.10.003
Jin, L., & Myers, S. (2006). R^2 around the world: New theory and new tests. *Journal of Financial Economics*, *79*(2), 257–292. doi:10.1016/j.jfineco.2004.11.003
Kan, S., & Gong, S. (2018). Does high stock return synchronicity indicate high or low price informativeness? Evidence from a regulatory experiment. *International Review of Finance*, *18*(4), 523–546. doi:10.1111/irfi.12157
Kim, J., & Shi, H. (2012). IFRS reporting, firm-specific information flows, and institutional environments: International evidence. *Review of Accounting Studies*, *17*(3), 474–517. doi:10.1007/s11142-012-9190-y
Kim, J., Zhang, H., Li, L., & Tian, G. (2014). Press freedom, externally-generated transparency, and stock price informativeness: International evidence. *Journal of Banking & Finance*, *46*, 299–310. doi:10.1016/j.jbankfin.2014.05.023
Kumar, A., & Charles, M. C. L. (2006). Retail investor sentiment and return comovements. *The Journal of Finance*, *61*(5), 2451–2486. doi:10.1111/j.1540-6261.2006.01063.x
Leung, R. C. W., & Tam, Y.-M. (2018). The cross-section of asset synchronicity by elastic-net. *SSRN*. Retrieved from https://ssrn.com/abstract=3300769. doi:10.2139/ssrn.3300769
Li, B., Rajgopal, S., & Venkatachalam, M. (2014). R^2 and idiosyncratic risk are not interchangeable. *The Accounting Review*, *89*(6), 2261–2295. doi:10.2308/accr-50826
Long, H., Jiang, Y., & Zhu, Y. (2018). Idiosyncratic tail risk and expected stock returns: Evidence from the Chinese stock markets. *Finance Research Letters*, *24*, 129–136. doi:10.1016/j.frl.2017.07.009
Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, *58*(1–2), 215–260. doi:10.1016/S0304-405X(00)00071-4
Morck, R., Yeung, B., & Yu, W. (2013). R^2 and the economy. *Annual Review of Financial Economics*, *5*(1), 143–166. doi:10.1146/annurev-financial-110112-120936
Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708. doi:10.2307/1913610
Nguyen, H. T., Lan, Y., & Treepongkaruna, S. (2018). *Firm-specific return variation and stock returns* (Working paper). Available at https://efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2018-Milan/papers/EFMA2018_0348_fullpaper.pdf
Patton, A., & Timmermann, A. (2010). Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts. *Journal of Financial Economics*, *98*(3), 605–625. doi:10.1016/j.jfineco.2010.06.006
Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563–602. doi:10.1016/j.jfineco.2005.05.003

Peng, L., Xiong, W., & Bollerslev, T. (2007). Investor attention and time-varying comovements. *European Financial Management*, *13*(3), 394–422. doi:10.1111/j.1468-036X.2007.00366.x

Peterson, K., Schmardebeck, R., & Wilks, T. J. (2015). The earnings quality and information processing effects of accounting consistency. *The Accounting Review*, *90*(6), 2483–2514. doi:10.2308/accr-51048

Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review*, *79*(4), 1119–1151. doi:10.2308/accr.2004.79.4.1119

Rajgopal, S., & Venkatachalam, M. (2011). Financial reporting quality and idiosyncratic return volatility. *Journal of Accounting and Economics*, *51*(1–2), 1–20. doi:10.1016/j.jacceco.2010.06.001

Roll, R. (1988). R^2. *The Journal of Finance*, *43*(3), 541–566. doi:10.1111/j.1540-6261.1988.tb04591.x

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), 9–16. doi:10.3905/jpm.1985.409007

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442. doi:10.2307/2977928

Szczygielski, J. J., Mikutowski, M., & Zaremba, A. (2019). Is there a low-risk anomaly in the UAE stock market? *Journal of Research in Emerging Markets*, *1*(2), 39–44. doi:10.30585/jrems.v1i2.348

Weigert, F. (2016). Crash aversion and the cross-section of expected stock returns worldwide. *Review of Asset Pricing Studies*, *6*(1), 135–178. doi:10.1093/rapstu/rav019

World Federation of Exchanges (WFE). (2019). Monthly report – January 2019. Retrieved from https://www.world-exchanges.org/our-work/statistics

Wurgler, J. (2000). Financial markets and the allocation of capital. *Journal of Financial Economics*, *58*(1–2), 187–214. doi:10.1016/S0304-405X(00)00070-2

Xu, N., Chan, K. C., Jiang, X., & Yi, Z. (2013). Do star analysts know more firm-specific information? Evidence from China. *Journal of Banking & Finance*, *37*(1), 89–102. doi:10.1016/j.jbankfin.2012.08.014

Zaremba, A. (2016). Is there a low-risk anomaly across countries. *Eurasian Economic Review*, *6*(1), 45–65. doi:10.1007/s40822-015-0036-3

Zaremba, A., & Shemer, J. (2016). Is risk always rewarded? Low-volatility anomalies. In *Country asset allocation* (pp. 81–104). New York: Palgrave Macmillan. doi:10.1057/978-1-137-59191-3_5

Zaremba, A., & Shemer, J. (2018). No pain, no gain? The puzzle of risk-return relationship. In *Price-based investment strategies* (pp. 125–165). Cham: Palgrave Macmillan. doi:10.1007/978-3-319-91530-2_4

Zhang, W., Li, X., Shen, D., & Teglio, A. (2016). R^2 and idiosyncratic volatility: Which captures the firm-specific return variation? *Economic Modelling*, *55*, 298–304. doi:10.1016/j.econmod.2016.02.025