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Does idiosyncratic volatility matter in emerging markets? Evidence from China

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ABSTRACT

We investigate the time series behavior of idiosyncratic volatility and its role in asset pricing in China. We find no evidence of a long-term trend in the time series behavior of idiosyncratic volatility. Idiosyncratic volatility in China is best characterized by an autoregressive process with regime shifts that coincide with structural market reforms. We also document evidence of a negative idiosyncratic volatility effect in China with anecdotal evidence suggesting that it could be driven by investor preference for high idiosyncratic volatility stocks.

1. Introduction

Idiosyncratic volatility (IVOL) has traditionally been regarded as unimportant in asset pricing because it can be costlessly eliminated through diversification. However it has received considerable attention in the recent literature because of the suggestion that IVOL matters after all. One strand of the research literature focuses on the time-series behavior of idiosyncratic volatility while another deals with the relationship between idiosyncratic volatility and cross-sectional stock returns. Research

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findings in these areas which are mostly confined to either the U.S. or other developed markets are highly contentious and are still vigorously debated in the literature. In one of the few extant studies on emerging markets, Nartea et al. (2011) report a positive relationship between idiosyncratic volatility and cross-sectional stock returns in Singapore, Thailand, Malaysia, and Indonesia, and none in the Philippines, contrary to the negative relationship found in the U.S. and other developed markets. In light of the inherent heterogeneity of emerging markets we find it timely and important to examine the evidence from China, the world's largest emerging market. First, we describe patterns and movements in market and aggregate firm-level volatilities, then we investigate the relationship between IVOL and cross-sectional stock returns.

Trends in idiosyncratic volatility and market volatility have important implications for the benefits of diversification. An increasing IVOL over time coupled with stable market volatility implies that the correlation among stocks is decreasing, which would normally mean an increase in the benefits from diversification. In the U.S., Campbell et al. (2001) find evidence of increased idiosyncratic volatility relative to market volatility in the period 1962–1997. But they also indicate that these trends lead to an increase in the number of stocks needed to achieve a certain level of diversification which implies that investors who cannot fully diversify will experience a deteriorating investment performance. Several studies have variously ascribed the apparent rise in idiosyncratic volatility in the U.S. to increased institutional ownership (Bennett et al., 2003; Xu and Malkiel, 2003), increased volatility of firm fundamentals (Wei and Zhang, 2006), increased competition in product markets (Irvine and Pontiff, 2009), and the increase in younger (Fink et al., 2009) and riskier (Brown and Kapadia, 2007) firms listing in stock markets. However, other studies dispute the claim of a long-term trend in idiosyncratic volatility. Through a regime-switching model, Bekaert et al. (2012) show that there is no trend in IVOL in the U.S. as well as in 22 other developed markets. They propose instead that IVOL followed a stationary autoregressive process that occasionally switched to a higher variance regime. Related to this, Brandt et al. (2010) argue that the pattern of idiosyncratic volatility over time is episodic and is driven by the behavior of retail investors. They show that the positive trend in the U.S. over the period 1962–1997 eventually reversed, and that the increase and subsequent reversal was concentrated among firms with low stock prices and high retail ownership. In his study of emerging markets, Angelides (2010) also suggests that the behavior of asset-specific risk is sample and period-specific.

The relationship between idiosyncratic volatility and cross-sectional stock returns is another contentious issue with Ang et al. (2006) presenting evidence of a "puzzling" negative relationship between IVOL and cross-sectional returns for U.S. stocks when finance theory suggests either a positive relationship or none at all. The classic CAPM suggests that there should be no relationship between idiosyncratic risk and stock returns if investors can fully diversify. However, in cases where investors cannot fully diversify, Levy (1978) and Merton (1987) suggest a positive relationship as investors demand compensation for bearing idiosyncratic risk. The evidence of a negative and significant IVOL effect over 1963–2000 for U.S. stocks is puzzling because it persists even after controlling for various firm characteristics (size, value, liquidity, momentum, analyst forecast dispersion) and market conditions (bull and bear markets, recessions and expansions, high and low market volatility). Brockman and Yan (2006) also find a negative IVOL effect in the U.S. for the period from 1926 to 1962. A follow up study by Ang et al. (2009) confirm their U.S. findings for 22 other developed markets around the world as they report a statistically significant difference in risk-adjusted returns between high and low IVOL portfolios of 1.31% per month.[3] In a related study on emerging markets, Angelides (2010) found a negative relationship between idiosyncratic volatility and market returns using regression analysis, but only when considered together with market risk and only in their pooled sample of 24 countries. On its own, Angelides (2010) reports that idiosyncratic volatility is unrelated to market returns, both on an individual country basis and in the pooled sample. Examining frontier markets, Bley and Saad (2012) also report a negative idiosyncratic volatility effect in Saudi Arabia and Qatar

[3] However, some studies suggest that Ang et al.'s findings are not robust to portfolio weighting schemes (Bali and Cakici, 2008) and controls for short-term reversals (Huang et al., 2010). Others argue that a positive relationship exists between idiosyncratic volatility and returns using alternative measures of expected idiosyncratic volatility (Malkiel and Xu, 2004; Spiegel and Wang, 2006; Divatopolous et al., 2008; Fu, 2009; Chua et al., 2010).

but none in Kuwait and Abu Dhabi. In the present study, we specifically relate idiosyncratic volatility with cross-sectional stock returns for better comparability with Ang et al. (2006, 2009).

Several studies have attempted to explain the negative IVOL "puzzle" but none appears totally convincing (see for example Guo, 2004; Guo and Savickas, 2006, 2008; Kearney and Poti, 2008). The basic argument in these studies is that idiosyncratic risk is a proxy for systematic risk omitted from the CAPM such as liquidity risk and the value premium. However, Ang et al. (2006, 2009) control for these variables in addition to other well-known effects, and yet the negative IVOL effect persists.

We contribute to the literature in two ways. First this is the first study that presents evidence from the world's largest emerging market that the behavior of stock level idiosyncratic volatility is episodic rather than exhibiting long-term trends, similar to that in the U.S. This episodic behavior is best characterized by an autoregressive process with regime shifts that seem to coincide with structural market reforms. It is important for investors who cannot fully diversify their investments to recognize these episodes as they could severely impact investment performance. In addition, since stock trading in China is dominated by retail investors, we present supporting evidence to Brandt et al.'s (2010) suggestion that the episodic behavior of idiosyncratic volatility is due to the trading activities of retail investors.

Second, our study presents evidence that the negative IVOL effect can also observed in emerging markets and contrasts with that of Nartea et al. (2011) who discounted the presence of a negative IVOL effect in the five largest emerging markets of Southeast Asia (Singapore, Malaysia, Thailand, Philippines and Indonesia). Our results underscore the diversity of emerging markets and highlight the need for independent country verification of anomalies that are initially evident in developed markets.

The rest of the paper is organized as follows: Section 2 provides a brief background on the Chinese stock markets; Section 3 describes our data and methods; Section 4 presents the empirical results on the behavior of idiosyncratic volatility; Section 5 deals with the relationship between idiosyncratic volatility and cross-sectional stock returns and Section 6 concludes.

2. Background on the Chinese stock markets

The Shanghai and Shenzhen stock exchanges, collectively referred to as the mainland Chinese stock markets comprise the world's largest emerging market and are only second to the U.S. stock markets in terms of market capitalization. However having established its first stock exchange only in 1990, the Chinese stock markets like other emerging markets are not as informationally efficient as the U.S. stock market and anecdotal evidence of insider trading is rife. In addition, the requirements of financial disclosure are less stringent leading to the scarcity of publicly available information (Tian et al., 2002). Chen et al. (2010) also report high return synchronicity relative to the U.S. stock markets, which implies low stock price informativeness. In addition to this, short sales are not allowed making it difficult to arbitrage any mispricing.

The Chinese stock markets commenced operations as relatively closed stock markets with a unique share structure that allowed domestic and foreign investors access only to certain types of shares. Some Chinese companies were allowed to issue two types of shares in the domestic stock exchanges – A-shares which were accessible only to Chinese residents and institutions until 2001 and B-shares which were open only to foreign investors. However, the liberalization process that started from the new millennium allowed domestic investors to purchase B shares. Likewise in early 2002, the Chinese government launched the qualified foreign institutional investors (QFII) scheme that allowed qualified foreign investors to invest in A-shares. Under the QFII scheme participating foreign institutional investors must obtain a license and an approved investment quota from the State Administration of Foreign Exchange (SAFE). In order to avoid foreign investors taking over Chinese companies a single foreign institutional investor is not allowed to buy more than 10% of the total outstanding shares and the proportion of outstanding A-shares held in total by foreign investors cannot exceed 20%. Furthermore, prior to April 2005, publicly listed Chinese companies had a split-share structure with approximately 60% of their shares that are held by state and legal persons deemed non-tradable. The rest of the shares mainly held by domestic retail and institutional investors were tradable. However, in January 2004 the Chinese government officially announced that the issue of non-tradable shares was a major hurdle in domestic financial development and made a commitment to address the issue. In

April 2005, the China Securities Regulatory Commission initiated the transformation of non-tradable shares to tradable status with a pilot program involving four companies. This was followed by another 42 companies in June 2005 and by August 2005 the program was opened to all listed firms. By the end of 2007, over 97% of publicly listed Chinese companies have completed the conversion.

3. Data and methods

Daily and monthly stock returns on individual firms were obtained from DataStream. We use A-shares listed in the Shanghai and Shenzhen stock exchanges.[4] The data set covered the period from January 1994 with 199 firms, to August 2011 with 1171 firms, with an average of 954 firms per month resulting in a total of 205,087 firm-month observations. The risk-free rate which is defined as the China official cash rate was also obtained from DataStream. Market returns are the value-weighted returns of all firms used in the study.

3.1. Estimating idiosyncratic volatility

Following Ang et al. (2006, 2009) the IVOL of each firm is computed at the beginning of every month as the standard deviation of the residuals ($\sigma_{\varepsilon i}$) from the Fama and French (1993, 1996) 3-factor model (1), henceforth FF3-factor model, using daily data for the previous 22 trading days.[5]

$$R_{i,t} = \alpha + \beta_{MKT,i,m} MKT_t + \beta_{SMB,i,m} SMB_t + \beta_{HML,i,m} HML_t + \varepsilon_{i,t} \tag{1}$$

where day t refers to the 22 trading days ending on the last trading day of month $m-1$. Therefore, $\sigma_{\varepsilon i}$ is a daily volatility measure that is computed monthly. In this model, systematic risk is obviously accounted for by three betas – β_{MKT}, β_{SMB}, and β_{HML}. The betas are allowed to vary through time as the model is re-estimated every month. $R_{i,t}$ and MKT are excess returns of firm i and the market, respectively, over the risk-free rate. SMB is the size factor defined as the excess return of small firms over big firms, and HML is the value factor defined as the excess return of high book-to-market (BM) firms over low BM firms. Therefore, SMB and HML are returns of zero-investment mimicking portfolios for the size and book-to-market effects whose coefficients in (1) are normally regarded as risk-factor loadings. SMB and HML are computed using an adaptation of the method followed by Ang et al. (2009). Accordingly, SMB is the return of the upper half less the return of the lower half of all firms ranked in ascending order according to market capitalization (i.e., share price times the number of shares) while HML is the return of the bottom third less the return of the top third of all firms ranked in ascending order according to BM.

3.2. Portfolio analysis and Fama–MacBeth regressions

To investigate the relationship between IVOL and one-month ahead raw returns, we perform portfolio-level analysis as well as firm-level Fama–MacBeth cross-sectional regressions. In portfolio-level analysis, portfolios are formed at the beginning of every month based on IVOL. Firms are sorted into tertiles based on IVOL and allocated to groups – high IVOL (HIV), medium IVOL (MIV) and low IVOL (LIV). We compute each portfolio's equal- and value-weighted raw returns for the current month, re-forming every month. Consistent with Ang et al. (2006, 2009), we also estimate each portfolio's alpha (α coefficient) from the FF3-factor model (Eq. (1)) estimated using the full sample of monthly value- or equal-weighted returns for each portfolio.

[4] B-shares are subject to different financial reporting and auditing standards compared to A-shares. They are also denominated in foreign currency – U.S. dollar in the Shanghai stock exchange and Hong Kong dollar in the Shenzhen market. Since 1997 no new B-shares have been listed.

[5] Drew et al. (2004) find that the market factor alone cannot sufficiently explain the variation in cross-section of average stock returns in China. They also find that the market and size factors are priced and generate 1% per month and 0.9773% per month respectively. The BM factor is also priced, but it generates a negative risk premium of about −0.20% per month. Wong et al. (2006) also find that FF3 factors are priced in the Chinese stock market.

Since a major disadvantage of portfolio analysis is the loss of too much information through aggregation, we also conduct firm-level Fama–MacBeth regressions and use it to control for various variables. We estimate the following model and its nested versions:

$$\begin{aligned} R_{i,t} = {} & \beta_{0,t-1} + \beta_{1,t-1} IVOL_{i,t-1} + \beta_{2,t-1} SIZE_{i,t-1} + \beta_{3,t-1} BM_{i,t-1} + \beta_{4,t-1} MOM_{i,t-1} \\ & + \beta_{5,t-1} REV_{i,t-1} + \beta_{6,t-1} ILLIQ_{i,t-1} + \beta_{7,t-1} SKEW_{i,t-1} + \beta_{8,t-1} NZV_{i,t-1} \\ & + \beta_{9,t-1} CP_{i,t-1} + \varepsilon_{i,t-1} \end{aligned} \quad (2)$$

R_t is realized stock return in month t. IVOL is realized idiosyncratic volatility as defined previously. SIZE at the end of month t is defined is the log of the firm's market capitalization at the end of month t. BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), MOM at time t is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month t is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). ILLIQ is illiquidity which is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. Illiquid stocks are expected to command a risk premium. There is also a suggestion in the literature of investor preference for positive skewness (Golec and Tamarkin, 1998; Mitton and Vorkink, 2007) which implies a negative skewness effect, hence we also include skewness as a control variable. SKEW is the third standardized moment of returns of the past 22 trading days. NZV is the number of zero volume trading days over the past 22 trading days, another measure of liquidity and CP is the stock's closing price at the end of month t. Closing price is another proxy for illiquidity (Brandt et al., 2010).

4. Time series behavior of volatility

4.1. Descriptive statistics

Panel A of Table 1 reports the descriptive statistics for three volatility series, MVOL, $IVOL^{EW}$, and $IVOL^{VW}$. MVOL is monthly market volatility computed using daily value-weighted market returns. For instance, MVOL as of the end of month m is the standard deviation of daily value-weighted market returns for the past 22 trading days ending on the last trading day of month m. Therefore, like IVOL, MVOL is a daily volatility measure that is computed monthly. $IVOL^{EW}$ and $IVOL^{VW}$ are respectively the equal-weighted and value-weighted average idiosyncratic volatility across all firms, where IVOL is the standard deviation of residuals from Eq. (1). $IVOL^{EW}$ has a higher mean and median than $IVOL^{VW}$ which implies that smaller firms have higher IVOL, consistent with results in other markets particularly the U.S. However, both series have virtually the same coefficient of variation indicating that they are equally variable. Compared with MVOL, both $IVOL^{EW}$ and $IVOL^{VW}$ have similar mean but significantly higher standard deviation. Consequently, MVOL has only about one-fifth the coefficient of variation (CV) of either $IVOL^{EW}$ or $IVOL^{VW}$ indicating that average IV is more variable than MVOL.

Panel B shows that $IVOL^{EW}$ and $IVOL^{VW}$ are highly correlated as expected with a correlation coefficient of 0.953. MVOL is moderately correlated with both $IVOL^{EW}$ and $IVOL^{VW}$ with a correlation coefficient of 0.539 and 0.506, respectively.

Panel C displays the autocorrelation structure of the three volatility series. Serial correlation is fairly high in all three series; hence, we test for the presence of unit roots. The augmented Dickey and Fuller (1979) test results shown in panel D however, rejects the presence of a unit roots for all three series at 1% level of significance, whether or not a trend is included. Hence our analysis of the volatility series will be in levels instead of first differences.

4.2. Is there a time trend in volatility?

Fig. 1 plots $IVOL^{EW}$, $IVOL^{VW}$, and MVOL. Panel A shows wild swings but no apparent trend in $IVOL^{EW}$ from August 1993 to August 2002, but it seems to trend upward from September 2002 to November

Table 1
Descriptive statistics.

Panel A: summary statistics (%)

	Mean	Median	Stdev	CV	Max	Min
$IVOL^{EW}$	0.0172	0.0169	0.0049	0.2819	0.0304	0.0076
$IVOL^{VW}$	0.0162	0.0154	0.0050	0.3084	0.0295	0.0068
MVOL	0.0175	0.0144	0.0110	0.6292	0.0763	0.0047

Panel B: correlation table

	$IVOL^{EW}$	$IVOL^{VW}$	MVOL
$IVOL^{EW}$	1.0000		
$IVOL^{VW}$	0.9533	1.0000	
MVOL	0.5394	0.5058	1.0000

Panel C: autocorrelation structure

	$IVOL^{EW}$	$IVOL^{VW}$	MVOL
ρ_1	0.703	0.703	0.587
ρ_2	0.554	0.528	0.461
ρ_3	0.443	0.412	0.389
ρ_4	0.385	0.344	0.275
ρ_6	0.316	0.304	0.227
ρ_{12}	0.364	0.376	0.182

Panel D: unit root test *t*-statistics

	Constant	Constant and trend
$IVOL^{EW}$	−4.8407	−4.8786
$IVOL^{VW}$	−5.9935	−5.9929
MVOL	−5.7019	−5.9788

This table presents the descriptive statistics of the monthly volatility measures, $IVOL^{EW}$, $IVOL^{VW}$ and MVOL which are respectively the equal- and value-weighted idiosyncratic volatility and market volatility. IVOL of each firm is computed at the beginning of every month as the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. MVOL is the standard deviation of daily value-weighted market returns for the past 22 trading days ending on the last trading day of month. The sample period is1994:01–2011:08. The augmented Dickey–Fuller test for unit roots in panel D are based on regressions with a constant, and regressions with a constant and a trend. The 1 percent critical values for the unit root test are −3.47 with a constant, and −4.01 with constant and a trend.

2007 and downward thereafter. Panel B that plots $IVOL^{VW}$ is virtually identical to panel A. Several spikes in $IVOL^{EW}$ stand out over the period until August 2002. The spikes occur in May (0.0268) and September (0.0332) 1994, August (0.0271) and November (0.0280) 1996, July (0.0297) 1999 and April (0.0268) 2000. This is mirrored by the behavior of $IVOL^{VW}$ with noticeable spikes in May (0.0261) and September (0.0317) 1994, July (0.0265) and November (0.0260) 1996, July (0.0305) 1999 and April (0.0255) 2000.

Panel C plots the MVOL series and shows that MVOL is higher in the period up to January 1998 compared with the period beyond. The market exhibits the highest volatility in the period from July 1994 to July 1995. Over this period, volatility ranged from a high of 0.0865 in September 1994, dropping to a low of 0.0140 in February 1995.

The relatively high volatility in the market in 1995–1996 could be due to a number of reasons. First, there were no trading price limits over this period. Trading price limits were removed in May 1992 and were not reintroduced until December 1996. Second, the adoption of the $T+0$ trading rule that allowed stocks to be sold immediately after it was bought provided a conducive environment for speculative behavior. Third, the absence of institutional investors and the dominance of relatively unsophisticated retail investors could have added to the volatility. Finally, anecdotal evidence of the presence of underground "dealer investors" called *ZhuangJia* with enormous amounts of funds at their

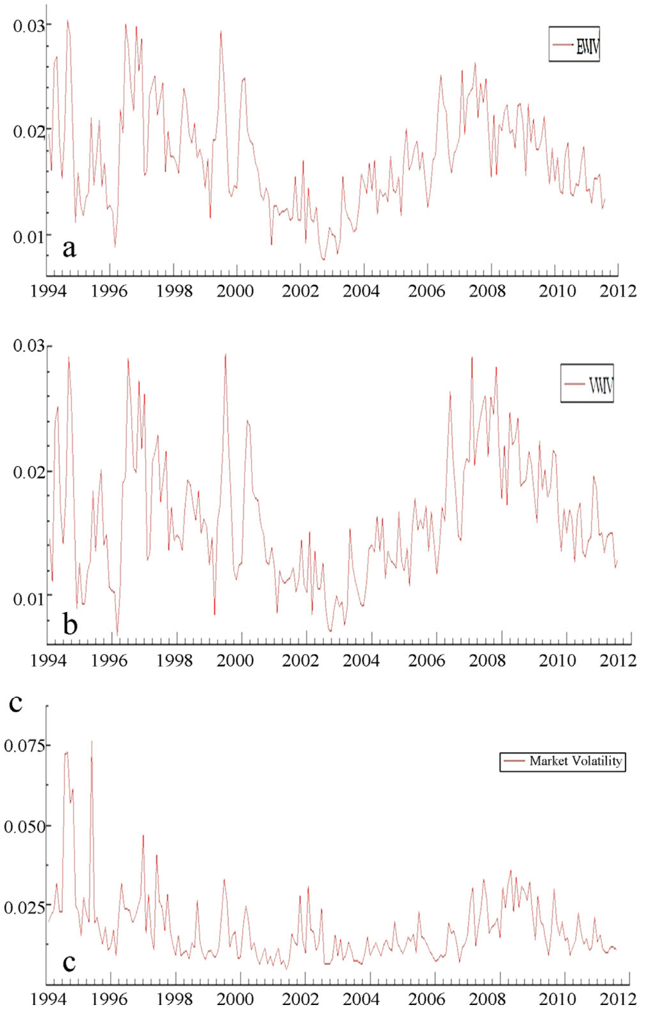

Fig. 1. Idiosyncratic and market volatility.

disposal who could easily corner certain sections of the market opens up the possibility of stock price manipulation leading to added volatility in the market.

It is interesting to note that the Asian financial crisis that started in July 1997 and whose effects were felt elsewhere until 1998 left the Chinese stock market relatively unscathed. Both market and idiosyncratic volatility were relatively stable over this period. During this period the RMB was pegged to the U.S. dollar protecting it from currency speculators. Likewise the People's Bank of China (Central Bank) exercised tight controls on capital flows. In addition, most of the foreign investment in China was in the form of infrastructure such as factories rather than securities preventing rapid capital flight.

Next we formally test for the presence of a time trend for each series using OLS to estimate the following time-series model of volatility on its first lag and a time trend:$\mathrm{VOL}_t = b_0 + b_1 t + b_2 \mathrm{VOL}_{t-1} + \varepsilon_t$where VOL represents IVOL^{EW}, IVOL^{VW}, and MVOL, and t is time. The estimated time trend b_1 parameter and its t-statistic are reported in Table 2. Over the full sample period from 1994:01 to 2011:08 the standard t-test shows no trend for both IVOL^{EW}, and IVOL^{VW},

Table 2
Trend test of the monthly volatility series.

	Full sample period 1994:01–2011:08			Prior to market liberalization 1994:01–2000:12			Market liberalization 2001:01–2004:01			Reform of split share structure 2004:02–2007:12			Financial crisis 2008:01–2011:08		
	Linear trend ($\times 10^{-5}$)	t-Stat	t-Dan	Linear trend ($\times 10^{-5}$)	t-Stat	t-Dan	Linear trend ($\times 10^{-5}$)	t-Stat	t-Dan	Linear trend ($\times 10^{-5}$)	t-Stat	t-Dan	Linear trend ($\times 10^{-5}$)	t-Stat	t-Dan
$IVOL^{EW}$	−0.82	−1.49	−0.81	−1.14	−0.48	−0.36	−1.48	−0.41	−0.25	22.23	7.88	7.14	−16.18	−6.20	−4.80
$IVOL^{VW}$	0.72	1.28	0.74	−0.03	−0.01	−0.01	−1.49	−0.45	−0.30	28.72	8.71	7.23	−19.04	−7.05	−5.71
MVOL	−4.10	−3.38	−2.40	−30.10	−5.20	−4.07	−5.88	−0.63	−0.41	21.82	3.82	2.76	−43.79	−6.79	−5.10

We formally test for the presence of a time trend for each volatility series by regressing the volatility measure on its first lag and a time trend: $VOL_t = b_0 + b_1 t + b_2 VOL_{t-1} + \varepsilon_t$ where VOL represents $IVOL^{EW}$, $IVOL^{VW}$, and MVOL, and t is time. IVOL of each firm is computed at the beginning of every month as the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. MVOL is the standard deviation of daily value-weighted market returns for the past 22 trading days ending on the last trading day of month. We report the estimated time trend b_1 parameter and its t-statistic and the Bunzel and Vogelsang (2005) t-dan test statistic for the full sample period and four sub-periods. The 5% critical value (two-sided) for t-dan is 1.726.

but a statistically significant negative trend in MVOL. However, Vogelsang (1998) points out that the null hypothesis of no trend is rejected too often when errors in the trend regression are persistent. Vogelsang (1998) suggests the use of *t*-PS1 which is a size-robust trend statistic that is valid in both $I(0)$ and $I(1)$ cases, i.e., whether or not a unit root exists in the error terms. In addition, Bunzel and Vogelsang (2005) developed the *t*-dan test which has better power than *t*-PS1 while retaining its good size properties. The corresponding *t*-dan test statistics reported in Table 2 confirm the absence of a trend in either $IVOL^{EW}$ or $IVOL^{VW}$ and the presence of a negative trend in MVOL.

Next we conduct sub-period analysis. Results in Table 2 show that prior to market liberalization (1994:01–2000:12), though both $IVOL^{EW}$ and $IVOL^{VW}$ were at a high level, they were flat while MVOL apparently trended downwards as the market matured. The high level of IVOL over this period could be a reflection of the lack of sophistication among market participants as the stock market was getting established. Over the next sub-period from 2001:01 to 2004:01 when the Chinese stock market began liberalizing by easing restrictions on capital inflow and allowing qualified foreign institutional investors to invest in A shares, both MVOL and IVOL remained stable, with insignificant *t*-dan values. The increased sophistication brought about by institutional investors appear to have stabilized the market. Our results do not conform to the suggestion of Xu and Malkiel (2003) and Bennett et al. (2003) that the rise in idiosyncratic volatility in the U.S. could be traced to increasing institutional involvement in stock markets. Our finding of stable market and idiosyncratic volatility levels amid market liberalization is interesting in the light of a recent study by Chen and Huang (2009) which relates stock market volatility to economic freedom. They find that a higher degree of economic freedom leads to less volatile equity markets, which leads us to conjecture that China's recent efforts to transition from a centrally planned to a market economy could have resulted to greater economic freedom leading to lower market volatility. Furthermore, De Santis and Imrohoroglu (1997) observe that the liberalization of emerging stock markets does not necessarily increase volatility. Our results conform to their findings and could offer some comfort for developing countries contemplating on liberalizing their stock markets.

The period from 2004:02 to 2007:12 show a marked upward trend in both IVOL and MVOL. This period coincides with the reform of the split-share structure in China which began with the announcement by the Chinese government in January 2004 of a looming reform of the split-share structure. Previous to this reform, untradeable shares on average accounted for up to 60% of a firm's total outstanding shares. This period of reform increased liquidity and understandably created uncertainty in the market due to asymmetric information associated with not knowing how many untradeable shares will be converted at any given time. As the split-share reform program commenced in April 2005 and was expanded to all listed firms by August 2005 the supply of A-shares increased significantly possibly leading to an increase in demand elasticity (Sun and Tong, 2000) and the consequent volatility in stock prices. Finally, the period from 2008:01 to 2011:08 which surrounds the immediate aftermath of the global financial crisis (GFC), IVOL and MVOL showed a downward trend. We suggest that the crisis could have tempered speculative market activity.

Our results suggest episodic behavior of idiosyncratic volatility rather than the presence of a long-term trend. It is important for undiversified investors to be cognizant of these episodes given obvious implications on the risk-return profile of their investment portfolios. The episodic behavior is consistent with the findings of Brandt et al. (2010) for the U.S. market but the episodic trends in the Chinese stock market do not necessarily follow those in the U.S. This could be partly due to the fact that we measured idiosyncratic volatility relative to a local version of the FF3-factor model. We report an episodic increase in idiosyncratic volatility during the period 2004:01–2007:12 which coincides with the reform of the Chinese stock split structure.[6] In contrast, over the same period, idiosyncratic volatilities of individual stocks in the U.S. fell dramatically, particularly during 2001–2006. We likewise observe an episodic decline in idiosyncratic volatility in the period 2008:01–2011:08 which surrounds the time of the global financial crisis. In contrast, stock return volatilities in the U.S. started to climb in the second half of 2007.

[6] The reform of the stock split structure involved the conversion of all non-tradable shares, which accounted for as much as 60% of all outstanding shares, to tradable status.

Complementing these results we also find that the correlation between market return volatility in the U.S. and Chinese markets is quite low. For the full sample the correlation coefficient between the market indices in the Shanghai Stock Exchange, and New York Stock Exchange is 0.0108 and the Shenzhen Stock Exchange and New York Stock Exchange is 0.0719.[7]

Finally, as stock trading in China is dominated by retail investors, we suggest that the episodic behavior of idiosyncratic volatility could not have been due to institutional investors as argued by Xu and Malkiel (2003) but more in line with Brandt et al.'s (2010) suggestion that it is due to the trading activities of retail investors.

4.3. Regime shifts in idiosyncratic volatility

Bekaert et al. (2012) suggests that idiosyncratic volatility in the U.S. and 22 other developed markets are best characterized by a stationary process that occasionally switches between high- and low-volatility regimes. They argue that early findings of an upward trend in the volatility series in the U.S. were driven by the chosen starting- and ending time points. For example, if the starting point is in a low volatility period, while the end point is in a high volatility period, then the trend test would easily show a positive trend.

We also investigate if there are regime shifts in the Chinese market. First we test for the presence of structural breaks in our sample period with the Quandt–Andrews unknown breakpoint test. The results of the structural break test indicate the presence of structural breaks suggesting occasional instances within the sample period when volatility temporarily switched between high and low volatility regimes.[8]

Next we follow Bekaert et al. (2012) and let volatility, y_t, follow an AR(1) model where all parameters can take on one of two values depending on the realization of a discrete regime variable, s_t. The regime variable follows a Markov chain with constant transition probabilities. Indexing the current regime by i the model is

$$y_t = (1 - b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t, \quad i \in \{0,\ 1\} \tag{4}$$

with $e_t \sim N(0, 1)$. In the model, we force regime 0 (regime 1) to be the low (high) volatility regime and the mean levels (μ_i) of the volatility series both regimes to be nonnegative (i.e., $\mu_1 > \mu_0 > 0$).

The transition probability matrix, matrix, Φ, is 2×2, where each probability represents $P[st = i|st - 1 = j]$, with $i, j \in \{1, 2\}$:

$$\Phi = \begin{pmatrix} p11 & 1 - p11 \\ 1 - p22 & p22 \end{pmatrix}$$

The model is parsimonious with only 8 parameters $\{\mu_0, \mu_1, b_0, b_1, \sigma_0, \sigma_1, p11, p22\}$.

Table 3 reports the estimation results for each volatility series (y_t = IVOL^{EW}, IVOL^{VW}, and MVOL) over the full sample period. The standard errors for each volatility series are computed with the robust White (1980) covariance matrix. The levels for both equal- and value-weighted IV in the low regime (μ_0) at 0.0131 (IVOL^{EW}) and 0.0138 (IVOL^{VW}) respectively are both statistically significant. The corresponding levels in the high regime (μ_1) at 0.0212 and 0.0198 are also both statistically significant. Results of the Wald test indicate that the differences between the levels of the two regimes for both volatility series are also statistically significant. Moreover, our results also show that regime 1 also has higher volatility than regime 0 for both EW (VW) IV, at 0.0040 (0.0038) and 0.0024 (0.0023) respectively. Thus consistent with the findings of Bekaert et al. (2012) for the developed stock markets we also find that idiosyncratic volatility in China can be characterized by a stationary autoregressive process that occasionally switches between high and low-variance regimes.

[7] We also find that the correlations of return volatilities between the two Chinese stock exchanges and the New York stock exchange are negative before 2004. This suggests that the Chinese stock market was isolated from the world's major stock market before 2004 consistent with the observation of Wong et al. (2006). Since 2004 after the reform of the split-share structure, the correlation between the two Chinese stock exchanges and the New York stock exchange has been getting stronger, but still weak in general. To save space, we do not report the results here, but they are available by request.

[8] To save space we do not report the results here but they are available upon request.

Table 3
Regime switching model estimation results.

	$IVOL^{EW}$		$IVOL^{VW}$		MVOL	
	Coeff.	Stan. error	Coeff.	Stan. error	Coeff.	Stan. error
$p11$	0.9133 (20.7365)	0.0440	0.9816 (62.9065)	0.0156	0.7050 (3.5973)	0.1960
$p22$	0.9527 (41.6742)	0.0229	0.9774 (51.8084)	0.0189	0.9713 (43.8904)	0.0221
σ_0	0.0024 (13.9210)	0.0002	0.0023 (12.3751)	0.0002	0.0056 (13.9006)	0.0004
σ_1	0.0040 (10.1275)	0.0004	0.0038 (14.3461)	0.0003	0.0205 (4.7263)	0.0043
b_0	0.5696 (7.9819)	0.0714	0.5885 (5.9850)	0.0983	0.5728 (9.0315)	0.0634
b_1	0.3287 (2.4819)	0.1324	0.5319 (6.4630)	0.0823	0.2066 (0.8334)	0.2479
μ_0	0.0131 (23.6492)	0.0006	0.0138 (19.8252)	0.0007	0.0152 (13.6946)	0.0011
μ_1	0.0212 (24.0321)	0.0009	0.0198 (23.8768)	0.0008	0.0370 (4.5562)	0.0081
Likelihood	−904.1392		−906.8261		−745.3658	

The regime-switching model results for volatility series. The model is: $y_t = (1 - b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t,\ i \in \{0, 1\}$

The transition probability matrix is: $\Phi = \begin{pmatrix} p11 & 1 - p11 \\ 1 - p22 & p22 \end{pmatrix}$

The transition probability parameters, $p11$ and $p22$, are constrained to be in (0, 1) over the study period. We also reparameterize to ensure $\mu_2 > \mu_1 > 0$. The estimation period is over 1994:01–2011:08. *T*-statistics are reported in parenthesis.

Fig. 2 shows the full sample period time series of the smoothed probabilities of being in regime 0 for our three volatility series. Unlike the evidence reported by Bekaert et al. (2012) in the U.S. stock market, we find that both high- or low-volatility regimes in the Chinese stock markets have the propensity to stay for a period before switching to another. This phenomenon occurs several times over the study period. For example, panel A of Fig. 2 shows that the $IVOL^{EW}$ was in a high volatility regime before the first quarter of 2000, before switching to a low volatility regime until the middle of 2004. It is back to a high volatility regime from the 2nd quarter of 2006 until the beginning of 2009 before switching to a high volatility regime until the end of study period. Panel B of Fig. 2 shows that $IVOL^{VW}$ switched between high- and low volatility regimes more frequently than $IVOL^{EW}$. If we define y_t to be in regime 0 if the probability of being in regime 0 is higher than 0.5, and vice versa for regime 1, then there are 8 regime switches in $IVOL^{VW}$ over 18-year study period, which is nearly 4 times more than the number of switches in $IVOL^{EW}$. However, $IVOL^{VW}$ was relatively stable in a low volatility regime from the middle of 2000 to the end of 2005. Panel C of Fig. 2 shows that MVOL was in a low volatility regime for most of the study period except for brief periods before 1998 and in early 2002.

More importantly, these regime shifts can explain the apparent short-term trends in the volatility series previously reported in Table 2. Prior to market liberalization (1994:01–2000:12) Table 2 shows no trend in IVOL. This is consistent with panels A and B of Figure 2 which shows $IVOL^{EW}$ staying in a high variance regime while $IVOL^{VW}$ exhibits several temporary regime shifts over this time period but with starting and ending points both in the low-volatility regimes. In the period we designate as the reform of the split-share structure (2004:02–2007:1) idiosyncratic volatility in panels A and B switch from a low volatility regime to a high volatility regime consistent with the upward trend reported in Table 2. The announcement of the looming reform of the split-share structure in early 2004 apparently did little to increase idiosyncratic volatility as it stayed in the low variance regime. However, idiosyncratic volatility switched to a high variance regime from the beginning of 2006, coinciding with the full implementation of the reform of split-share structure presumably as the increased supply of tradable shares led to increased demand elasticity (Sun and Tong, 2000) and a consequent increase in the volatility of stock prices. Finally, in the period we designate as the aftermath of the GFC (2008:01–2011:08) we see both idiosyncratic volatility series move initially from a high-volatility to a low-volatility regime. This regime-switching behavior explains the negative downward trend in idiosyncratic volatility that was evident in Table 2 over this period. We suggest that panic among investors in the early stages of the GFC increased volatility which eventually gave way to reduced speculative activity in the market leading to a low volatility regime.

The regime switching behavior of MVOL is also generally consistent with the short-term trends in MVOL reported in Table 2. The declining trend in MVOL prior to market liberalization (1994:01–2000:12) reported in Table 2 is consistent with a regime shift from a high volatility regime

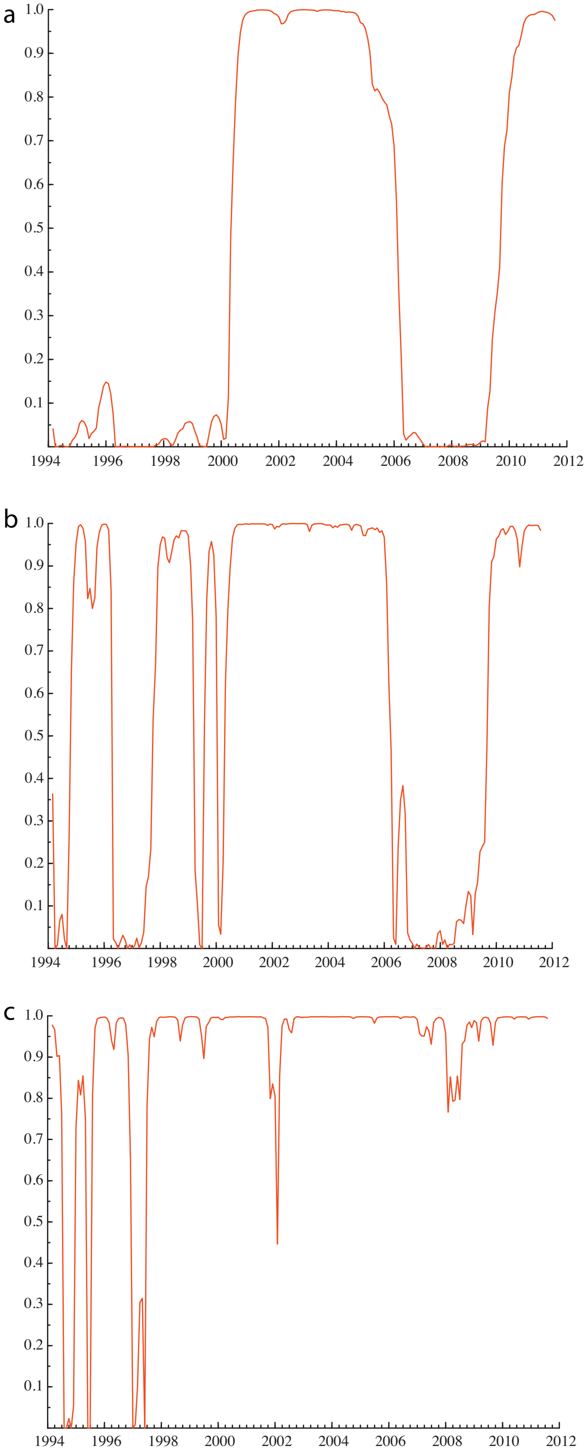

Fig. 2. Regime probabilities for China idiosyncratic volatilities.

in the first quarter of 1994 to a low volatility regime from 1998 in panel C of Fig. 2. There was no trend in MVOL over the period 2001:01–2004:01 as MVOL stayed mostly in the low volatility regime. The weak upward trend in MVOL for 2004:02–2007:12 followed by a downward trend from 2008:01 to 2001:08 reported in Table 2 are not fully consistent with the regime shifts shown in panel C of Fig. 2 though there is some evidence that MVOL could have temporarily shifted out of a low volatility regime in 2008 before going back to it shortly thereafter.

In sum, results from Table 3 and Fig. 2 are generally consistent with our trend test results showing no long-term trend in any of our volatility series. Instead we find evidence of episodic behavior consistent with occasional regime shifts throughout the study period.

5. Idiosyncratic volatility and the cross-section of expected returns

5.1. Portfolio-level analysis

In the next section we investigate the relationship between idiosyncratic volatility and one-month ahead cross-sectional stock returns. Table 4 shows the average monthly returns and FF-3 alpha of equal-weighted (EW) and value-weighted (VW) portfolios sorted according to idiosyncratic volatility.

Table 4 shows that high IVOL portfolios have lower average returns than low IVOL portfolios, irrespective of whether the portfolio returns are equal- or value-weighted. However the return spreads are not statistically significant. Comparing FF3-alphas paints a clearer picture. For both equal- and value-weighted portfolios, the alpha spread is significantly negative at 1.09% and 0.66% per month, respectively. This alpha spread is not as high as the 1.31% per month reported by Ang et al. (2006) for the U.S. but the apparent negative IVOL effect is consistent with the anomalous and puzzling evidence documented by Ang et al. (2006, 2009) and Brockman and Yan (2006) for the U.S. market.

Next, we also divide our sample into sub-periods corresponding to those in Table 2. In the period 1994:01–2000:12 (prior to market liberalization), we find a significant negative IVOL effect with equal-weighted portfolios, but none for value-weighted portfolios. Over the next two sub-periods from 2001:01 to 2004:01 (market liberalization) and 2004:02 to 2007:12 (reform of the split share structure) we find a significant negative IVOL effect for both EW and VW portfolios. Finally, the period from 2008:01 to 2011:08 (aftermath of the global financial crisis), we find a marginal negative IVOL effect for EW but none for VW portfolios. On balance, the negative IVOL effect appears somewhat robust to the episodic behavior of idiosyncratic volatility. We provide further evidence of a negative IVOL effect in the next section in the context of firm-level Fama–MacBeth regressions.

In Table 5 we report the average of the monthly averages of various characteristics of the IVOL-sorted portfolios over the full sample period. We report values for IVOL, size, BM, momentum, short-term reversal, closing price, number of zero volume trading days, illiquidity, and skewness. These variables are as defined previously. The high IVOL portfolio has three times as much IVOL as the low IVOL portfolio and the difference is highly statistically significant as expected. Size increases monotonically from high to low IVOL portfolios and the difference in size between the high and low IVOL portfolios is highly significant which indicates that the high IVOL portfolio is dominated by small stocks. This is good news for the negative IVOL effect since the size effect implies higher returns for the high IVOL portfolio but we find the opposite, hence the IVOL effect is not driven by the size effect. High IVOL stocks also tend to be high BM stocks which again are good news for the negative IVOL effect since high BM stocks tend to have higher returns yet we find the opposite so the IVOL effect is not driven by the BM effect. The momentum variable is marginally significant which indicates that high IVOL stocks tend to be winners over the prior 11 months. This is also good news since the momentum effect implies that past intermediate-term winners continue winning but we do not see this with high IVOL stocks, hence the negative IVOL effect is not due to momentum. The short-term reversal variable indicates that high IVOL portfolios are also recent winners, while low IVOL portfolios are losers. This implies that short-term reversal, where recent winners turn into losers, could potentially explain why we see lower (higher) returns for high (low) IVOL portfolios in the succeeding month. We test this formally using cross-sectional regression and report the results in later sections. High IVOL stocks also tend to be more liquid than low IVOL stocks given the smaller number of zero trading volume days for the former which could potentially explain the negative IVOL effect since illiquid stocks attract a

Table 4
Portfolios sorted by idiosyncratic volatility.

	1994:01–2011:08		1994:01–2000:12		2001:01–2004:01		2004:02–2007:12		2008:01–2011:08	
	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha
Equal-weighted										
High IVOL	−0.0011 (−0.1478)	−0.0090 (−5.2727)	0.0073 (0.6314)	−0.0068 (−3.5376)	−0.0198 (−1.6532)	−0.0059 (−2.1336)	0.0091 (0.5849)	−0.0186 (−4.1212)	−0.0121 (−0.5652)	−0.0049 (−1.0334)
Medium IVOL	0.0090 (1.1648)	0.0012 (0.7888)	0.0171 (1.3743)	0.0033 (1.8668)	−0.0156 (−1.4074)	−0.0020 (−0.9947)	0.0232 (1.4837)	−0.0068 (−1.7499)	−0.0008 (−0.0389)	0.0032 (0.7024)
Low IVOL	0.0086 (1.4340)	0.0019 (1.3805)	0.0129 (1.1788)	0.0019 (1.3805)	−0.0103 (−1.0781)	0.0012 (0.5698)	0.0180 (1.5653)	−0.0040 (−1.2236)	0.0061 (0.4566)	0.0050 (1.7394)
High-Low	−0.0097 (−1.0071)	−0.0109 (−4.9494)	−0.0056 (−0.3541)	−0.0087 (−3.6863)	−0.0095 (−0.6235)	−0.0071 (−2.0757)	−0.0089 (−0.4629)	−0.0146 (−2.6441)	−0.0182 (−0.7214)	−0.0099 (−1.7653)
Value-weighted										
High IVOL	−0.0029 (−0.3873)	−0.0050 (−3.2820)	0.0058 (0.4818)	−0.0020 (−0.8424)	−0.0199 (−1.8925)	−0.0053 (−1.8561)	0.0102 (0.7140)	−0.0099 (−2.3992)	−0.0189 (−0.9342)	0.0001 (0.0293)
Medium IVOL	0.0052 (0.7081)	0.0031 (2.9659)	0.0120 (0.9986)	0.0041 (2.7201)	−0.0124 (−1.2427)	−0.0003 (−0.2375)	0.0253 (1.9800)	0.0054 (2.0061)	−0.0145 (−0.6782)	0.0027 (0.9433)
Low IVOL	0.0043 (0.6792)	0.0016 (1.0821)	0.0070 (0.6239)	−0.0011 (−0.5297)	−0.0072 (−0.7559)	0.0034 (1.4513)	0.0200 (1.7093)	0.0016 (1.0821)	−0.0079 (−0.4901)	−0.0019 (−0.5479)
High-Low	−0.0072 (−0.7371)	−0.0066 (−3.1113)	−0.0012 (−0.0698)	−0.0009 (−0.2890)	−0.0127 (−0.8932)	−0.0087 (−2.3505)	−0.0099 (−0.5339)	−0.0115 (−2.6341)	−0.0110 (−0.4251)	0.0020 (0.3546)

At the beginning of every month we sort stocks into tertiles based on IVOL, i.e., high IVOL (HIV), medium IVOL (MIV) and low IVOL (LIV). IVOL of each firm is computed at the beginning of every month as the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. We compute each portfolio's equal- and value-weighted raw returns for the current month. We also estimate each portfolio's alpha (α coefficient) from the FF3-factor model (Eq. (1)) estimated using the full sample of monthly value- or equal-weighted returns for each portfolio. The last low of each panel presents the difference in monthly returns and differences in alpha between the high and low IVOL portfolios. *T*-statistics are reported in parenthesis. We conduct the analysis for the full sample period (1994:01–2011:08) and for four sub-periods.

Table 5
Characteristics of portfolios sorted by idiosyncratic volatility: full sample period, 1994:01–2011:08.

	IVOL	Size	BM	Momentum	REV	Number of zero trading volume	Illiquidity	Skewness	Closing price
High IVOL	0.0268 (55.9426)	3512.52 (19.3632)	0.3676 (36.6093)	0.0860 (3.0865)	0.0334 (3.8921)	2.4981 (14.7679)	0.0045 (1.1945)	0.1589 (6.0567)	8.3359 (36.4462)
Medium IVOL	0.0159 (46.3301)	4187.86 (19.3629)	0.3489 (40.8294)	0.0563 (2.0386)	−0.0015 (−0.2072)	1.8708 (10.9552)	0.0001 (1.1120)	0.0600 (1.8655)	6.8648 (31.5538)
Low IVOL	0.0090 (41.0893)	4307.19 (22.9690)	0.3025 (30.9279)	0.0171 (0.8307)	−0.0167 (−3.1103)	4.9867 (20.5295)	0.0001 (3.2522)	−0.0381 (−0.9853)	6.6932 (46.8609)
High-Low	0.0179 (33.9147)	−794.68 (-3.0459)	0.0651 (4.6472)	0.0689 (1.9915)	0.0502 (4.9496)	−2.4885 (−8.4072)	0.0044 (1.1646)	0.1971 (4.2147)	1.6427 (6.0918)

At the beginning of every month we sort stocks into tertiles based on IVOL, i.e., high IVOL (HIV), medium IVOL (MIV) and low IVOL (LIV). The table reports for each tertile the average of the monthly averages of various characteristics of the IVOL-sorted portfolios over the full sample period. IVOL is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. Size at the end of month t is defined is the log of the firm's market capitalization at the end of month t, BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), momentum at time t is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month t is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). The number of zero volume trading days is computed over the past 22 trading days. Illiquidity is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. Skewness is the third standardized moment of returns of the past 22 trading days. Closing price is the price of the stock at the end of month t. The last row is the difference between the high and low IVOL portfolio. *T*-statistics are reported in parenthesis.

premium. However there is no significant difference between high and low IVOL stocks in terms of our measure of illiquidity. High IVOL stocks tend to be positively skewed which could potentially explain the negative IVOL effect if investors exhibit a preference for positive skewness (see Golec and Tamarkin (1998) and Mitton and Vorkink (2007)). Finally, high IVOL stocks also tend to have higher closing price than low IV stocks. Since some of these variables could potentially explain the negative IVOL effect, we control their various effects using firm-level cross-sectional regressions in the next section.

5.2. Firm-level cross-sectional regressions

To control for multiple effects simultaneously we conduct firm-level Fama–MacBeth regressions (2) for the full sample period, 1994:01–2011:08, and the sub-periods defined previously. Aside from being able to control variables simultaneously, firm-level analysis also makes better use of all the available information as portfolio analysis loses too much information through aggregation.

Table 6 reports the time-series averages of the slope coefficients over the 212 months from 1994:01–2011:08 for univariate regressions. The Newey and West (1987) *t*-statistics are given in parenthesis. The univariate regression shows a statistically significant negative relation between IVOL and the cross-section of one-month ahead stock returns. The results also show a negative short-term reversal effect consistent with expectations that recent winners become losers in the next period. We also observe a negative closing price effect which indicates that low price stocks tend to have higher expected returns.

The result of the bivariate regressions with IVOL reported in Table 7 shows that if we control for the variables individually, the IVOL effect remains significantly negative. None of our control variables can individually explain the negative IVOL effect. More importantly, even if we control for all eight variables simultaneously, the IVOL coefficient remains negative and highly significant. Therefore, firm-level cross-sectional regression results indicate a strong negative IVOL effect.

We also report cross-sectional regression results for the sub-periods before and after market liberalization. The results for the period before market liberalization (1994:01–2000:12) reported Table 8 show no significant IVOL effect, in univariate, bivariate, and multivariate regressions. However in the period after market liberalization (2001:01–2011:08) reported in Table 9, a significant negative IVOL effect is clearly evident.[9] This implies that though we document a negative IVOL effect over the full sample period, this effect is obviously stronger in the period when the market was liberalized. We suggest that the insignificant IVOL effect in the period before 2001 could be partly due to the smaller number of data points in this period compared with the period after.[10]

The fact that we find a statistically significant negative relation between idiosyncratic volatility and expected cross-sectional stock returns similar to the findings of Ang et al. (2006, 2009) for the U.S. and 22 other developed markets is initially quite surprising given the wide disparities between the Chinese and U.S. stock markets in matters of market efficiency and price informativeness. However, recall that the period 2001:01–2011:08 was characterized by market reforms which included the reform of the split-share structure wherein almost 60% of total outstanding shares converted from non-tradable to tradable status. Likewise China has been steadily liberalizing its markets and easing capital restrictions by providing qualified foreign institutional investors (QFII) access to A-shares that are the subject of this study. In fact, Lee and Wong (2009) report a positive and significant impact on liquidity of China's market reforms. They find that from mid-2005 to mid-2007 liquidity increased significantly. This is important because an increase in market liquidity signifies an improvement in capital allocation efficiency in China's equity market. Likewise, Qu et al. (2010) show that the gradual lifting of capital controls in mainland China through the implementation of QFII scheme has led to a decrease in the price differential of Chinese stocks dual-listed in the mainland market (A-shares) and in the Hong Kong stock market (H-shares). Considering Hong Kong as a benchmark, this further

[9] We also conducted cross-sectional regressions for the sub-periods 2001:01–2004:01, 2004:02–2007:12, and 2008:01–2011:08 and likewise document a significant negative IVOL effect. To save space we do not report the results here but they are available from the authors upon request.

[10] Over the period from 1994:02 to 2000:12 the number of firms in our sample ranged from 199 to 1061 with an average of 617 but from 2001:01 to 2011:08 our sample firms ranged from 1072 to 1171 with an average of 1167.

Table 6
Univariate Fama–Macbeth regression results (full sample period, 1994:01–2011:08).

Intercept	IVOL	SIZE	BM	MOM	REV	ILLIQ	NZV	SKEW	CP
0.0151 (1.99)	−0.6714 (−4.19)								
0.0660 (0.79)		−5.87E−7 (−1.35)							
0.0023 (0.28)			0.0017 (0.23)						
0.0056 (0.76)				0.0018 (0.35)					
0.0030 (0.40)					−0.0520 (−3.47)				
0.0040 (0.54)						328.55 (0.69)			
0.0138 (1.33)							−0.0027 (−1.68)		
0.0034 (0.47)								−0.0021 (−1.45)	
0.0146 (1.82)									−0.0018 (−4.53)

Each month from 1994:01 to 2011:08 we run a firm-level Fama–MacBeth cross-sectional regression of the return on that month with one-month lagged values of the control variables. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. IVOL is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. SIZE at the end of month *t* is defined is the log of the firm's market capitalization at the end of month *t*, BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), MOM at time *t* is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month *t* is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). ILLIQ is illiquidity which is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. SKEW is skewness, the third standardized moment of returns of the past 22 trading days. NZV is the number of zero volume trading days over the past 22 trading days, and CP is the stock's closing price at the end of month *t*.

Table 7
Bivariate and multivariate Fama–Macbeth regression results (full sample period, 1994:01–2011:08).

Intercept	IVOL	SIZE	BM	MOM	REV	ILLIQ	NZV	SKEW	CP
0.0179 (2.33)	−0.7221 (−4.50)	−6.86E−7 (−1.62)							
0.0143 (1.72)	−0.7758 (−4.96)		0.0046 (0.64)						
0.0159 (2.09)	−0.6601 (−4.26)			0.0035 (0.70)					
0.0108 (1.40)	−0.5844 (−3.66)				−0.0439 (−2.75)				
0.0148 (1.96)	−0.6749 (−4.23)					429.37 (0.96)			
0.0244 (2.42)	−0.5985 (−3.85)						−0.0022 (−1.38)		
0.0153 (2.04)	−0.6885 (−3.94)							−0.0018 (−1.23)	
0.0253 (3.16)	−0.7001 (−4.40)								−0.0017 (−4.31)
0.0272 (2.67)	−0.5528 (−3.22)	−5.77E−7 (−1.23)	0.0046 (0.62)	0.0072 (1.69)	−0.0445 (−2.54)	1089.98 (1.16)	−0.0029 (−2.23)	−0.0031 (−2.01)	−0.0017 (−5.93)

Each month from 1994:01 to 2011:08 we run a firm-level Fama–MacBeth cross-sectional regression of the return on that month with one-month lagged values of the control variables. Each row reports the time-series averages of the slope coefficients and their associated t-statistics. IVOL is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. SIZE at the end of month t is defined is the log of the firm's market capitalization at the end of month t, BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), MOM at time t is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month t is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). ILLIQ is illiquidity which is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. SKEW is skewness, the third standardized moment of returns of the past 22 trading days. NZV is the number of zero volume trading days over the past 22 trading days, and CP is the stock's closing price at the end of month t.

Table 8
Bivariate and multivariate Fama–Macbeth regression results (sub-period, 1994:01–2000:12).

Intercept	IVOL	SIZE	BM	MOM	REV	ILLIQ	SKEW	NZV	CP
0.0151 (1.18)	−0.4333 (−1.24)								
0.0213 (1.64)	−0.5485 (−1.55)	−1.66E−6 (−1.57)							
0.0175 (1.15)	−0.6369 (−1.88)		−0.0029 (−0.16)						
0.0155 (1.19)	−0.4088 (−1.20)			0.0022 (0.23)					
0.0110 (0.80)	−0.3502 (−1.02)				−0.0530 (−1.56)				
0.0126 (0.98)	−0.3019 (−0.87)					1143.42 (1.01)			
0.0145 (1.14)	−0.4376 (−1.13)						−0.0013 (−0.42)		
0.0347 (1.66)	−0.2849 (−0.87)							−0.0052 (−1.34)	
0.0303 (2.25)	−0.5701 (−1.64)								−0.0024 (−2.74)
0.0393 (1.89)	−0.3113 (−0.81)	−1.33E−6 (−1.08)	−0.0022 (−0.12)	0.0089 (1.09)	−0.0503 (−1.27)	2684.75 (1.13)	−0.0064 (−2.12)	−0.0067 (−1.76)	−0.0027 (−3.98)

Each month from 1994:01 to 2000:12 we run a firm-level Fama–MacBeth cross-sectional regression of the return on that month with one-month lagged values of the control variables. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. IVOL is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. SIZE at the end of month *t* is defined is the log of the firm's market capitalization at the end of month *t*, BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), MOM at time *t* is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month *t* is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). ILLIQ is illiquidity which is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. SKEW is skewness, the third standardized moment of returns of the past 22 trading days. NZV is the number of zero volume trading days over the past 22 trading days, and CP is the stock's closing price at the end of month *t*.

Table 9
Bivariate and multivariate Fama–Macbeth regression results (sub-period, 2001:01–2011:08).

Intercept	IVOL	SIZE	BM	MOM	REV	ILLIQ	SKEW	NZV	CP
0.0151 (1.62)	−0.9258 (−6.06)								
0.0157 (1.66)	−0.8347 (−6.32)	−5.6E−8 (−0.46)							
0.0122 (1.29)	−0.8659 (−6.37)		0.0094 (3.23)						
0.0161 (1.74)	−0.8230 (−6.53)			0.0043 (0.81)					
0.0107 (1.16)	−0.7363 (−5.29)				−0.0381 (−2.60)				
0.0162 (1.75)	−0.9167 (−6.80)					−33.6566 (−0.78)			
0.0158 (1.71)	−0.8511 (−6.03)						−0.0021 (−1.77)		
0.0177 (1.84)	−0.8018 (−5.72)							−0.0002 (−0.33)	
0.0221 (2.22)	−0.7843 (−5.84)								−0.0012 (−4.04)
0.0194 (1.93)	−0.7094 (−5.44)	4.96E−9 (0.05)	0.0091 (2.56)	0.0060 (1.32)	−0.0407 (−3.12)	55.8657 (0.72)	−0.0007 (−0.77)	−0.0008 (−1.39)	−0.0011 (−5.78)

Each month from 2001:01 to 2011:08 we run a firm-level Fama–MacBeth cross-sectional regression of the return on that month with one-month lagged values of the control variables. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. IVOL is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. SIZE at the end of month *t* is defined is the log of the firm's market capitalization at the end of month *t*, BM is the firm's book-to-market ratio six months prior, i.e., at the end of $t-6$. Following Jegadeesh and Titman (1993), MOM at time *t* is the stock's 11-month past return lagged one month, i.e., return from month $t-12$ to month $t-2$. REV in month *t* is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). ILLIQ is illiquidity which is measured following Amihud (2002) as the ratio of the absolute monthly stock return and its dollar trading volume. SKEW is skewness, the third standardized moment of returns of the past 22 trading days. NZV is the number of zero volume trading days over the past 22 trading days, and CP is the stock's closing price at the end of month *t*.

implies a positive move toward market efficiency and price informativeness among China's A-shares. If we take these into consideration, it is less surprising to see the same negative IV effect in the Chinese stock market that is evident in the U.S. and other developed markets.

Our preferred explanation of the negative IV effect in China is behavioral. Anecdotal evidence suggests that the negative IVOL effect in the Chinese market could be driven by investors with a preference for high risk, high volatility stocks. Investors with such a preference overpay for high volatility stocks which eventually results in underperformance. There is strong evidence in the extant literature for such a preference among Chinese investors. Analyzing 64.22 million trades of 6.8 million institutional and individual brokerage accounts across mainland China for the period April 2001 to April 2002, Ng and Wu (2006) report that Chinese investors tend to prefer stocks with large betas and high idiosyncratic risk. Likewise, Lee and Wong (2009) also suggest that Chinese investors tend to trade more heavily on riskier stocks. Using panel data drawn from the Shanghai stock market they find that higher market activity and liquidity are associated with stocks that experience higher volatility. This is consistent with Fong et al. (2010) who find evidence that investors in A- and H-shares have different risk profiles, with the mainland Chinese investors (A-shares) being more speculative and having higher risk appetites than the Hong Kong and international investors (H-shares). They find that the price premium between H- and A-shares are larger for stocks with higher price volatility in their A-shares than in their H-shares which implies that mainland Chinese investors are more willing to pay a higher price for an asset at the same level of risk. In an earlier study, Ma (1996) presents evidence of risk-seeking behavior among mainland Chinese investors by documenting a positive relationship between A-share prices and domestic beta risk. The psychology literature is also consistent with the suggestion of risk-seeking behavior among Chinese investors. In a comprehensive study of the gambling behavior among Chinese, Loo et al. (2008) find that social gambling is widespread in Chinese communities being a preferred form of entertainment. In a related study, Raylu and Oei (2004) suggest that the acceptance of gambling varies from culture to culture with gambling being an acceptable form of social activity in Chinese communities. More importantly, the literature on behavioral economics indicates that people's risk-taking propensity in one setting predicts risky behavior in other settings (Barsky et al., 1997). In line with this Kumar (2009) argues that people's gambling behavior predicts their behavior in other socioeconomic activities, including investing in stock markets. Our preferred explanation of the negative idiosyncratic volatility effect is admittedly based on anecdotal evidence but we suggest that the relationship between risk-seeking behavior and the idiosyncratic volatility effect merits further exploration in future studies.

6. Concluding remarks

Though idiosyncratic volatility (IVOL) has traditionally been regarded as unimportant in asset pricing it has received considerable attention in the recent literature because of the suggestion that IVOL matters after all. As the extant literature on the time-series behavior of idiosyncratic volatility and the relationship between idiosyncratic volatility and cross-sectional stock returns is mostly confined to either the U.S. or other developed markets, we find it timely and important to examine the evidence from the world's largest emerging market. We find that idiosyncratic volatility also matters in emerging markets. We find no evidence of a long-term trend in idiosyncratic volatility, instead we find that time series behavior of idiosyncratic volatility in China is episodic that is best characterized by an autoregressive process with regime shifts that coincide with structural market reforms. It is important for investors who cannot fully diversify their investments, to recognize these episodes as they could severely impact investment performance.

We also present evidence that the negative IVOL effect can also observed in emerging markets which contrasts with that of Nartea et al. (2011) who discounted the same in the five largest emerging markets of Southeast Asia (Singapore, Malaysia, Thailand, Philippines and Indonesia). This result underscores the diversity of emerging markets and highlights the need for independent country verification of anomalies that are initially evident in developed markets. Inasmuch as anecdotal evidence in China suggests that the negative idiosyncratic volatility effect could be driven by investor preference for risky stocks, we suggest that the relationship between risk-seeking behavior and the idiosyncratic volatility effect merits further exploration in future studies.

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