Pacific-Basin Finance Journal 33 (2015) 23–37

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Risk and return in the Chinese stock market: Does equity return dispersion proxy risk?☆

Chun-Da Chen [a], Riza Demirer [b,]*, Shrikant P. Jategaonkar [b]

[a] Department of Economics and Finance, College of Business, Lamar University, 4400 S. Martin Luther King Jr. Parkway, Beaumont, TX 77710, USA
[b] Department of Economics & Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102, USA

ARTICLE INFO

Article history:
Received 10 December 2013
Accepted 23 March 2015
Available online 28 March 2015

JEL classification:
G11
G12

Keywords:
Equity return dispersion
Asset pricing
Chinese stock market

ABSTRACT

We examine whether equity return dispersion, measured by the cross-sectional standard deviation of stock returns, is systematically priced in the cross-section of stock returns in China. We find that return dispersion carries a positive price of risk even after controlling for market, size, book-to-market, and idiosyncratic volatility effects. We observe that stocks with greater sensitivities to equity return dispersion yield higher average returns. The finding of a significant return dispersion effect is robust to alternative portfolio sorts based on the well-established risk factors as well as industry portfolios. We argue that equity return dispersion captures the fundamental uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring that cannot be captured by market and firm level factors. To that end, return dispersion serves as a more meaningful proxy for risk in this emerging market that has experienced a significant economic transition during much of the sample period.

1. Introduction

As one of the main drivers of global economic output and demand, China and its stock markets have attracted much attention in the literature. Due to its unique institutional and investor characteristics, researchers have examined the Chinese stock market from many different angles.[1] However, the strand of the literature focusing on asset pricing models for this market is still evolving. Previous studies on the Chinese

☆ We thank an anonymous referee for helpful comments and suggestions. Any remaining errors are our own.
* Corresponding author at: Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102. Tel.: +1 618 650 2939; fax: +1 618 650 3047.
E-mail address: rdemire@siue.edu (R. Demirer)
[1] Chan et al. (2007) provide a comprehensive review of the published works on China.

http://dx.doi.org/10.1016/j.pacfin.2015.03.005
0927-538X/

stock market document mixed findings on the systematic risk factors that drive the variation in the cross-section of returns.[2] Overall, the evidence reported so far is generally against the Capital Asset Pricing Model (CAPM) and suggests that the market factor does not explain the cross-sectional variation in returns in this emerging market (e.g. Drew et al., 2004; Wang and Xu, 2004; Wong et al., 2006; Eun and Huang, 2007). The evidence related to the alternative determinants of stock returns is mixed at best. Nevertheless, as one of the key drivers of global economic activity, understanding the systematic drivers of stock market returns in this country is of interest to not only market regulators and domestic investors, but also to international investors who play an increasingly active role in this market.

An increasing number of studies on U.S. stock returns focus on equity return dispersion measured by the cross-sectional standard deviation of stock returns in the market in a given period. In the literature on U.S. stock returns, equity return dispersion has been associated with business cycles (Christie and Huang, 1994; Duffee, 2001), aggregate market volatility (Stivers, 2003), idiosyncratic volatility (Stivers, 2003; Connolly and Stivers, 2006), and the value and momentum premium in stock returns (Stivers and Sun, 2010; Bhootra, 2011).

In an extension to asset pricing models, recent studies document that return dispersion also carries a significant positive price of risk even after controlling for alternative systematic risk factors. The findings reported by Jiang (2010) and, more recently, by Demirer and Jategaonkar (2013) suggest that return dispersion captures the uncertainty related to fundamental economic restructuring that cannot be explained by the alternative well-established market and firm level risk factors. These studies also suggest that the inclusion of return dispersion in asset pricing models leads to lower pricing errors and improves the goodness of fit over the CAPM and Fama and French (1993) three factor alternatives.

Given these findings, a natural question to ask is whether return dispersion is significantly priced in the cross-section of stock returns in China that has experienced a significant economic transformation over the past several decades. Therefore, this study contributes to the literature on asset pricing in the Chinese stock market by enlarging our understanding of the dimension of uncertainty in market fundamentals captured by equity return dispersion. To the best of our knowledge, this study is the first to examine return dispersion as a systematic factor in asset pricing models for Chinese stock returns.

This study has several contributions to the literature. First, using recent data, we re-examine the validity of the CAPM and the Fama and French (1993) factors on the cross-section of stock returns in China. Second, we use alternative portfolio sorts to examine the prevalence of the idiosyncratic volatility (IV) effect on returns in this market.[3] Finally, we extend the asset pricing literature for China by examining whether equity return dispersion carries a significant price of risk even after controlling for alternative risk factors. By examining the dimension of uncertainty captured by return dispersion in an emerging market, this study contributes to not only the asset pricing literature on China, but also to the emerging literature on equity return dispersion.

Consistent with the evidence on U.S. stock returns (Jiang, 2010; Demirer and Jategaonkar, 2013), we find that equity return dispersion cross-sectionally drives stock returns, even after controlling for market, size, book-to-market, and idiosyncratic volatility effects. We observe that stocks with greater sensitivities to equity return dispersion indeed yield higher average returns and that the return dispersion effect is robust to alternative portfolio sorts. Following the suggestion by Chen and Petkova (2012) that idiosyncratic volatility may be associated with real option opportunities with a firm, the finding of a robust return dispersion effect in the presence of an insignificant idiosyncratic volatility effect suggests that return dispersion indeed captures what Berk et al. (1999) term the real growth options and the flexibility of adaptability to fundamental economic restructuring associated with a firm. This is also in line with the hypothesis by Pastor and Veronesi (2009) that the risk that is idiosyncratic to particular firms during the initial phase of technological shifts transforms into a market wide systematic risk as the adoption probability of the new technology across the market increases over time.

It is possible that equity return dispersion is what Kogan and Papanikolaou (2013) term as the common systematic risk factor associated with firms' sensitivities to technology shocks which also drive the difference in the returns among firms sorted on various firm level characteristics including idiosyncratic volatility.

[2] See, for example, Drew et al. (2004), Wang and Xu (2004), Wong et al. (2006), Eun and Huang (2007), Chen et al. (2010), Narayan and Zheng (2010), Opie and Zhang (2013), and Choi et al. (2013). The findings of these studies are discussed in detail in the literature review section.

[3] Drew et al. (2004) argue that size and idiosyncratic volatility may serve as proxies for systematic risk in China whereas Eun and Huang (2007) document a significantly negative relationship between firm-specific risk and expected returns.

Overall, our findings suggest that equity return dispersion captures the uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring and thus serves as a more meaningful systematic risk factor in China which has experienced a significant economic transition during much of the sample period.

The remainder of this paper is organized as follows. Section 2 briefly discusses the asset pricing literature on the Chinese stock market, Section 3 explains the data and methodology, Section 4 presents empirical findings and Section 5 concludes the paper.

2. Asset pricing literature on China

Earlier studies on pricing issues in the Chinese stock market start with Drew et al. (2003) who present a multi-factor model explaining returns and note that the market factor alone is not sufficient to explain the variation in the cross-section of returns in China. While they document a significant size effect, they conclude that the book-to-market effect is not as pervasive in China as in the United States. Similarly, Wang and Xu (2004) report a significant size effect whereas market beta and the book-to-market ratio are found to be insignificant. Later, Drew et al. (2004) provide further support for a multifactor model of returns against the CAPM and argue that size and idiosyncratic volatility may serve as proxies for systematic risk in this market. Wong et al. (2006) find that smaller firms and value stocks yield greater returns whereas market beta is not found to be priced. However, market risk is found to be negatively significant in down markets only, suggesting a role for beta in market downturns.

Utilizing principal component analysis, Chen et al. (2007) find that size and book-to-market ratio are linked to several risk factors including liquidity, financial stress, and market volatility. Following a modified version of the two-pass approach by Fama and MacBeth (1973) and focusing on A shares only, Eun and Huang (2007) find that firm size and book-to-market ratio are systematically priced in the cross-section of stock returns, with significantly greater returns for small capitalization and high book-to-market stocks. While their findings suggest that market risk is not significantly priced in stock returns, they find a significantly negative relationship between firm-specific risk and expected returns.

In more recent studies, Chen et al. (2010) examine the role of eighteen firm-specific variables that have been documented to be significant drivers of U.S. stock returns and find that book-to-market ratio, net operating assets, R&D spending, asset growth, and illiquidity are the only significant variables explaining the cross-section of returns in China. They attribute the weak predictability of returns in China relative to the U.S. to the homogeneity in firm-specific characteristics across firms and persistent mispricing in this market. Narayan and Zheng (2010), on the other hand, suggest that market liquidity as a risk factor can well capture the impact of size, book-to-market, turnover, and momentum. Opie and Zhang (2013) find a positive relation between stock returns and divergence of opinion, even after controlling for the well-established factors including book-to-market ratio, size, momentum, etc. However, they find mixed results regarding the sign of this relationship depending on the proxy used to measure divergence of opinion. Finally, examining investor heterogeneity from a different perspective, Choi et al. (2013) find that the increase in ownership breadth predicts low returns when small retail investors are considered whereas the opposite holds among institutional investors. Overall, the asset pricing literature documents consistent evidence that the market beta is insignificant in the cross section of stock returns in this market, with mixed results regarding the effect of the other systematic risk factors.

Despite the growing number of asset pricing studies applied to the Chinese stock market, equity return dispersion as a systematic risk factor has not yet been introduced to the asset pricing literature in China. Given the recent findings by Jiang (2010) and Demirer and Jategaonkar (2013) on U.S. stock returns that equity return dispersion is likely to capture the fundamental uncertainty associated with economic transitions, it is therefore possible that return dispersion is a systematic risk factor driving returns in China that has experienced significant economic transformation over the past several decades.

3. Data and methodology

3.1. Data

We focus on all A-shares listed on the Shanghai and Shenzhen stock exchanges for the period July 1996 through June 2011. Focusing on A-shares allows us to compare our findings with the evidence documented in the literature as most asset pricing studies on China utilize A-shares in their analysis (e.g. Wang and Xu, 2004; Chen et al., 2007; Eun and Huang, 2007; Chen et al., 2010). The stock return, book equity, and the three-month household deposit rate (as a proxy of risk-free rate, R_f) data are obtained from the Taiwan Economic Journal (TEJ) database with a total of 2,138 listed firms. We delete the financial firms, utilities, and firms that do not have an industry code available.[4]

Daily (monthly) stock returns are used to calculate the return dispersion (RD) for each day (month) expressed as the cross-sectional standard deviation of daily (monthly) stock returns. The return dispersion, RD_t, for period t is calculated as

$$RD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(r_{i,t}-r_{m,t}\right)^2} \tag{1}$$

where $r_{i,t}$ and $r_{m,t}$ are the return for stock i and the market for period t, respectively and N is the number of stocks in the sample. Since our sample consists of A-shares from both the Shanghai and Shenzhen stock exchanges, we construct series of daily and monthly value-weighted average returns using all A-shares listed on the two exchanges as a proxy for the market return. Using a market model benchmark, return dispersion can be linked to the cross-sectional correlation of asset returns (Solnik and Roulet, 2000), however, unlike traditional measures of correlation and volatility, return dispersion provides an aggregate measure of comovement in a portfolio for a given time period.

There is indeed a well-established literature associating return dispersion with different aspects of risk. Earlier studies on U.S. stock returns including Christie and Huang (1994) and Duffee (2001) associate return dispersion with economic expansions and recessions. Later, Stivers (2003) and Connolly and Stivers (2006) suggest that return dispersion provides signals about future aggregate market volatility. In an extension to the asset pricing context, Stivers and Sun (2010) and Bhootra (2011) document a link between the time variation in the value and momentum premiums and the variation in the market's cross-sectional return dispersion. Finally, Jiang (2010) documents the first formal evidence that return dispersion indeed carries a positive price of risk even after controlling for firm and market level factors whereas, later, Demirer and Jategaonkar (2013) find that return dispersion risk is asymmetrically priced and conclude that return dispersion is more likely to capture shocks related to fundamental economic restructuring, rather than the business cycle.

3.2. Estimating factor risk premiums

3.2.1. Market, firm size, and book-to-market effects

As explained earlier, we construct a series of value-weighted average returns for all A-shares listed on the Shanghai and Shenzhen markets. We use this series of market returns, adjusted for the risk-free rate, as our proxy for the market factor. The SMB (size) and HML (book-to-market) factors are constructed using six value-weighted portfolios formed on the market value of equity and the book-to-market ratio for the firms. Following Drew et al. (2004), at the end of December of each year, we assign stocks to two size portfolios (Big and Small) based on whether the firm's market value of equity (MVE) is above or below the median MVE. Independently, we assign the stocks to three book-to-market portfolios (Low, Medium, and High) based on the breakpoints for the bottom 33.33% and top 66.67%. Every month, the SMB (Small minus Big) factor is the average return on the three small portfolios (SL, SM, SH) minus the average return for the three big portfolios (BL, BM, BH). Similarly, every month, the HML (High minus Low) factor is calculated by subtracting the return for the two growth portfolios (SL, BL) from that of the two value portfolios (SH, BH).

3.2.2. The effect of idiosyncratic volatility

Drew et al. (2004) argue that size and idiosyncratic volatility may serve as proxies for systematic risk in the Chinese stock market. In order to validate our findings on return dispersion in the presence of idiosyncratic volatility, we calculate the idiosyncratic volatility (IV) factor to be included in the asset pricing tests. Following Drew et al. (2004), for each month, we calculate the total risk, defined as the variance of returns over the past

[4] Our initial sample period covers data from 1991 through 2011 and consists of 943 A shares listed on Shanghai and 1,343 A shares listed on Shenzhen. However, we observe that there are very few firms that have data prior to 1996. Also, as Wang and Xu (2004) state, price stabilization was implemented in the latter part of 1996. Therefore, our final sample starts in July 1996.

24 months, for each stock in the sample. We define the idiosyncratic risk as the difference between the total risk and the systematic risk for the stock. For each month, the systematic risk is the product of the beta from the market model, based on the past 24 month returns for the stock and the weighted-average market index returns, and the variance of the index returns over the same 24 month period.[5] At the end of December each year, we assign the stocks to three IV portfolios (Low IV, Medium IV, High IV) based on the breakpoints for the bottom 33.33% and top 66.67%. We then construct six (SIZE,IV) portfolios and calculate the HMLIV (high minus low IV) factor as the difference between the average returns for the two high idiosyncratic volatility portfolios (SH, BH) and the average returns for the two low idiosyncratic volatility portfolios (SL, BL).

3.2.3. The return dispersion risk factor

Similar to Jiang (2010), we use the daily data to construct portfolios based on the factor loadings on market return and return dispersion defined in Eq. (1). For each stock, the factor loadings on the market return are obtained each month by estimating

$$R_{i,t} = \beta_0 + \beta_{i,RM} R_{m,t} + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t}$ and $R_{m,t}$ are the excess return for stock i and the weighted average return for the market for day t respectively, and $\beta_{i,RM}$ is the loading on the market return for stock i for that month. We run the above model for each stock each month and estimate the factor loadings on the market return. In order to estimate the loadings on the return dispersion for each stock, each month, we estimate

$$R_{i,t} = \beta_0 + \beta_{i,RM} R_{m,t} + \beta_{i,RD} RD_t + \varepsilon_{i,t} \tag{3}$$

where RD_t is the return dispersion for day t, and $\beta_{i,RD}$ is the loading on the return dispersion for stock i during that month. We run the above model for each stock each month and estimate the factor loadings on the return dispersion. Note that, following Jiang (2010) and Demirer and Jategaonkar (2013), daily data is used in the estimation of market and return dispersion loadings for each month. Once the loadings on the market return and the return dispersion are estimated for each month, subsequent asset pricing tests are done using monthly data.

Having estimated market and RD loadings, we first sort the stocks into five portfolios based on the loadings on the market return. We then sort each of these five portfolios into quintiles based on the loadings on the return dispersion. This procedure yields 25 (5x5) portfolios for each month based on the loadings on the market return and the return dispersion from July 1996 through June 2011.

Having constructed 25 portfolios based on the loadings on the market return and return dispersion, we then run rolling regressions of each one of the 25 portfolio returns on the three Fama-French (1993) factors (market, size and book/market), the return dispersion factor, and the idiosyncratic volatility factor to estimate the betas for each month. More specifically, the following time-series regressions are used to estimate the coefficients for the Fama-French, idiosyncratic volatility and the return dispersion risk factors

$$R_{p,T} = \alpha_{p,t} + \beta^{m}_{p,t} R_{m,T} + \beta^{smb}_{p,t} R_{smb,T} + \beta^{hml}_{p,t} R_{hml,T} + \beta^{iv}_{p,t} HMLIV_T + \beta^{rd}_{p,t} RD_T + \varepsilon_{p,T} \tag{4}$$

where T = t-24, t-23, t-22, …, t-1. In this equation, $R_{p,T}$, $R_{m,T}$, $R_{smb,T}$, and $R_{hml,T}$ denote the excess return on portfolio p, the market, SMB and HML factors for month T, respectively. Finally, the model incorporates the idiosyncratic volatility and the return dispersion risk factors denoted by $HMLIV_T$ and RD_T for month T, respectively. The sensitivities of portfolio p to the three Fama and French (1993) risk factors, the idiosyncratic volatility and the return dispersion factor for month t are denoted by $\beta^{m}_{p,t}$, $\beta^{smb}_{p,t}$, $\beta^{hml}_{p,t}$, $\beta^{iv}_{p,t}$ and $\beta^{rd}_{p,t}$, respectively. The betas are estimated by running rolling regressions where we roll a window of 24-month returns forward one month at a time. Since the sample period starts in July 1996, the betas are estimated for each month during July 1998 through June 2011 period.

[5] We require the stocks to have 24 months of continuous returns for these calculations. Stocks that do not satisfy this condition are excluded from this part of the analysis.

Following the Fama and MacBeth (1973) methodology, we next use post-ranking beta estimates from the time-series regression in Eq. (4) and estimate the following cross-sectional regression

$$R_{p,t} = \gamma_{0,t} + \gamma_{m,t}\hat{\beta}^{m}_{p,t} + \gamma_{smb,\ t}\hat{\beta}^{smb}_{p,t} + \gamma_{hml,t}\hat{\beta}^{hml}_{p,t} + \gamma_{iv,t}\hat{\beta}^{iv}_{p,t} + \gamma_{rd,t}\hat{\beta}^{rd}_{p,t} + \epsilon_{p,t} \tag{5}$$

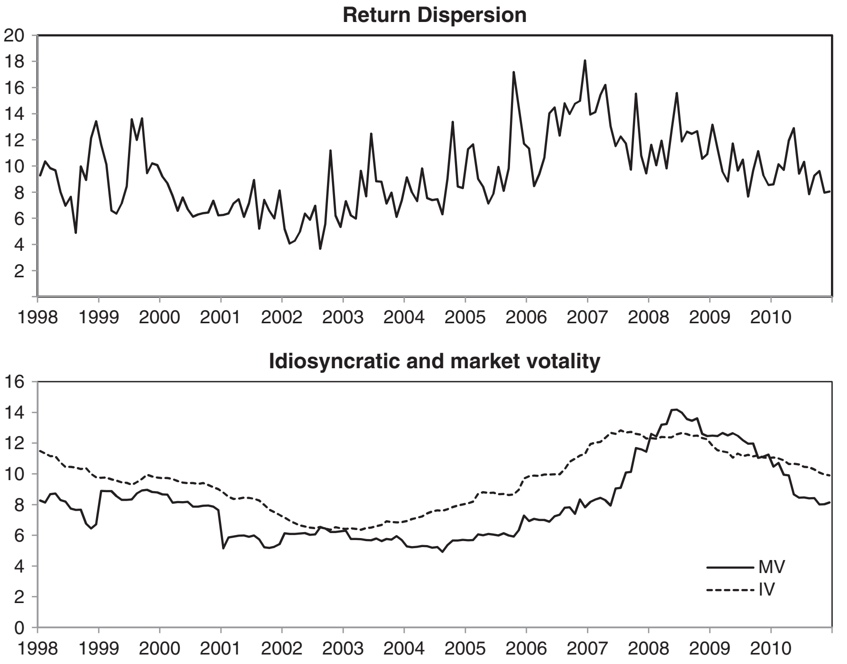
where $\gamma_{m,t}$, $\gamma_{smb,\ t}$, $\gamma_{hml,t}$ $\gamma_{iv,t}$ and $\gamma_{rd,t}$ denote the risk premium on each of the three Fama-French factors, the idiosyncratic volatility, and the return dispersion risk factor, respectively. Having obtained an estimate for each γ term each month, we then calculate the average of monthly γ values and estimate the risk premium for risk factor f as $\gamma_f = \frac{1}{N}\sum_{t=1}^{N}\hat{\gamma}_{f,t}$ where N is the number of months. In Eq. (5), obtaining statistically significant estimates for $\gamma_{f,t}$ suggests that factor f is priced in the cross section of returns.

4. Empirical results

4.1. Return dispersion and market risk

Fig. 1 presents the plots of monthly return dispersion, market volatility, and idiosyncratic volatility values. Not surprisingly, we observe a significant upward trend in the market and idiosyncratic volatility values during the period corresponding to the 2008 global financial crisis that originated in the U.S. financial markets. However, the return dispersion plot seems to capture the dot-com boom and the subsequent crash in the U.S. market during late 1990s as well as the market boom during much of the 2000s, indicated by the relatively high values of return dispersion.

Table 1 provides several descriptive statistics along with the cross-correlations. We estimate the correlations between return dispersion and the market return to be 42%, return dispersion and market volatility to be 39%, and return dispersion and idiosyncratic volatility to be 58% suggesting that equity return dispersion



Note: Figure shows the monthly return dispersion calculated using Equation 1 and market and idiosyncratic volatility calculated following the procedure in Section 3.2.2.

Fig. 1. Return dispersion, idiosyncratic volatility and market volatility. Note: Figure shows the monthly return dispersion calculated using Eq. (1) and market and idiosyncratic volatility calculated following the procedure in Section 3.2.2.

Table 1
Summary statistics.

Panel A: Descriptive statistics					
Variable	Mean	Std. Dev.	Min.	Max.	
RD (%)	9.942	2.936	4.062	18.717	
IV (%)	9.598	1.920	6.359	12.837	
MV (%)	8.072	2.448	5.145	14.186	
SMB (%)	0.751	4.837	−14.063	13.501	
HML (%)	−0.037	3.388	−13.837	8.803	
R_m (%)	1.750	8.711	−21.104	29.489	
Panel B: Cross-correlations					
	RD	IV	MV	SMB	HML
IV	0.583				
MV	0.385	0.825			
SMB	−0.0217	0.249	0.254		
HML	−0.098	−0.097	−0.041	0.018	
R_m	0.421	0.089	0.025	0.104	0.078

Note: This table reports the descriptive statistics for the period July 1996 through June 2011. RD, IV and MV are the monthly return dispersion, idiosyncratic volatility and market volatility, respectively. Similarly, SMB, HML and R_m are the monthly returns for (small-big) and (high B/M-low B/M) portfolios and the market portfolio, respectively.

is likely to be associated with risk at the market and firm level. We observe that return dispersion has a larger mean (9.942%) than idiosyncratic volatility whereas idiosyncratic volatility is less volatile. In Fig. 1, the high values of return dispersion in China during the dot-com era as well as the boom period experienced in much of the 2000s is consistent with the observation by Jiang (2010) of extremely high values of return dispersion in the U.S. during late 1990's when the economy was in a major transition period to a new technology termed as the "new" economy.

In order to establish preliminary evidence on the relation between return dispersion and market risk in China, we first estimate a model that examines the behavior of return dispersions during periods of large market gains and losses as well as during market crisis periods

$$RD_t = \underset{(0.07)^{***}}{1.895} + \underset{(3.6\text{x}10^{-5})^{***}}{8.6 \times 10^{-5}}t + \underset{(0.05)^{***}}{0.621D_{ext}^{-}} + \underset{(0.51)^{***}}{0.231D_{ext}^{+}} + \underset{(0.08)^{***}}{0.173D_t^{Asian}} + \underset{(0.06)^{***}}{0.479D_t^{global}} + e_t \tag{6}$$

where t is a trend variable and D_{ext}^{-} (D_{ext}^{+}) takes on the value of unity if the market return on day t is lower (greater) than the 10 percent tail of the empirical distribution of market returns. The market crisis periods are represented by D_t^{crisis} (*crisis*= Asian, global) capturing the Asian crisis and the 2008 global crisis periods.[6]

Eq. (6) yields an R^2 value of 0.154 with the heteroskedasticity and autocorrelation consistent standard errors reported in parentheses. The inclusion of the time trend follows Baur (2006) who suggests that the return dispersion statistic can be regarded as a proxy for the degree of association across multiple assets. Eq. (6) yields a positive and significant trend in return dispersion, suggesting that the degree of association across stock returns in China has decreased over time. It is possible that the positive trend in the dispersion of stock returns is partly due to the significant economic transition experienced in this country that led to technological shifts and is consistent with the observation by Jiang (2010) for the U.S. market.

Similarly, we see that both positive and negative shocks increase the dispersion in returns but the increase is significantly stronger for negative shocks. It is possible that this is related to the "leverage effect" argument provided by Black (1976) so that negative return implies greater financial leverage and thus leads to an increase in equity return volatility. From a different perspective, however, considering the return dispersion as a proxy for cross-sectional correlation along the lines of Solnik and Roulet (2000), the asymmetric response

[6] Following Chiang and Zheng (2010), the Asian crisis period refers to 7/1/1997–12/31/1998 and the 2008 global crisis period refers to 3/1/2008–3/31/ 2009.

of return dispersion to bad versus good news implies asymmetric response of stock correlations to market movements.

We observe significantly higher equity return dispersions during both the Asian and the 2008 global crisis periods, supporting a possible link between market volatility and equity market dispersion. We also observe that stock returns are more dispersed during periods of market stress, characterized by large market movements, regardless of the direction of the movement. Overall, our preliminary analysis implies that return dispersion may capture some aspect of risk in the market that is related to transitionary periods and business cycles caused by market shocks which is consistent with earlier suggestions by Christie and Huang (1994), Duffee (2001), Stivers (2003) and Connolly and Stivers (2006). However, whether return dispersion is systematically priced in the cross section of returns is yet to be explored. We next proceed with the formal asset pricing tests.

4.2. Market, size, book-to-market and idiosyncratic volatility effects re-examined

We begin our analysis by first examining the significance of the well-established Fama and French (1993) risk factors. Table 2 presents the Fama and MacBeth (1973) cross-sectional regression coefficients for twenty-five (5×5) portfolios sorted first by firm size and then by book-to-market ratio. In the table, M denotes the excess market return, SMB and HML are the Fama-French size and book-to-market factors, and IV is the idiosyncratic volatility factor. The table reports the Fama-MacBeth t-statistics (in parentheses) as well as the Shanken (1992) t-statistics (in brackets) adjusted for the errors-in-variables problem.[7] Results for Model 1 suggest that the market factor does not explain the variation in stocks returns in China. Consistent with the findings in Drew et al. (2003, 2004), Wang and Xu (2004), Wong et al. (2006) and Eun and Huang (2007), the market factor is found to be insignificant in all alternative model specifications. The finding of an insignificant market factor is also robust to portfolios sorted on size and IV, presented in Table 3.

In the case of the size and book-to-market factors, we get mixed results depending on the portfolio sort employed in the analysis. While the size factor is found to be insignificant in Table 2, the findings for size and IV based portfolios reported in Table 3 yield a negative size effect in the cross-section of returns.[8] A similar argument can also be made in the case of the book-to-market factor. While we find a significant and negative HML factor for portfolios sorted on size and book-to-market ratio (Table 2), we observe that the HML factor is insignificant for portfolios sorted on firm size and IV in Table 3, consistent with Drew et al. (2004). As will be shown later, the inclusion of the return dispersion factor leads the Fama and French (1993) factors to be insignificant in most cases and, coupled with the mixed results reported in Tables 2 and 3, we conclude that the size and book-to-market effects are not as prevalent in the Chinese stock market as in the case for the U.S. market.

We next direct our attention to the idiosyncratic volatility factor documented in Drew et al. (2004). Examining all firms listed in the Shanghai stock exchange, Drew et al. (2004) find that small and low-idiosyncratic volatility firms generate superior returns compared to big and high-idiosyncratic-volatility firms, indicated by a significant negative premium on the idiosyncratic volatility factor. Similarly, Eun and Huang (2007) document a significant and negative relationship between firm-specific risk and expected returns. In Table 3, we present our findings for the 25 portfolios based on size and idiosyncratic volatility as in Drew et al. (2004). Although the premium on the IV factor is found to be negative, consistent with Drew et al. (2004), our tests do not yield any significance for the IV coefficient, suggesting that the idiosyncratic volatility effect is not pervasive in the Chinese stock market. It is interesting that idiosyncratic volatility is found to be insignificant even in the case of portfolios sorted on firm size and IV. Once again, the insignificance of idiosyncratic volatility is robust to alternative model specifications and portfolio sorts reported in Tables 2 and 3.

Finally, it must be noted that the pricing errors in Tables 2 and 3 are generally found to be insignificant based on the chi-square test for the null hypothesis that the pricing errors are jointly equal to zero. The findings are also robust to the number of dependent portfolios in the cross section; the additional tables are not

[7] Following the discussion in Petersen (2009), in order to mitigate the effects of the time-series and the cross-sectional correlation prevalent in panel data sets, we also apply the Newey and West (1987) adjustment on the standard errors. The findings are robust to this adjustment and are available upon request.

[8] Earlier studies including Drew et al. (2004), Wang and Xu (2004), Wong et al. (2006) and Eun and Huang (2007) report a significant size effect whereas Chen et al. (2010), using more recent data, do not find a size effect on returns.

Table 2
Multi-factor model results for portfolios formed on *size* and *book-to-market ratio*.

Model	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_{IV}	Adj. R^2
1 (CAPM)	1.24	−0.334				0.189
	(0.65)	(−0.20)				
	[0.65]	[−0.18]				
2 (CAPM+FF)	0.811	0.193	−0.555	−2.384***		0.583
	(0.65)	(0.17)	(−1.37)	(−7.84)		
	[0.51]	[0.12]	[−0.85]	[−4.96]		
3 (CAPM+FF+IV)	1.743	−0.447	−0.784	−2.205***	0.064	0.607
	(1.36)	(−0.39)	(−1.78)	(−7.23)	(0.22)	
	[1.11]	[−0.28]	[−1.15]	[−4.67]	[0.15]	

Note: This table reports the Fama and MacBeth (1973) cross-sectional regression coefficients for 25 portfolios sorted by firm size and book-to-market ratios. The coefficients are obtained using monthly data during July 1996 through June 2011. M represents the monthly excess market return; SMB and HML are size and book-to-market factors; and IV is the idiosyncratic volatility factor. The Fama and MacBeth t-statistics are in parentheses and Shanken (1992) t-statistics adjusted for the error-in-variables problem are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level. The superscript 1, 5, and 10 for the pricing error term (γ_0) indicate significance at 1, 5, and 10% level for the chi-square test statistic for the null hypothesis that the N pricing errors are jointly equal to zero. Lack of superscript indicates insignificance.

included due to space considerations and are available upon request. Having re-examined the findings of earlier tests on Chinese returns, we next proceed with the analysis of return dispersion as a possible risk factor.

4.3. Return dispersion risk premium

Following Jiang (2010) and Demirer and Jategaonkar (2013), we apply the two-step procedure explained in Eqs. (2) and (3) and estimate the return dispersion risk loading for each stock each month. At the end of each month, we sort stocks into quintiles based on the value of return dispersion risk loadings for the month. Firms in Quintile 1 have the lowest loadings indicating stocks that are least sensitive to return dispersion. Similarly, firms in Quintile 5 are the most sensitive with the highest return dispersion loadings. Having placed each stock in each quintile each month, we then create equally- and value-weighted portfolios and form time-series returns for each portfolio in Quintiles 1 through 5. Table 4 reports the average returns for five portfolios sorted on return dispersion loadings. Panels A and B report the findings for equally- and value-weighted portfolios, respectively. We observe that portfolios with higher return dispersion loadings yield greater returns with an average monthly return of −1.023% (5.334%) estimated for Quintile 1 (5) reported in Panel A. The spread in average return between these two quintiles is found to be 6.357% per month and is

Table 3
Multi-factor model results for portfolios formed on *size* and *idiosyncratic volatility*.

Model	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_{IV}	Adj. R^2
1 (CAPM)	2.705**	−1.743				0.148
	(2.25)	(−1.62)				
	[2.18]	[−1.32]				
2 (CAPM+FF)	0.399	1.209	−1.279**	0.216		0.440
	(0.47)	(1.54)	(−3.01)	(0.77)		
	[0.45]	[1.10]	[−2.12]	[0.53]		
3 (CAPM+FF+IV)	0.242	1.589	−1.355**	0.211	−0.358	0.492
	(0.28)	(1.93)	(−3.10)	(0.74)	(−1.32)	
	[0.26]	[1.38]	[−2.17]	[0.50]	[−0.95]	

Note: This table reports the Fama and MacBeth (1973) cross-sectional regression coefficients for 25 portfolios sorted by firm size and idiosyncratic volatility. The coefficients are obtained using monthly data during July 1996 through June 2011. M represents the monthly excess market return; SMB and HML are size and book-to-market factors; and IV is the idiosyncratic volatility factor. The Fama and MacBeth t-statistics are in parentheses and Shanken (1992) t-statistics adjusted for the error-in-variables problem are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level. The superscript 1, 5, and 10 for the pricing error term (γ_0) indicate significance at 1, 5, and 10% level for the chi-square test statistic for the null hypothesis that the N pricing errors are jointly equal to zero. Lack of superscript indicates insignificance.

Table 4
Portfolios sorted by exposure to return dispersion.

Portfolio Ranks	β_{RD}	Return	Std. dev.
Panel A: Equally-weighted			
1	−2.832	−1.023	10.065
2	−1.198	−0.694	9.209
3	−0.314	0.343	9.079
4	0.599	1.786	9.304
5	2.361	5.334	10.415
5 − 1		6.357***	
		(5.64)	
Panel B: Value-weighted			
1	−2.799	−1.221	14.605
2	−1.158	−1.191	11.644
3	−0.321	0.851	13.257
4	0.650	1.053	12.502
5	2.331	5.240	13.709
5-1		6.462***	
		(4.14)	

Note: This table reports the average returns (in percent) during the July 1996 through June 2011 period for three portfolios sorted based on return dispersion risk loadings. Stocks are first ranked into quintiles based on return dispersion risk loadings estimated using Eq. (3): $R_{i,t} = \beta_0 + \beta_{i,RM} * R_{m,t} + \beta_{i,RD} * RD_t + \varepsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return for stock i and the market index for day t respectively, RD_t is the return dispersion for day t, and $\beta_{i,RD}$ is the loading on the return dispersion for stock i during that month. Next, equally-weighted (Panel A) and value-weighted (Panel B) portfolios are constructed using stocks in each quintile from the lowest (Quintile 1) to the highest (Quintile 5) based on return dispersion loadings. The row "5-1" represents the difference in monthly returns between Portfolio 5 and Portfolio 1 (t-statistic reported in parentheses). *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

significant at one percent level. We observe similar results in the case of value-weighted portfolios (reported in Panel B) with an estimated spread in average return between Quintiles 5 and 1 of 6.462% per month, once again significant at one percent level. This finding suggests that stocks with greater sensitivity to equity return dispersion indeed yield significantly higher returns.

In order to see whether the high return observed for stocks that are more sensitive to return dispersion is driven by the idiosyncratic volatility of these stocks, we examine the return statistics for portfolios sorted first by return dispersion sensitivity and then by idiosyncratic volatility. Findings reported in Table 5 show that the

Table 5
Sample characteristics: Portfolios formed on return dispersion and idiosyncratic volatility.

		Idiosyncratic volatility				
		1	2	3	4	5
Return Dispersion	1	−0.615	−1.002	−1.341	−1.628	−1.774
		(12.302)	(12.866)	(13.115)	(13.486)	(14.204)
		[27]	[28]	[28]	[28]	[27]
	2	−0.913	−1.039	−0.757	−1.013	−1.113
		(10.639)	(11.313)	(11.7440	(11.914)	(12.879)
		[28]	[29]	[29]	[29]	[29]
	3	−0.122	−0.067	−0.342	−0.303	−0.105
		(10.629)	(11.2830	(11.310)	(12.010)	(12.697)
		[29]	[29]	[29]	[29]	[29]
	4	1.162	1.333	1.115	1.428	1.169
		(10.786)	(11.632)	(11.769)	(12.561)	(13.059)
		[29]	[29]	[29]	[29]	[29]
	5	4.118	4.418	4.212	4.237	4.172
		(12.076)	(12.854)	(13.243)	(13.834)	(14.602)
		[28]	[28]	[28]	[28]	[28]

Note: This table reports the mean and standard deviation (in percent) of returns for 25 portfolios sorted by return dispersion and idiosyncratic volatility. For each portfolio, the standard deviation and the number of stocks are reported in parentheses and brackets, respectively.

average portfolio returns do not vary across the high and low IV portfolios. For instance, the average returns for the five low IV portfolios are −0.615%, −0.913%, −0.122%, 1.162%, and 4.118%, the returns for the corresponding high IV portfolios are −1.774%, −1.113%, −0.105%, 1.169%, and 4.172%. We find a high variation between the average returns for the low and high return dispersion portfolios. While the average returns for five low RD portfolios are all negative, the average returns for five high RD portfolios are all positive and significantly greater than those with lower RD sensitivities. These findings confirm that higher returns are mainly driven by stocks' sensitivities to equity return dispersion and not by their idiosyncratic volatility, further supporting our findings in Section 4.2.

Table 6 reports our findings for 25 portfolios sorted first by market risk loadings and then by return dispersion risk loadings as explained in Eqs. (2) and (3). Comparing Models 1 and 2 and Models 4 and 5, we observe that the inclusion of the return dispersion factor leads to higher average R^2 values suggesting that including the return dispersion factor improves the goodness of fit over the alternative model specifications. We also observe that the pricing error is generally insignificant in the models. Examining the estimated risk premiums, we observe a positive risk premium on the return dispersion factor significant at one percent level in each case. The risk premium on the return dispersion factor is estimated to be 3.297%, 2.393%, and 1.795% per month for Models 2, 3, and 5, respectively and is consistent with the findings in Jiang (2010) and Demirer and Jategaonkar (2013) for the U.S. market. Overall, the findings suggest that return dispersion risk indeed carries a positive price of risk even after controlling for market, size, book-to-market, and idiosyncratic volatility effects.

4.4. Robustness checks

In a critique of asset pricing tests, Lewellen et al. (2010) note the tendency of researchers to use the size and book-to-market portfolios to test their proposed models and suggest that researchers should use alternative portfolio specifications sorted on industry or factor loadings. For this purpose, we perform additional robustness tests using alternative portfolios based on factor loadings and examine the significance of the return dispersion risk factor for alternative portfolios. Table 7 presents robustness checks for the return dispersion risk factor using an expanded set of portfolios formed on alternative factor specifications including size and book-to-market ratio (Panel A), size and idiosyncratic volatility (Panel B), size and return dispersion (Panel C), and return dispersion and idiosyncratic volatility (Panel D). Additionally, in order to test the robustness

Table 6
Price of return dispersion risk.

Model	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_{RD}	γ_{IV}	Adj. R^2
1 CAPM	−0.159	0.778					0.167
	(−0.18)	(0.84)					
	[−0.17]	[0.66]					
2 CAPM+RD	1.619	0.299			3.297***		0.465
	(1.71)	(0.29)			(12.91)		
	[1.07]	[0.17]			[6.93]		
3 CAPM+FF+RD	1.853	0.847	−2.620***	−2.448***	2.393***		0.605
	(1.67)	(0.72)	(−4.50)	(−6.04)	(8.33)		
	[1.08]	[0.43]	[−2.66]	[−3.57]	[4.73]		
4 CAPM+FF+IV	1.846	1.059	−3.953***	−3.421***		1.068*	0.563
	(1.55)	(0.89)	(−7.46)	(−7.97)		(3.11)	
	[0.92]	[0.49]	[−4.01]	[−4.38]		[1.70]	
5 CAPM+FF+RD+IV	2.939*	−0.152	−3.218***	−2.739***	1.795***	0.962	0.629
	(2.64)	(−0.14)	(−5.92)	(−6.97)	(6.32)	(2.79)	
	[1.67]	[−0.08]	[−3.37]	[−3.99]	[3.49]	[1.62]	

Note: This table reports the Fama and MacBeth (1973) cross-sectional regression coefficients for 25 portfolios sorted by first market risk loadings and then by return dispersion risk loadings. The coefficients are obtained using monthly data during July 1996 through June 2011. M represents the monthly excess market return; SMB, HML, RD and IV are size and book-to-market, return dispersion and idiosyncratic volatility factors, respectively. The Fama and MacBeth t-statistics are in parentheses and Shanken (1992) t-statistics adjusted for the error-in-variables problem are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level. The superscript 1, 5, and 10 for the pricing error term (γ_0) indicate significance at 1, 5, and 10% level for the chi-square test statistic for the null hypothesis that the N pricing errors are jointly equal to zero. Lack of superscript indicates insignificance.

Table 7
Robustness checks for return dispersion risk using alternative portfolios.

Model	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_{RD}	γ_{IV}	Adj. R^2
Panel A: Portfolios formed on size and book-to-market ratio							
1 CAPM+RD	2.903*	−1.291			1.829***		0.420
	(2.20)	(−1.07)			(6.96)		
	[1.72]	[−0.76]			[4.40]		
2 CAPM+FF+IV+RD	3.478**	−2.259	−0.257	−1.811***	1.830***	−0.026	0.644
	(2.76)	(−2.02)	(−0.59)	(−6.17)	(6.69)	(−0.09)	
	[2.01]	[−1.32]	[−0.35]	[−3.65]	[4.05]	[−0.06]	
Panel B: Portfolios formed on size and idiosyncratic volatility							
1 CAPM+RD	0.735	0.597			1.145***		0.355
	(0.83)	(0.73)			(3.99)		
	[0.77]	[0.52]			[2.90]		
2 CAPM+FF+RD+IV	0.328	1.436	−1.224**	0.149	0.853***	−0.302	0.529
	(0.38)	(1.73)	(−2.86)	(0.52)	(3.95)	(−1.13)	
	[0.35]	[1.25]	[−2.00]	[0.36]	[2.63]	[−0.82]	
Panel C: Portfolios formed on size and return dispersion							
1 CAPM+RD	−7.304**,5	8.45**			3.252***		0.466
	(−5.85)	(7.46)			(11.27)		
	[−2.12]	[2.53]			[4.94]		
2 CAPM+FF+RD+IV	−7.854**,1	9.268**	−0.589	−0.182	2.949***	0.696	0.639
	(−6.69)	(8.78)	(−1.38)	(−0.50)	(11.14)	(2.17)	
	[−2.19]	[2.56]	[0.02]	[−0.88]	[3.89]	[0.67]	
Panel D: Portfolios formed on return dispersion and idiosyncratic volatility							
1 CAPM+RD	−5.404**,10	7.119***			2.979***		0.420
	(−5.71)	(8.76)			(12.53)		
	[−2.37]	[3.23]			[6.78]		
2 CAPM+FF+RD+IV	−2.611*	6.039***	−3.193	−0.634	2.518***	0.282	0.839
	(−2.47)	(6.47)	(−6.04)	(−1.51)	(11.32)	(1.18)	
	[−1.76]	[3.11]	[−1.15]	[−0.56]	[5.15]	[0.08]	
Panel E: Industry portfolios							
1 CAPM+RD	−0.217***	1.607			0.723*		0.169
	(−16.82)	(1.64)			(2.05)		
	[−16.24]	[1.29]			[1.67]		
2 CAPM+FF+RD+IV	−0.220***	2.076*	0.639	0.295	0.712**	0.260	0.302
	(−19.49)	(2.47)	(1.85)	(1.26)	(3.07)	(0.96)	
	[−18.53]	[1.80]	[1.16]	[0.78]	[2.40]	[0.70]	

Note: This table reports the Fama and MacBeth (1973) cross-sectional regression coefficients for alternative (5×5) portfolio sorts as well as for 42 industry portfolios formed by assigning each stock to an industry based on the first two digits of its disclosed industry code following the industry classification issued by the China Securities Regulatory Commission. The Fama and MacBeth t-statistics are in parentheses and Shanken (1992) t-statistics adjusted for the error-in-variables problem are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level. The superscript 1, 5, and 10 for the pricing error term (γ_0) indicate significance at 1, 5, and 10% level for the chi-square test statistic for the null hypothesis that the N pricing errors are jointly equal to zero. Lack of superscript indicates insignificance.

of the RD effect on portfolios that were not formed on a measure of variance, we formed industry portfolios following the industry classification issued by the China Securities Regulatory Commission based on the first two digits of each stock's disclosed industry code. Panel E reports the findings for 42 industry portfolios.[9]

Since our focus is the robustness of a significant return dispersion effect, we only present in Table 7 the test results for the models that include return dispersion. Providing support for our earlier findings on return dispersion, the risk premium on the return dispersion factor is found to be positive and highly significant in each alternative portfolio sort and after controlling for the alternative risk factors. We also find that the RD effect remains robust even in the case of portfolios that are not based on a measure of variance implied by significant and positive RD premiums observed even in the case of industry portfolios (Panel E). Overall, the findings

[9] We thank an anonymous referee for the suggestion on testing RD on industry portfolios as well. The list of the industries included and additional findings are available upon request.

clearly indicate that return dispersion risk is systematically priced in the cross-section of returns in China and that this result is robust to alternative portfolio specifications.

4.5. Equity return dispersion and fundamental uncertainty

Vassalou (2003) argues that a model with a factor related to news about the future GDP growth along with the market factor can price equities as well as the three-factor model. In a recent paper, Kogan and Papanikolaou (2013) show that the difference in returns among firms sorted on various firm-level characteristics including idiosyncratic volatility is largely driven by their differences in exposures to a common systematic risk factor associated with these firms' sensitivities to technology shocks. Given the finding of a robust return dispersion effect in the cross-section of returns in China even in the presence of idiosyncratic volatility, it can be argued that equity return dispersion is likely to capture fundamental uncertainty associated with future economic growth and technological transitions.

In a related study, Garcia et al. (2012) show that the cross-sectional variance of stock returns is a consistent and asymptotically efficient estimator for idiosyncratic volatility. Therefore, it can be argued that return dispersion serves as an estimator for idiosyncratic volatility and therefore controls for the idiosyncratic volatility effect in the cross-sectional tests, rendering the IV factor insignificant. However, in the case of the Chinese stock market, idiosyncratic volatility is almost never significant in our prior tests, even in the models that do not include return dispersion as a risk factor. Therefore, one cannot suggest that return dispersion controls for the idiosyncratic volatility effect in our tests. In a related study focusing on idiosyncratic volatility, Chen and Petkova (2012) note that high (low) IV stocks have high (low) research and development expenditure which can be considered an indicator of real options associated with a firm (Cao et al., 2008). Therefore, the finding of an insignificant IV effect in the presence of a robust RD effect suggests that equity return dispersion captures what Berk et al. (1999) term the real growth options and the flexibility of adaptability to fundamental economic restructuring.

The above interpretation is also consistent with the suggestion by Pastor and Veronesi (2009) that, during the initial phase of technological shifts in the economy, risk is mostly idiosyncratic to firms associated with the new technology, leading new economy stocks to be priced at high valuation ratios. However, as the adoption probability of the new technology increases, the uncertainty related to the new technology transforms into market wide systematic risk pushing up discount rates and thus depressing stock prices across the market and this fundamental uncertainty can be what is captured by equity return dispersion in the case of Chinese stock returns. Overall, the evidence reported so far implies that equity return dispersion captures shocks related to fundamental economic restructuring and supports what Jiang (2010) terms as heterogeneous effects associated with the changes in the relative competitive advantage of firms and resource allocation as a result of technological shifts. To that end, it is not surprising to find a robust systematic risk factor that is associated with the difference in firms' sensitivities to technological shocks in China, a country that has experienced a significant economic transition during much of the sample period. Nevertheless, it can be argued that equity return dispersion as a systematic risk factor provides a more meaningful proxy for risk in this emerging market.

Clearly, the finding of a significant return dispersion effect on the cross-section returns has implications for asset pricing and portfolio management. Given the finding of a significant and positive return dispersion risk premium in Chinese stock returns, portfolio strategies based on stocks' sensitivities to return dispersion could be exploited in order to generate abnormal returns. Furthermore, a stock's sensitivity to equity return dispersion can be explored in order to assess growth opportunities for firms. Following the arguments in Cao et al. (2008) and Chen and Petkova (2012), it can be argued that a stock's sensitivity to return dispersion serves as an indicator of real options associated with a firm and this assessment can be utilized in the construction of growth portfolios in the Chinese stock market. It is possible that, in the case of the Chinese stock market, growth is not indicated by the book-to-market ratio, but rather by the stock's sensitivity to equity return dispersion. Similarly, regarding capital budgeting decisions, the return dispersion premium associated with a firm should be taken into account in the analysis of investment opportunities since rational investors will require a compensation for the added systematic risk driven by exposure to return dispersion.

5. Conclusion

This study extends the literature on asset pricing tests for Chinese stock returns by examining whether equity return dispersion, measured by the cross-sectional standard deviation of stock returns in the market, carries a significant price of risk. We find that equity return dispersion is indeed systematically priced in the cross-section of returns in this emerging market even after controlling for market, size, book-to-market and idiosyncratic volatility effects. We observe that stocks with greater sensitivities to equity return dispersion yield significantly higher average returns, corresponding to a monthly spread in returns between stocks with the highest and lowest sensitivity to return dispersion of 6.357% and 6.462% in equally and value weighted portfolios, respectively. The finding of a significant and positive return dispersion effect is robust to alternative portfolio sorts based on the well-established risk factors as well as for industry portfolios.

Following the suggestion by Chen and Petkova (2012) that idiosyncratic volatility may be associated with real option opportunities with a firm and the finding by Kogan and Papanikolaou (2013) that the difference in returns among firms sorted on various firm-level characteristics is largely driven by their differences in exposures to a common systematic risk factor associated with these firms' sensitivities to technology shocks, the finding of a robust return dispersion effect in the presence of an insignificant idiosyncratic volatility effect suggests that equity return dispersion indeed captures what Berk et al. (1999) term the real growth options and the flexibility of adaptability to fundamental economic restructuring associated with a firm. This is also in line with the hypothesis by Pastor and Veronesi (2009) that the risk that is idiosyncratic to particular firms during the initial phase of technological shifts transforms into a market wide systematic risk as the adoption probability of the new technology across the market increases over time. Therefore, our findings suggest that equity return dispersion indeed captures the fundamental uncertainty associated with economic transitions and the flexibility of adaptability to fundamental economic restructuring that cannot be captured by market and firm level factors. Given the mixed, and sometimes inconsistent, findings in the literature regarding the determinants of stock returns in China, equity return dispersion as a systematic risk factor provides a more meaningful proxy for risk in this emerging market that has experienced a significant economic transition during much of the sample period.

References

Baur, D., 2006. Multivariate market association and its extremes. J. Int. Financ. Mark. Inst. Money 16, 355–369.

Berk, J., Green, R.C., Naik, V., 1999. Optimal investment, growth options, and security returns. J. Financ. 54, 1553–1607.

Bhootra, A., 2011. Are momentum profits driven by the cross-sectional dispersion in expected stock returns? J. Financ. Mark. 14, 494–513.

Black, F., 1976. Studies of stock price volatility changes. Proceedings of the Business and Economics Section of the American Statistical Association, pp. 177–181.

Cao, C., Simin, T., Zhao, J., 2008. Can growth options explain the trend in idiosyncratic risk? Rev. Financ. Stud. 21, 2599–2633.

Chan, K.M., Fung, H., Thapa, S., 2007. China financial research: A review and synthesis. Int. Rev. Econ. Financ. 16, 416–428.

Chen, Z., Petkova, R., 2012. Does idiosyncratic volatility proxy for risk exposure? Rev. Financ. Stud. 25 (9), 2745–2787.

Chen, J., Kan, K.L., Anderson, H., 2007. Size, book/market ratio and risk factor returns: evidence from China A-share market. Manag. Financ. 33 (8), 574–594.

Chen, X., Kim, K.A., Yao, T., Yu, T., 2010. On the predictability of Chinese stock returns. Pac. Basin Financ. J. 18, 403–425.

Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. Financ. 34 (8), 1911–1921.

Choi, J., Jin, L., Yan, H., 2013. What does stock ownership breadth measure? Eur. Finan. Rev. 17, 1239–1278.

Christie, W., Huang, R., 1994. Equity return dispersions. Working paper. Vanderbilt University.

Connolly, R., Stivers, C., 2006. Information content and other characteristics of the daily cross-sectional dispersion in stock returns. J. Empir. Financ. 13, 79–112.

Demirer, R., Jategaonkar, S., 2013. The conditional relation between dispersion and return. Rev. Financ. Econ. 22, 125–134.

Drew, M.E., Naughton, T., Veeraraghavan, M., 2003. Firm size, book-to-market equity and security returns: evidence from the Shanghai Stock Exchange. Aust. J. Manag. 28 (2), 119–139.

Drew, M.E., Naughton, T., Veeraraghavan, M., 2004. Is idiosyncratic volatility priced? Evidence from the Shanghai Stock Exchange. Int. Rev. Financ. Anal. 13, 349–366.

Duffee, G.R., 2001. Asymmetric cross-sectional dispersion in stock returns: Evidence and implications. Working paper. U.C. Berkeley.

Eun, C.S., Huang, W., 2007. Asset pricing in China's domestic stock markets: Is there a logic? Pac. Basin Financ. J. 15, 452–480.

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

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

Garcia, R., Mantilla-Garcia, D., Martellini, L., 2012. Aggregate idiosyncratic volatility and the cross-sectional variance of stock returns. Working paper.

Jiang, X., 2010. Return dispersion and expected returns. Fin. Mkts. Portfolio Mgmt. 24, 107–135.

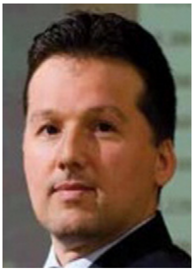
Kogan, L., Papanikolaou, P., 2013. Firm characteristics and stock returns: the role of investment-specific shocks. Rev. Financ. Stud. 26 (11), 2718–2759.

Lewellen, J., Nagel, S., Shanken, J., 2010. A skeptical appraisal of asset pricing tests. J. Financ. Econ. 96, 175–194.

Narayan, P.K., Xinwei Zheng, X., 2010. Market liquidity risk factor and financial market anomalies: Evidence from the Chinese stock market. Pac. Basin Financ. J. 18, 509–520.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Opie, W., Zhang, H.F., 2013. Investor heterogeneity and the cross-sectional stock returns in China. Pac. Basin Financ. J. 25, 1–20.
Pastor, L., Veronesi, P., 2009. Technological revolutions and stock prices. Am. Econ. Rev. 99, 1451–1483.
Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22 (1), 435–480.
Shanken, J., 1992. On the estimation of beta pricing models. Rev. Financ. Stud. 5, 1–34.
Solnik, B., Roulet, J., 2000. Dispersion as cross-sectional correlation. Financ. Anal. J. 56 (1), 54–61.
Stivers, C.T., 2003. Firm-level return dispersion and the future volatility of aggregate stock market returns. J. Financ. Mark. 6, 389–411.
Stivers, C., Sun, L., 2010. Cross-sectional return dispersion and time variation in value and momentum premiums. J. Financ. Quant. Anal. 45 (4), 987–1014.
Vassalou, M., 2003. News related to future GDP growth as a risk factor in equity returns. J. Financ. Econ. 68 (1), 47–73.
Wang, F., Xu, Y., 2004. What determines Chinese stock returns? Financ. Anal. J. 60 (6), 65–77.
Wong, K.A., Tan, R.S.K., Liu, W., 2006. The cross-section of stock returns on the Shanghai Stock Exchange. Rev. Quant. Finan. Acc. 26, 23–39.



Dr. Riza Demirer is an associate professor of finance at Southern Illinois University Edwardsville. His recent work focuses on the issues surrounding market efficiency and asset pricing in a number of emerging and frontier stock markets. He has recently published in refereed journals including *Energy Economics*, *Pacific-Basin Finance Journal*, *Journal of Economic Behavior* & *Organization*, *Review of Financial Economics*, *Journal of International Financial Markets*, *Institutions* & *Money* and *International Review of Economics* & *Finance*. He has served as an ad hoc reviewer for numerous academic journals as well as the National Science Foundation (NSF) Decision, Risk, and Management Science – Economics program. Dr. Demirer is a research fellow at the Economic Research Forum based in Egypt.

Dr. Shrikant P. Jategaonkar received his Ph.D. in 2009 from The University of Arizona. He joined Southern Illinois University Edwardsville as an assistant professor in Fall 2009. Dr. Jategaonkar's work has been published in finance journals such as *Financial Management*, *Financial Review*, and *Review of Financial Economics*. Dr. Jategaonkar's work was also cited in *The Wall Street Journal*. He has served as a referee for *The Financial Review*, *Managerial Finance*, *Emerging Markets Finance and Trade* and *Borsa Istanbul Review*. In addition, Dr. Jategaonkar regularly serves as a reviewer for the *Financial Management Association* (FMA) and *Midwest Finance Association* (MFA) annual meetings.

Dr. Chun-Da Chen is an Associate Professor of Finance at Lamar University. He holds a Ph.D. in Finance from Tamkang University in Taiwan. Dr. Chen's research interests include investor behavior, market efficiency, econometric models and risk management. He has published in journals including Journal of Behavioral Finance, Quarterly Journal of Business and Economics, International Review of Financial Analysis, International Review of Economics and Finance, and Emerging Markets Finance and Trade. He is the funding editor for Journal of Finance and Management and is also on the editorial advisory board for the International Journal of Bonds and Currency Derivatives, Contemporary Management Research, etc.