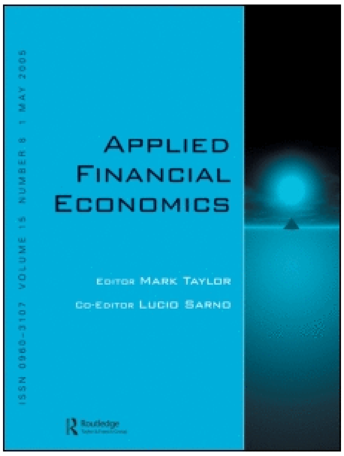

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Idiosyncratic volatility and stock returns: a cross country analysis

Kuntara Pukthuanthong-Le [a]; Nuttawat Visaltanachoti [b]
[a] Department of Finance, College of Business Administration, San Diego State University, San Diego, CA 92182, USA [b] Department of Commerce, Massey University, Auckland, New Zealand

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Idiosyncratic volatility and stock returns: a cross country analysis

Kuntara Pukthuanthong-Le[a,*] and Nuttawat Visaltanachoti[b]

[a]*Department of Finance, College of Business Administration, San Diego State University, 5500 Campanile Dr, San Diego, CA 92182, USA*
[b]*Department of Commerce, Massey University, Auckland, New Zealand*

Empirical evidences regarding the association of idiosyncratic volatility and stock returns are inconsistent with the Capital Asset Pricing Model (CAPM), which implies that idiosyncratic risk should not be priced because it would be fully eliminated through diversification. Using Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) estimated conditional idiosyncratic volatility of individual stocks across 36 countries from 1973 to 2007, we find that idiosyncratic risk is priced on a significantly positive risk premium for stock returns. The evidence is statistically and economically significant. It overwhelmingly supports the prediction of existing theories that idiosyncratic risk is positively related to expected returns.

I. Introduction

The Capital Asset Pricing Model (CAPM) implies that only the systematic risk should be priced in equilibrium and idiosyncratic risk should be fully eliminated through diversification. Merton (1987) suggests that idiosyncratic volatility does matter in asset pricing model because many investors hold underdiversified portfolios. Campbell *et al.* (2001) show an increase in firm-specific risk among stock returns in the US. Applying Campbell *et al.*'s (2001) volatility decomposition method, Vo and Daly (2008) examine the firms listed in the index Dow Jones Eurostoxx50 for the period 1992 to 2001 and find firm-specific volatility is trended upwards. Campbell *et al.* (2001) point out that in presence of idiosyncratic volatility a portfolio with a large numbers of individual stocks may not be well-diversified. Supporting this underdiversification argument, Goetzman and Kumar (2008) study a sample of more than 62 000 household investors during 1991–1996 and show that over 25% of the investor portfolios have only one stock, over 50% of the investor portfolios do not have more than three stocks, and only 5–10% of them have more than 10 stocks. In addition, Campbell (2006) argues that some households make serious investment mistakes, one of which is underdiversification of risky portfolios.

Although the extant literature show evidences of increasing idiosyncratic volatility, empirical evidence regarding the role of idiosyncratic risk in the asset pricing model is inconclusive. Douglas (1969) finds that the variation of average stock returns can be explained by the residual variance based on a single cross-sectional regression. On the contrary, a more powerful test proposed by Fama and MacBeth (1973) using month-by-month cross-sectional regressions of monthly stock returns on βs reject the role of idiosyncratic risk in cross-sectional stock returns.

Since the findings of Campbell *et al.* (2001), several studies have attempted to explain the factors that are attributed to an increase in idiosyncratic risk. Malkiel and Xu (2003) suggest that idiosyncratic risk has

*Corresponding author. E-mail: kpukthua@mail.sdsu.edu

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a positive relationship with the institutional ownership and expected earning growth. On the other hand, Pastor and Veronesi (2003) suggest that idiosyncratic risk is negatively related to firm age. Along the same line, Fink *et al*. (2005) claim that the increase in idiosyncratic risk is caused by firms going public at the early stage of their life cycle. In contrast, Brown and Kapadia (2007) argue that an increase in idiosyncratic risk in the US is not because of an increase in young firms going public but an increase of *risky* firms having been listed publicly causing a change in the overall composition of publicly traded firms in the US over the last 40 years.

Following Campbell *et al*.'s (2001) findings, another strand of research attempts to answer, perhaps, the most important question, which is whether idiosyncratic risk is priced. Some recent research, most notably, Goyal and Santa-Clara (2003), suggests that idiosyncratic volatility reflects a nontraded human capital on asset prices and it should be priced on an asset pricing model. They report a positive relationship between stock returns and the 1-month lagged average idiosyncratic volatility. A more recent study by Eiling (2008) addresses Goyal and Santa-Clara's (2003) comment by applying Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)' estimated conditional idiosyncratic volatilities and concludes that idiosyncratic risk premium is positively related to human capital returns. She observes that the positive relation between expected returns and idiosyncratic volatilities depends on the hedging demand induced by nontradable human capital.

Employing estimated-EGARCH conditional idiosyncratic volatilities on the US stocks, Spiegel and Wang (2005) find that idiosyncratic risk is priced and dominates liquidity factors. They suggest that firms with high idiosyncratic risk are likely to be least liquid. Ang, Hodrick, Xing and Zhang (2006, 2009; hereafter, AHXZ) apply the Fama–French three-factor regression model to measure idiosyncratic volatility and show that cross-sectional stock returns are lower when stocks have higher idiosyncratic volatilities. They conclude that this result is 'a substantive puzzle' since it is 'inconsistent with any extant asset pricing theory'. In contrast to AHXZ's finding, Angelidis and Tessaromatis (2008) show that equally-or value-weighted idiosyncratic volatilities cannot predict stock returns of 10 European markets; however, those measured as the equally-weighted average variance of all stocks can significantly predict future size and value premium.

Recently, Fu (2009) points that the inference on the relation between expected returns and idiosyncratic volatilities cannot be drawn from lagged realized idiosyncratic volatilities which AHXZ apply in their study. Theoretically, the relation between risk and return should be contemporaneous, i.e. risk related to returns should be measured at the same period as returns. Nevertheless, expected returns and expected idiosyncratic volatility are difficult to measure. Previous studies always use realized returns as a dependent variable in a cross-sectional regression assuming that realized returns equal to expected returns plus error term. Similar to Fu (2009), we argue that the expected idiosyncratic volatility in the same period that the expected returns are measured, not lagged idiosyncratic volatility, should be used to explain expected returns. The reasons are the followings.

First, in contrast to some firm characteristics, we find idiosyncratic volatilities are volatile over time. On average, the US individual stock has SD of its monthly idiosyncratic volatilities as of 56% of the mean. As a consequence, lagged idiosyncratic volatilities should not be used to draw inference on the relation between idiosyncratic risk and expected return. Further, we compute first-order autocorrelation of idiosyncratic volatility in our sample, which is only 0.30–0.40 and perform Dickey–Fuller tests. Overall, the results show that idiosyncratic volatility of most stocks does not have a random walk process whereas logged size of individual stocks, in particular month, does.

As a result, the relation between *lagged* idiosyncratic volatility and *average* return is not the same as the relation between idiosyncratic volatility and *expected* return. The relation between lagged idiosyncratic volatility in this month to predict average returns in the next month should not be used to draw an inference on the relation between idiosyncratic volatilities and expected returns. In addition, Fu (2009) finds that firms that have high realized idiosyncratic risks are small in size. Theoretically, trading small-sized stocks has high transaction costs making arbitrage profits difficult. From the practical standpoint, to make profit based on AHXZ's finding is still questionable.

So far, a large body of research on idiosyncratic risk has focused on the US stock market. The existence of idiosyncratic risk in the well-functioned and highly transparent market like the US stock market is indeed a surprising result. One would expect the US stock market to be highly efficient such that investors should not be compensated for an idiosyncratic risk. The evidence of idiosyncratic risk on the US stock market is a direct challenge to the CAPM, which withstands numerous critics for more than four decades. To argue that systematic risk is not the only risk to be compensated, one should at least be able to confirm that idiosyncratic risk is generally priced on any stock market and not only on the US stock market. This article contributes to the literature by investigating whether idiosyncratic risk is priced on expected stock returns across international stock markets. We apply the EGARCH model to estimate expected idiosyncratic volatility and test whether it is priced.

To explain cross-section expected returns, we apply Fama–MacBeth regressions of monthly stock returns on the estimated EGARCH idiosyncratic volatility, β, size and momentum. To control for cross-correlation in residuals, we apply the new methodology of computing error-in-variable-adjusted SEs developed by Shanken (1992) and Shanken and Weinstein (2006) to compute t-statistics for testing whether idiosyncratic volatility is priced. The results of this study are consistent with those in Spiegel and Wang (2005), Fu (2009) and Eiling (2008) in which EGARCH-estimated conditional idiosyncratic volatility is positively related to expected returns.

We find that the results are strongly significant and consistent across 36 countries from January 1973 to December 2007. They imply, for instance, a Thai stock that has idiosyncratic volatility of one SD higher than other stocks earn a return of 1.39% higher in a month. Overall, the positive relation between expected returns and estimated idiosyncratic volatility is intact with the prevailing theories.

Our article is organized as follows. Section II describes data and methodology. Section III presents empirical results and Section IV concludes this article.

II. Data Description and Methodology

Data description

We use the monthly stock returns from the Thompson Financial DataStream for the period covering January 1973 to December 2007 across 36 countries: Argentina, Australia, Austria, Belgium, Canada, Chile, Colombia, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, India, Ireland, Italy, Japan, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Pakistan, Philippines, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, the UK and the US. We only consider common stocks and exclude other security types such as Global Depository Receipts (GDRs), American Depository Receipts (ADRs), warrants and closed-end funds. Returns are computed in local currency and adjusted for capital distribution events such as dividends and stock splits. If a country has more than one stock exchange, we select the largest stock exchange in that country. For example, in the US, we select the New York Stock Exchange (NYSE) as our sample. Our sample period starts from the earliest possible period available in the database, where we require to have at least 30 stocks. We present the number of stocks and covering period in Table 1. For most countries, the sample period starts from January 1973 to December 2007. We address the survivorship bias in our sample by using both active stock list and dead stock list; nevertheless, not all firms that cease trading are included on the Datastream constituent lists of inactive firms. We compute market return by value-weighting all stocks in the market and collect the data of 3-month Treasury bill yield to proxy the risk free from the Global Financial Database (http://www.globlafinancialdata.com). Moreover, we apply several filters to ensure that our sample is robust to potential problems documented by Ince and Porter (2006). Specifically, if the daily return is above 10% and is reversed within 1 day, we assign missing value to the return on that trading day. We exclude the day when the daily return index changes by more than 50%. If returns of more than 90% of stocks in the sample are zero on any day, we assume that the exchange closes on that day and missing values are assigned to all stocks. We also require that in any month there are at least two nonzero return days otherwise the stocks are excluded on that month. Lastly, we apply SAS/STAT as a statistical programme to conduct all empirical tests.

Methodology

Estimating idiosyncratic risk. Ang *et al.* (2006) use the 1-month lagged idiosyncratic volatility (IVOL) as a proxy for the expected idiosyncratic risk. The idiosyncratic volatility of a stock in each month is the SD of the regression residuals in Equation 1

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it} \qquad (1)$$

where R_{it} is the daily returns of stock i and IVOL is the SD of ε_{it}.

We compute the realized idiosyncratic volatility from Equation 1. Table 2 presents the descriptive statistics of monthly individual stock idiosyncratic volatility for 36 exchanges.

India has the highest mean, median and SD IVOLs (22.26, 19.88 and 11.72%, respectively). Although having the lowest mean and median of IVOLs (7.39% and 5.83%, respectively), Austria has the highest mean coefficient of variation across firm of 0.91 implying that the SD of IVOL for an average Austrian stock is 91% of its time-series mean. On the other hand, Taiwan has the lowest SD of IVOLs

Table 1. Selected stock markets

Country	Market	Start	*N*(Start)	End	*N*(End)
Argentina	Buenos Aires SE	Jul 1988	30	Dec 2007	73
Australia	Australian SE	Jan 1973	152	Dec 2007	1632
Austria	Vienna SE	Jan 1973	49	Dec 2007	109
Belgium	Brussels SE	Jan 1973	46	Dec 2007	213
Canada	Toronto SE	Jan 1973	113	Dec 2007	1643
Chile	Santiago SE	Jul 1989	116	Dec 2007	162
Colombia	Bogota SE	Feb 1992	31	Dec 2007	42
Denmark	Copenhagen SE	Jan 1973	43	Dec 2007	186
Egypt	Cairo SE	Oct 1996	53	Dec 2007	105
Finland	Helsinki SE	Mar 1988	72	Dec 2007	141
France	Paris SE	Jan 1973	118	Dec 2007	884
Germany	Frankfurt SE	Jan 1973	166	Dec 2007	1138
Greece	Athens SE	Jan 1988	75	Dec 2007	281
Hong Kong	Hong Kong SE	Jan 1973	58	Dec 2007	971
India	Mumbai SE	Jan 1990	672	Dec 2007	936
Ireland	Dublin SE	Jan 1969	32	Dec 2007	58
Italy	Italian SE	Jan 1973	83	Dec 2007	310
Japan	Tokyo SE	Jan 1973	769	Dec 2007	2377
Malaysia	Kuala Lumpur SE	Jan 1986	179	Dec 2007	596
Mexico	Mexican SE	Jan 1988	62	Dec 2007	116
New Zealand	New Zealand SE	Jan 1988	103	Dec 2007	127
Norway	Oslo SE	Jan 1980	46	Dec 2007	225
Pakistan	Karachi SE	Jul 1992	113	Dec 2007	213
Philippines	Philippines SE	Dec 1989	79	Dec 2007	200
Singapore	SE of Singapore	Jan 1983	92	Dec 2007	500
South Africa	Johannesburg SE	Jan 1973	46	Dec 2007	330
Spain	Madrid SE	Mar 1987	72	Dec 2007	130
Sri Lanka	Colombo SE	Jun 1987	83	Dec 2007	222
Sweden	Stockholm SE	Jan 1982	113	Dec 2007	480
Switzerland	Swiss Exchange	Jan 1973	112	Dec 2007	227
Taiwan	Taiwan SE	Sep 1987	31	Dec 2007	671
Thailand	The SE of Thailand	Jan 1987	72	Dec 2007	480
The Netherlands	Amsterdam SE	Jan 1973	188	Dec 2007	144
Turkey	Istanbul SE	Jan 1988	60	Dec 2007	293
UK	London SE	Dec 1964	777	Dec 2007	1948
US	New York SE	Jan 1973	2577	Dec 2007	2071

Notes: This table presents data coverage of 36 selected stock markets. Market shows the Thomson Finance Datastream stock exchange code. *N* (start) and *N* (end) show the number of stocks at the starting and ending sample period. Market rate of return is the value-weighted of all stocks available in that time period. Risk-free rate is the 3-month Treasury bill rate or equivalent obtained from the Global Financial Database.

(4.28%) and the lowest coefficient of variation across firm (0.47%). Overall, the results imply that idiosyncratic volatilities of individual stocks vary substantially over time, at least about 50% of its time-series mean; as a result, using lagged idiosyncratic volatility to proxy for expected idiosyncratic risk is inappropriate. By doing so, it implicitly assumes that the realized idiosyncratic volatility follows a random walk while an extensive number of articles have shown that volatility is predictable and time varying. Next, we conduct an analysis on the time-series properties of realized idiosyncratic volatility using autocorrelation and Dickey–Fuller test. If a variable follows a random walk, its expected value can be approximated by its first lag and the first-order autocorrelation for a random walk process to be one.

Table 3 shows that the idiosyncratic volatility is only 0.30–0.40 at the first lag and decays slowly. We conduct another test of random walk process by regressing the change in idiosyncratic volatility with the lagged idiosyncratic volatility.

$$X_{i,t+1} - X_{i,t} = \gamma_{0i} + \gamma_{1i} X_{it} + \eta_i,$$
$$i = 1, 2, \ldots, N; \;\; t = 1, 2, \ldots, T_i \qquad (2)$$

where X_{it} represent realized idiosyncratic volatility of stock i in month t. The regression aims to examine whether the time-series idiosyncratic volatility of individual stocks follows a random walk, where its first difference is a white noise process. The process is a white noise when autocorrelation coefficients at all lags are zero. The coefficient γ_{1i} should be zero if the

Table 2. Monthly individual stock idiosyncratic volatility

Country	*N*	Mean (%)	Med (%)	SD (%)	CV	Skew
Argentina	106	11.38	9.77	7.09	0.62	1.93
Australia	2081	17.53	15.69	8.96	0.52	1.39
Austria	242	7.39	5.83	5.91	0.91	2.09
Belgium	392	10.23	9.07	6.05	0.63	1.57
Canada	3503	16.63	14.38	9.39	0.57	1.53
Chile	248	8.33	6.54	6.83	0.87	2.11
Colombia	71	9.21	7.04	7.70	0.87	1.95
Denmark	355	8.62	6.97	6.39	0.75	1.89
Egypt	111	9.92	9.02	5.53	0.56	2.04
Finland	253	11.76	10.35	6.58	0.56	1.34
France	1620	12.37	10.67	7.71	0.63	1.62
Germany	1297	12.32	10.64	7.35	0.66	1.82
Greece	455	12.02	10.91	6.00	0.51	1.43
Hong Kong	1033	15.54	13.38	9.28	0.60	1.56
India	1887	22.26	19.88	11.72	0.52	1.16
Ireland	118	12.33	10.34	8.40	0.74	1.86
Italy	597	8.93	7.79	5.27	0.58	1.86
Japan	2734	10.65	9.46	5.62	0.53	1.57
Malaysia	715	11.20	9.48	6.91	0.61	1.95
Mexico	285	9.41	7.62	7.07	0.80	1.84
New Zealand	237	11.85	10.31	6.80	0.57	1.71
Norway	397	13.07	11.23	7.70	0.59	1.65
Pakistan	311	14.30	12.29	8.99	0.64	1.57
Philippines	273	17.12	14.14	11.54	0.69	1.64
Singapore	538	13.15	11.50	7.00	0.55	1.61
South Africa	814	15.69	13.58	9.54	0.63	1.56
Spain	247	8.01	6.89	4.92	0.63	1.84
Sri Lanka	256	14.66	12.14	10.03	0.69	1.58
Sweden	951	14.26	12.35	8.39	0.59	1.59
Switzerland	539	8.72	7.34	5.74	0.65	2.04
Taiwan	811	10.15	9.55	4.28	0.43	0.86
Thailand	624	12.64	10.32	8.74	0.68	1.95
The Netherlands	413	9.56	7.87	6.69	0.68	2.07
Turkey	347	14.79	13.44	7.34	0.51	1.03
UK	4925	9.82	8.00	7.24	0.77	1.96
US	8744	12.39	10.84	6.88	0.56	1.65

Notes: This table summarizes the time-series statistics of individual stock idiosyncratic volatilities. Following AHXZ (2006), first the time-series statistics of idiosyncratic volatilities for each stock are computed. Then the mean, median (Med), SD (SD), coefficient of variation (CV) and skewness (Skew) statistics across all stocks in that country are calculated. *N* denotes number of stocks. In every month, excess daily returns of each individual stock are regressed on the excess market return. The monthly idiosyncratic volatility of the stock is the product of the SD of the regression residuals and the square root of the number of observations in the month. Included stocks have at least 30 monthly observations.

time-series follow a random walk. As one can view Equation 2 as a unit-root test, we estimate Equation 2 for each stock in each exchange and compare its t-statistics with the Dickey–Fuller critical values for the unit-root tests.[1] When we estimate coefficients in Equation 2, we require that firms have at least 30 consecutive observations.

As shown in Table 4, the rejection rate of random walk null hypothesis for realized idiosyncratic volatility is more than 90% in all countries. The results are consistent with Fu (2009) for the US, which rejects the null hypothesis for 90% of the firms in the sample. The evidence overwhelmingly shows we should not use lagged idiosyncratic volatility to draw an inference on the relation between expected returns and idiosyncratic volatility because it does not follow a random walk. As a comparison, we replace idiosyncratic volatility by logged market capitalization and conduct the same regression in Equation 2. The coefficient γ_{1i} of logged market capitalization is closed to zero and its rejection rate is below 10% in almost all countries. The series of market

[1] The critical t-statistics at 99% confidence level for sample size of 25, 50, 100 and 500 are −3.75, −3.59, −3.50 and −3.44, respectively.

Table 3. Autocorrelation of individual stock idiosyncratic volatility

	Autocorrelation at lags						
Country	1	2	3	4	5	6	12
Argentina	0.26	0.22	0.18	0.14	0.12	0.10	0.07
Australia	0.26	0.20	0.17	0.15	0.13	0.12	0.07
Austria	0.35	0.28	0.24	0.22	0.20	0.16	0.11
Belgium	0.27	0.20	0.17	0.14	0.13	0.11	0.09
Canada	0.39	0.31	0.28	0.24	0.22	0.20	0.13
Chile	0.23	0.16	0.13	0.09	0.10	0.08	0.05
Colombia	0.17	0.11	0.07	0.06	0.07	0.06	0.00
Denmark	0.31	0.24	0.22	0.20	0.19	0.17	0.13
Egypt	0.23	0.17	0.13	0.09	0.08	0.08	0.06
Finland	0.33	0.27	0.24	0.20	0.18	0.17	0.11
France	0.28	0.21	0.18	0.14	0.12	0.11	0.07
Germany	0.33	0.26	0.24	0.20	0.19	0.17	0.14
Greece	0.36	0.28	0.26	0.21	0.20	0.18	0.09
Hong Kong	0.34	0.25	0.20	0.18	0.15	0.13	0.08
India	0.35	0.28	0.24	0.21	0.19	0.17	0.10
Ireland	0.32	0.25	0.22	0.19	0.16	0.16	0.09
Italy	0.33	0.26	0.21	0.18	0.15	0.14	0.09
Japan	0.40	0.31	0.28	0.24	0.23	0.22	0.14
Malaysia	0.36	0.27	0.23	0.19	0.16	0.16	0.07
Mexico	0.28	0.20	0.15	0.12	0.09	0.07	0.03
New Zealand	0.26	0.19	0.16	0.14	0.12	0.12	0.06
Norway	0.32	0.24	0.20	0.15	0.14	0.10	0.08
Pakistan	0.25	0.16	0.13	0.12	0.09	0.08	0.06
Philippines	0.25	0.15	0.12	0.11	0.09	0.08	0.05
Singapore	0.34	0.27	0.25	0.21	0.19	0.18	0.09
South Africa	0.30	0.24	0.21	0.19	0.17	0.15	0.08
Spain	0.33	0.24	0.18	0.16	0.15	0.13	0.08
Sri Lanka	0.22	0.16	0.14	0.11	0.09	0.08	0.03
Sweden	0.36	0.28	0.24	0.19	0.16	0.14	0.10
Switzerland	0.34	0.25	0.20	0.18	0.15	0.13	0.08
Taiwan	0.40	0.28	0.24	0.22	0.20	0.18	0.11
Thailand	0.41	0.32	0.28	0.24	0.22	0.21	0.11
The Netherlands	0.37	0.29	0.26	0.23	0.21	0.19	0.15
Turkey	0.37	0.31	0.25	0.22	0.19	0.16	0.14
UK	0.28	0.21	0.18	0.16	0.15	0.14	0.08
US	0.39	0.32	0.29	0.24	0.21	0.20	0.12

Notes: This table summarizes the autocorrelation of monthly individual stock idiosyncratic volatilities. Following AHXZ (2006), first the time-series statistics of idiosyncratic volatilities for each stock are computed. Then the autocorrelation at lags across all stocks in that country are calculated. In every month, excess daily returns of each individual stock are regressed on the excess market return. The monthly idiosyncratic volatility of the stock is the product of the SD of the regression residuals and the square root of the number of observations in the month. Included stocks have at least 30 monthly observations.

capitalization is consistent and follows a random walk. In contrast, realized idiosyncratic volatility estimated from the residual of CAPM is time varying and does not follow a random walk. Employing realized idiosyncratic volatility of the last period as a proxy of expected idiosyncratic volatility to study the relation between idiosyncratic volatility and expected return is theoretically incorrect and inappropriate. To estimate idiosyncratic volatility, we apply EGARCH-estimated conditional idiosyncratic volatility to capture serial correlation and heteroscedasticity in idiosyncratic volatility series.

We follow Fu (2009) to estimate the expected idiosyncratic risk at time t' which is the squared root of the conditional variance (σ_{it}^2) from the market model residuals estimated using an EGARCH model (EIVOL) in Equations 3 and 4

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}, \text{ where } \varepsilon_{it} \sim N(0, \sigma_{it}^2) \tag{3}$$

$$\ln \sigma_{it}^2 = a_i + \sum_{l=1}^{p} b_{il} \ln \sigma_{it-l}^2 + \sum_{k=1}^{q} c_{ik} \left\{ \theta\left(\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right) + \gamma\left[\left|\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right| - \sqrt{2/\pi}\right] \right\} \tag{4}$$

where R_{it} is the monthly returns of stock i. We estimate nine different EGARCH specifications

Table 4. Do monthly idiosyncratic volatilities follow a random walk process?

	IVOL			ln(ME)		
Country	γ_1	$t(\gamma_1)$	% RW reject	γ_1	$t(\gamma_1)$	% RW reject
Argentina	−0.73	−7.71	97.17	−0.05	−1.19	5.69
Australia	−0.71	−7.67	96.72	−0.06	−1.00	7.57
Austria	−0.64	−7.69	94.63	−0.05	−1.21	4.51
Belgium	−0.72	−8.50	97.17	−0.07	−1.34	9.59
Canada	−0.59	−6.77	91.99	−0.08	−1.63	11.03
Chile	−0.77	−8.64	98.38	−0.06	−1.21	6.01
Colombia	−0.83	−7.71	100	−0.23	−0.88	9.17
Denmark	−0.68	−8.52	97.45	−0.03	−0.68	4.92
Egypt	−0.76	−8.09	100	−0.05	−1.33	7.69
Finland	−0.67	−7.19	95.68	−0.06	−1.23	3.67
France	−0.71	−7.87	96.51	−0.07	−1.50	7.08
Germany	−0.66	−8.44	97.44	−0.06	−1.76	11.62
Greece	−0.63	−7.78	98.89	−0.06	−1.72	9.66
Hong Kong	−0.65	−7.81	97.17	−0.06	−1.42	10.74
India	−0.64	−7.12	96.91	−0.09	−0.94	11.97
Ireland	−0.67	−9.51	96.58	−0.04	−1.01	7.87
Italy	−0.66	−8.55	98.65	−0.04	−1.37	5.21
Japan	−0.60	−9.62	97.65	−0.04	−1.91	3.71
Malaysia	−0.63	−8.41	98.46	−0.05	−1.59	6.60
Mexico	−0.70	−6.95	95.74	−0.04	−0.72	7.71
New Zealand	−0.72	−7.37	94.08	−0.07	−1.32	1.94
Norway	−0.67	−7.05	93.33	−0.05	−1.10	3.23
Pakistan	−0.75	−7.97	98.06	−0.05	−0.90	7.63
Philippines	−0.74	−8.22	97.79	−0.09	−1.96	13.82
Singapore	−0.65	−7.41	96.83	−0.07	−1.50	7.87
South Africa	−0.69	−7.59	94.07	−0.06	−1.14	9.31
Spain	−0.66	−8.01	97.55	−0.04	−0.98	4.28
Sri Lanka	−0.77	−9.02	98.43	−0.04	−1.45	5.45
Sweden	−0.63	−6.39	91.06	−0.06	−1.34	3.99
Switzerland	−0.65	−8.67	97.01	−0.04	−0.94	7.29
Taiwan	−0.60	−7.25	99.26	−0.07	−1.87	4.76
Thailand	−0.57	−6.68	91.28	−0.06	−1.80	7.74
The Netherlands	−0.61	−8.74	93.44	−0.03	−0.84	4.46
Turkey	−0.62	−7.76	99.13	−0.04	−0.82	1.77
UK	−0.71	−8.87	96.66	−0.04	−1.02	5.56
US	−0.59	−7.16	87.31	−0.07	−1.36	8.19

Notes: This table presents estimations of the time-series regression: $X_{i,t+1} - X_{i,t} = \gamma_{0i} + \gamma_{1i}X_{it} + \eta_i, i = 1, 2, \ldots, N; t = 1, 2, \ldots, T_i$. X_{it} represent realized idiosyncratic volatility, IVOL or logged market capitalization, ln(ME), of stock i in month t. The regression aims to examine whether the time-series idiosyncratic volatility of individual stocks follows a random walk. As a comparison, we run above regression on ln(ME). The results are shown in the last three columns. The coefficient γ_{1i} should be zero if the time-series follow a random walk. We perform a unit-root test by estimating above equation for each stock in each exchange and compare its t-statistics with the Dickey–Fuller critical values for the unit-root tests. The critical t-statistics at 99% confidence level for sample size of 25, 50, 100 and 500 are −3.75, −3.59, −3.50 and −3.44, respectively (Fuller, 1996). We require that firms have at least 30 consecutive observations.

where p and q are 1, 2 and 3. The following analysis is based on the EGARCH(1, 1). Other specifications yield qualitatively similar findings.

Table 5 shows the descriptive statistics of estimated expected idiosyncratic volatility, denoted by EIVOL. The average cross-sectional correlation between the EIVOL and IVOL are positive and statistically significant indicating that the cross-sectional EIVOL can closely track the realized idiosyncratic volatility. The mean of EIVOL is slightly higher than the mean of realized idiosyncratic volatility in some countries.

Furthermore, we examine whether idiosyncratic volatility is priced using the Fama–MacBeth cross-sectional regression approach to control the cross-correlation in residuals. Fu (2009) argues that forming portfolio should not be used to test the relation between expected returns and idiosyncratic volatility because idiosyncratic volatility can be diversified. Idiosyncratic volatility of portfolio is certainly lower than that of individual stock. In addition, Ang *et al.* (2008) confirm that grouping stocks into portfolios shrinks the dispersion of βs

Table 5. Descriptive statistics of 1-month ahead expected idiosyncratic volatility

Country	*N*	Mean (%)	Med (%)	SD (%)	CV	Skew	Corr
Argentina	115	20.58	17.92	13.03	0.53	2.11	0.30***
Australia	2077	17.22	15.85	7.74	0.39	1.55	0.20***
Austria	230	10.18	8.96	5.98	0.55	2.63	0.25***
Belgium	401	13.32	12.05	6.84	0.39	1.64	0.21***
Canada	3458	14.93	13.54	7.06	0.41	1.66	0.25***
Chile	265	11.25	10.08	7.00	0.54	2.21	0.23***
Colombia	95	13.54	12.59	7.39	0.53	2.05	0.31***
Denmark	361	10.37	9.65	4.53	0.38	1.96	0.22***
Egypt	113	13.95	12.51	6.87	0.45	2.26	0.16***
Finland	250	11.06	10.22	4.37	0.36	1.36	0.25***
France	1646	13.68	12.24	6.74	0.41	1.80	0.24***
Germany	1274	13.24	11.93	6.23	0.40	1.77	0.25***
Greece	446	16.64	14.01	8.54	0.48	2.32	0.24***
Hong Kong	1005	19.20	17.10	10.34	0.47	2.32	0.22***
India	1914	21.93	19.69	10.66	0.43	1.84	0.19***
Ireland	120	13.43	12.28	5.86	0.39	2.06	0.28***
Italy	592	9.68	8.76	4.46	0.41	2.04	0.26***
Japan	2718	10.75	9.90	4.15	0.34	2.10	0.28***
Malaysia	697	12.23	10.80	6.42	0.46	2.69	0.24***
Mexico	329	12.57	11.32	7.04	0.52	1.85	0.28***
New Zealand	248	12.47	11.43	5.57	0.37	1.40	0.24***
Norway	396	13.60	12.48	5.89	0.38	1.40	0.24***
Pakistan	333	16.38	14.80	8.29	0.45	2.29	0.16***
Philippines	297	17.88	16.05	9.22	0.50	2.51	0.21***
Singapore	531	12.30	11.19	5.20	0.40	1.98	0.24***
South Africa	826	16.93	15.29	8.17	0.40	1.56	0.25***
Spain	236	10.08	9.08	5.07	0.43	1.85	0.24***
Sri Lanka	265	15.98	14.33	8.66	0.47	2.53	0.15***
Sweden	948	14.13	12.62	7.03	0.41	1.53	0.26***
Switzerland	524	8.73	8.02	3.62	0.33	1.70	0.22***
Taiwan	796	12.89	11.75	5.34	0.37	1.96	0.27***
Thailand	607	14.95	13.03	8.97	0.54	2.40	0.29***
The Netherlands	413	10.67	9.69	4.94	0.39	1.84	0.31***
Turkey	347	21.20	19.47	9.88	0.40	1.65	0.22***
UK	4974	13.03	11.89	5.92	0.41	1.61	0.28***
US	8754	12.00	10.94	5.28	0.38	1.38	0.28***

Notes: This table summarizes the time-series statistics of individual stock idiosyncratic volatilities following Fu's (2009) methodology. This idiosyncratic volatility is a 1-month ahead expected idiosyncratic volatility estimated by an EGARCH model using monthly excess stock returns and monthly excess market returns. Then the mean, median (Med), SD (SD), coefficient of variation (CV) and skewness (Skew) statistics across all stocks in that country are calculated. Corr denotes the average cross-section correlation between the expected idiosyncratic volatility and realized idiosyncratic volatility. *N* denotes number of stocks. Included stocks have at least 30 monthly observations.
*** denotes significance at 1% level.

causing an increase in asymptotic SEs of risk premia estimates. As a consequence, for each month t, we conduct the following cross-sectional regression for each stock

$$r_{i,t} - r_{f,t} = \gamma_{0,t} + \gamma_{1,t}\,\mathrm{BETA}_{i,t} + \gamma_{2,t}\,\mathrm{SIZE}_{i,t} + \gamma_{3,t}\,\mathrm{MOMENTUM}_{i,t} + \gamma_{4,t}\,\mathrm{EIVOL}_{i,t} + u_{i,t} \quad (5)$$

where $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T_i$. Variable $r_{i,t}$ is the realized return of stock i in month t. In each month, $\mathrm{BETA}_{i,t}$ is estimated β of stock i by regressing the excess stock i return with the excess market return using previous 60 monthly observations. The slope coefficient is the estimated β (BETA). $\mathrm{SIZE}_{i,t}$ is the natural logarithm of market capitalization of stock i in month t. $\mathrm{MOMENTUM}_{i,t}$ is the monthly returns of stock i from month $t-7$ to $t-3$. $\mathrm{EIVOL}_{i,t}$ is the expected idiosyncratic volatility (EIVOL) and is estimated using the EGARCH(1, 1) of stock i. $u_{i,t}$ captures the deviation of the realized return from its expected value. N denotes number of stocks in month t, which is different in each month. The maximum month, T, is 420 in this study.

We control for size and momentum as in the previous literature. Banz (1981), Fama and French (1992, 1993) and Hawawini and Keim (1995) control for size in cross-sectional return regression.

Jegadeesh and Titman (1993) and Rouwenhorst (1998) control for past returns or momentum. In addition, Brennan and Subrahmanyam (1996), Datar *et al*. (1998), Chordia *et al*. (2001) and Amihud (2002) control for liquidity, and Fama and French (1992, 1993) control for book-to-market. Since international data is limited and international data on book value is unreliable, we do not control for liquidity and book-to-market. The estimate $\hat{\gamma}_k$ is computed as follows:

$$\hat{\gamma}_k = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{kt}$$

The average slope is the time-series mean of the 420 monthly estimates from January 1973 to December 2007.

Unavoidably, any inference of the estimated coefficients is plagued by the measurement error problems. Following Shanken (1992) and Shanken and Weinstein (2006), we address the problem that the second pass estimator is subject to Errors In Variable (EIV) problems by using the SEs that are the square root of the EIV-adjusted asymptotic variance

$$\text{EIV-adjusted asymptotic variance} = [\mathrm{Var}(\gamma_k) - \mathrm{Var}(_k)](1+c) + \mathrm{Var}(_k) \quad (6)$$

where

$$c = \Gamma^t S_F^{-1}\Gamma$$

$$\mathrm{Var}(\hat{\gamma}_k) = \frac{\sum_{t=1}^{T}(\hat{\gamma}_{kt} - \hat{\gamma}_k)^2}{T(T-1)}$$

$\mathrm{Var}(_k)$ is the variance of the mean for factor k in the second pass cross-sectional regression and $\mathrm{Var}(_k)$ is zero when k is zero; Γ is the vector of estimated coefficients $\gamma_{k,t}$ in Equation 5 and S_F is the sample covariance matrix of the factor. The t-statistics is the average slope divided by the square root of the EIV-adjusted asymptotic variance.

We test the null hypothesis that $\gamma_{2,t}$ is indifferent from zero. Rejecting the null hypothesis suggests that expected idiosyncratic risk does have explanation power on expected returns.

Another concern is related to employing panel data where the residuals of a given year may be correlated across different firms (cross-sectional dependence), called a time effect, or across years for a given firm, called a firm effect. Or, both effects may occur. Petersen (2009) shows that the Fama–MacBeth and the clustered SE approaches produce unbiased SEs and correctly sized confidence intervals in the presence of a time effect. Nevertheless, in the presence of a firm effect, SEs are biased when estimated by Fama–MacBeth. All in all, Petersen (2009) suggests a technique such as fixed effects, generalized least squares or generalized method of moments to improve the efficiency of estimates since a bias in ordinary least squares SEs implies there is information in the residual that the researcher is not using or the residuals are correlated.

Given Petersen's critique, Jagannathan and Wang (1998) show that the Fama–MacBeth (1973) SEs do not necessarily overestimate t-statistics when heteroscedasticity is present. A more recent study by Eiling (2008) confirms this claim by applying EGARCH to explain idiosyncratic risk premium as we do and finds that unadjusted Fama–MacBeth t-values are very close to t-values using the Jagannathan and Wang (1996, 1998) adjustment.

Market proxy problem

Another problem involved in the estimation procedure is that we could only use a market portfolio proxy, not the true market portfolio. Roll (1977) argues that CAPM could never be tested based on the market portfolio proxy. An optimiztic view from Stambaugh (1982) suggests that the test on CAPM is 'not sensitive to altering the composition of market index'. As a hope, the market proxy problem could be mitigated by our broad market index.

III. Empirical Result and Discussion

The test procedure is repeated country-by-country. Note that the EIVOL and BETA are not observable and are estimated from the model. Table 6 reports the coefficients of BETA, SIZE, MOMENTUM and EIVOL variables. As a comparison, we show the regression of cross-sectional expected return controlling only for BETA and EIVOL and another controlling for all four variables. The estimate reported in Table 6 is the average of time-series month estimated coefficients from January 1973 to December 2007. The t-statistics is computed using EIV-adjusted SEs.

Interestingly, estimated coefficients of EIVOL variables are all positive and statistically significant in both regressions with and without SIZE and MOMENTUM. The size of EIVOL coefficient is slightly bigger when we control for SIZE and MOMENTUM. On the other hand, none of the market included in this study show that the estimated coefficients of BETA are significant. SIZE is positively significant for all countries implying large stocks have higher returns. MOMENTUM is negatively significant only in some markets such as

Table 6. Fama–MacBeth regressions of stock returns on idiosyncratic volatility

Country	BETA	EIVOL	SIZE	MOMENTUM	Adj. R^2 (%)
Argentina	0.0062 (0.73)	0.0833 (2.32)	–	–	7.70
	0.0048 (0.41)	0.0941 (2.18)	0.0029 (2.35)	−0.0065 (−0.63)	11.99
Australia	−0.0021 (−0.57)	0.1687 (6.51)	–	–	8.19
	−0.0070 (−1.50)	0.2514 (6.59)	0.0086 (7.85)	−0.0184 (−3.80)	10.49
Austria	0.0060 (1.43)	0.0814 (3.47)	–	–	11.07
	0.0020 (0.41)	0.0869 (3.53)	0.0025 (4.25)	−0.0044 (−0.55)	15.66
Belgium	0.0054 (1.49)	0.0688 (2.79)	–	–	9.04
	0.0007 (0.17)	0.0853 (3.37)	0.0018 (4.53)	−0.0119 (−1.80)	12.44
Canada	0.0014 (0.43)	0.1057 (7.25)	–	–	6.15
	−0.0010 (−0.28)	0.1291 (7.86)	0.0036 (7.87)	−0.0068 (−2.29)	7.75
Chile	−0.0044 (−0.67)	0.1150 (2.73)	–	–	8.09
	−0.0102 (−1.14)	0.1162 (2.31)	0.0022 (2.78)	0.0014 (0.18)	10.05
Colombia	0.0138 (1.79)	0.1155 (2.10)	–	–	11.09
	0.0148 (1.67)	0.1313 (2.29)	−0.0000 (−0.05)	−0.0068 (−0.81)	13.20
Denmark	0.004 (1.20)	0.0886 (2.60)	–	–	6.79
	−0.0018 (−0.36)	0.1288 (2.87)	0.0029 (3.10)	0.0126 (1.72)	10.13
Egypt	0.0086 (1.55)	0.1394 (3.06)	–	–	10.04
	0.0063 (0.95)	0.1912 (3.54)	0.0031 (2.70)	−0.0172 (−2.55)	13.94
Finland	−0.0001 (−0.02)	0.1144 (3.03)	–	–	9.82
	−0.0035 (−0.57)	0.1527 (4.06)	0.0023 (3.18)	−0.0082 (−1.45)	14.08
France	0.0014 (0.37)	0.1069 (4.86)	–	–	7.34
	−0.0023 (−0.56)	0.1318 (5.42)	0.0036 (7.92)	−0.0102 (−2.65)	9.18
Germany	0.0004 (0.11)	0.0605 (3.39)	–	–	6.98
	−0.0020 (−0.59)	0.0924 (4.81)	0.0027 (8.20)	−0.0060 (−1.65)	9.04
Greece	−0.0001 (−0.01)	0.1631 (3.54)	–	–	7.89
	0.0000 (0.00)	0.1952 (3.78)	0.0047 (3.60)	−0.0208 (−1.90)	12.36
Hong Kong	0.0086 (1.55)	0.1149 (3.43)	–	–	8.55
	0.0029 (0.42)	0.1825 (3.78)	0.0074 (6.66)	−0.0086 (−1.42)	12.06
India	0.0118 (1.78)	0.0953 (5.42)	–	–	5.95
	0.0115 (1.66)	0.1214 (7.50)	0.0022 (2.50)	−0.0194 (−5.40)	8.50
Ireland	0.0055 (1.11)	0.0957 (3.21)	–	–	8.54
	−0.0076 (−1.19)	0.1829 (5.21)	0.0072 (6.63)	−0.0183 (−2.48)	11.92
Italy	0.0040 (0.81)	0.1000 (3.96)	–	–	7.03
	0.0038 (0.70)	0.0947 (3.55)	0.0004 (1.74)	0.0142 (1.74)	9.54
Japan	0.0026 (0.89)	0.0487 (2.67)	–	–	7.02
	0.0006 (0.18)	0.0928 (5.24)	0.0039 (5.40)	−0.0265 (−5.80)	10.81
Malaysia	0.0071 (0.98)	0.0995 (3.81)	–	–	8.01
	0.0090 (1.16)	0.1318 (4.51)	0.0066 (4.45)	−0.0207 (−2.68)	11.89
Mexico	0.0015 (0.21)	0.1740 (3.28)	–	–	8.37
	−0.0095 (−0.99)	0.2235 (3.05)	0.0037 (3.34)	0.0011 (0.13)	12.46
New Zealand	−0.0021 (−0.41)	0.0604 (1.65)	–	–	8.23
	−0.0058 (−0.92)	0.1565 (2.74)	0.0059 (4.63)	−0.0094 (−0.99)	12.11
Norway	0.0006 (0.14)	0.1267 (3.02)	–	–	8.34
	−0.0095 (−1.72)	0.1906 (3.81)	0.0081 (6.93)	0.0040 (0.63)	11.49
Pakistan	0.0057 (0.57)	0.1613 (4.71)	–	–	8.72
	−0.0073 (−0.64)	0.2405 (5.57)	0.0086 (6.41)	−0.0327 (−5.35)	11.96
Philippines	−0.0019 (−0.26)	0.1660 (4.34)	–	–	8.57
	−0.0045 (−0.63)	0.1917 (5.32)	0.0047 (5.91)	−0.0392 (−6.09)	10.71
Singapore	0.0029 (0.66)	0.0723 (2.97)	–	–	7.79
	0.0005 (0.12)	0.1048 (4.52)	0.0037 (5.48)	−0.0197 (−3.26)	11.06
South Africa	−0.0008 (−0.16)	0.1343 (5.35)	–	–	12.72
	−0.0061 (−1.20)	0.1883 (7.83)	0.0048 (6.71)	−0.0280 (−6.06)	15.74
Spain	−0.0017 (−0.35)	0.1663 (2.47)	–	–	7.91
	−0.0031 (−0.57)	0.1922 (2.31)	0.0024 (3.19)	0.0056 (0.72)	12.19
Sri Lanka	−0.0003 (−0.05)	0.1201 (4.15)	–	–	6.36
	−0.0051 (−0.67)	0.1361 (4.35)	0.0064 (4.63)	−0.0305 (−5.77)	8.86
Sweden	−0.0005 (−0.09)	0.0888 (2.93)	–	–	10.01
	−0.0086 (−1.27)	0.1481 (4.26)	0.0051 (6.63)	−0.0061 (−0.97)	12.91
Switzerland	0.0013 (0.46)	0.0357 (1.44)	–	–	9.02
	−0.0030 (−0.94)	0.0771 (2.91)	0.0032 (6.98)	−0.0076 (−1.49)	12.44

(continued)

Table 6. Continued

Country	BETA	EIVOL	SIZE	MOMENTUM	Adj.R^2 (%)
Taiwan	0.0054 (0.72)	0.0535 (1.44)	–	–	7.85
	−0.0050 (−0.53)	0.1235 (2.97)	0.0091 (5.87)	−0.0161 (−1.68)	13.02
Thailand	0.0029 (0.30)	0.1210 (3.62)	–	–	9.62
	−0.0050 (−0.43)	0.1549 (3.30)	0.0078 (6.40)	−0.0010 (−1.39)	12.73
The Netherlands	0.0035 (1.05)	0.0835 (2.66)	–	–	9.64
	−0.0006 (−0.13)	0.1242 (2.73)	0.0025 (4.53)	0.0128 (2.15)	12.30
Turkey	0.0322 (1.76)	0.1005 (3.68)	–	–	4.26
	0.0313 (1.60)	0.1344 (4.47)	0.0052 (4.58)	−0.0205 (−4.01)	7.65
UK	0.0023 (0.75)	0.0858 (6.52)	–	–	5.14
	−0.0024 (−0.72)	0.1197 (8.21)	0.0035 (10.63)	−0.0021 (−1.08)	6.28
US	−0.0014 (−0.52)	0.1383 (8.47)	–	–	6.50
	−0.0044 (−1.41)	0.1577 (8.56)	0.0028 (9.39)	−0.0021 (−0.83)	7.70

Notes: This table presents estimations of the Fama–MacBeth cross-sectional regression approach. For each month t. we conduct the following cross-sectional regression for each stock: $r_{i,t} - r_{f,t} = \gamma_{0,t} + \gamma_{1,t}\text{BETA}_{i,t} + \gamma_{2,t}\text{SIZE}_{i,t} + \gamma_{3,t}\text{MOMENTUM}_{i,t} + \gamma_{4,t}\text{EIVOL}_{i,t} + u_{i,t}$, where $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T_i$. $r_{i,t}$ is the realized return of stock i in month t. In each month, $\text{BETA}_{i,t}$ is estimated beta of stock i by regressing the excess stock i return with the excess market return using previous 60 monthly observations. The slope coefficient is the estimated β (BETA). $\text{SIZE}_{i,t}$ is the natural logarithm of market capitalization of stock i in month t. $\text{MOMENTUM}_{i,t}$ is the monthly returns of stock i from month $t-7$ to $t-3$. $\text{EIVOL}_{i,t}$ is the expected idiosyncratic volatility (EIVOL) is estimated using the EGARCH(1, 1) of stock i. $u_{i,t}$ captures the deviation of the realized return from its expected value. N denotes number of stocks in month t, which is different in each month.

Australia, Canada, Egypt, France, India, Ireland, Japan, Malaysia, the Netherlands, Pakistan, Philippines, Singapore, Sri Lanka, South Africa and Turkey. The results of insignificant relationship between β and average stock returns are contradictory with those implied by the CAPM theory documenting that investors demand a positive risk premium for bearing risk. Empirically, Fama and MacBeth (1973) test the US stock market over the period of 1935 to 1968 and find a positive relationship between monthly stock returns and β. Reinganum (1981) also finds that β is positively related to stock returns for a sample of monthly stock returns; however, it is negatively related to stock returns using daily stock returns. He argues that the positive relationship between β and stock returns is inconsistent across period. Furthermore, Tinic and West (1984) find that the relationship between β and stock returns is inconsistent across months in a year. Our results are consistent with Lakonishok and Shapiro (1986) and Fama and French's (1992) finding of an insignificant relationship between β and stock returns. Fama and French (1992) conclude that portfolio stock returns are well explained by the market capitalization and the ratio of book value to market value. Malkiel and Xu (2003) confirm the findings of the other studies that the significance on β is varied depending on sample periods and portfolio groupings.

The results on β from previous literatures are inconclusive. High stock returns involve high risk and market stock returns are very unlikely to be less than risk-free rate; therefore, a positive relationship between β and stock returns should be warranted. However, the negative relationship occurs frequently in down market (Fletcher, 2000). Our test period is from January 1973 to December 2007 including both up and down periods. The results show that β is insignificantly related to expected returns.

Premium on idiosyncratic risk

The results show that the coefficients of conditional expected idiosyncratic risk are positive for all countries. Evidently, conditional expected idiosyncratic risk has significant positive relation with expected returns in all countries except for New Zealand, Switzerland and Taiwan only in the regression without SIZE and MOMENTUM, where the coefficients are positive but insignificant. However, EIVOL is significant in these three countries when we control for SIZE and MOMENTUM. The significantly positive $\gamma_{2,t}$ is consistent with the ICAPM prediction of Merton (1987) that due to underdiversification, expected idiosyncratic risk is positively related to expected stock returns in the cross section. The results imply, for instance, a stock in Thailand that has an idiosyncratic volatility of one SD higher than other stocks earns a return of 1.39% higher in a month, which is the product of the β coefficient of Thailand, 0.1549 shown in Table 6 and SD of estimated-EGARCH idiosyncratic volatility, 8.97% shown in Table 5. On the other hand, a Swedish stock that has an idiosyncratic volatility of one SD higher than other stocks earns a return of 1.05% higher in a month.

IV. Conclusion

The contribution of our article is to extend the analysis on idiosyncratic risk in international stock markets. Our result from the US stock market is different from Fama and MacBeth's (1973) conclusion in which idiosyncratic risk does not play role on stock returns.

Applying estimated-EGARCH conditional idiosyncratic volatility, we find that idiosyncratic volatility is positively related expected returns. Our result is economically and statistically significant and is robust across 36 countries from January 1973 to December 2007. Merton (1987) states '...financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action'. However, the judgement of invalid idiosyncratic measure by CAPM is imprudent. Rather, we are more interested in the characteristics of idiosyncratic risk priced on a negative premium in those countries.

There is a limitation in our study. We employ residual from CAPM instead of Fama and French three-factor model to estimate expected idiosyncratic volatility from EGARCH model. The Fama–French factors are not publicly available like the Fama–French factors of the US stocks. Some data items such as book value of international stocks are unreliable. Due to data limitation, Fama–French factors are difficult to construct for the non-US companies. We leave this task for future research. Another possible reason that idiosyncratic risk is priced may be due to the market proxy problem. This problem is always present as portfolios that are not the same as index markets can always show returns, which are not explained by the proxy. The existence of idiosyncratic risk may be due to the differences between the portfolio and index holdings. A portfolio may be well diversified but still has idiosyncratic risk. As such, idiosyncratic risk cannot be reduced by diversification because it captures the differences in holdings. Higher differences in holdings may cause higher idiosyncratic risk. Future research should investigate this issue.

Another possible research that may be of interest for practitioners is to examine the relation between the portfolio performance, expected idiosyncratic volatility, and the level of β. First, we can apply Fama and French three-factor model and derive the residual, and then apply EGARCH to estimate expected idiosyncratic volatility as we do in this study. Instead of deriving β for each stock, we can construct β for each portfolio as in Fu (2009) and Fama and French (1992). We can employ a typical methodology of portfolio performance measurement such as an extended α Jensen's including the Fama–French factors and relate the α with the idiosyncratic volatility obtained from EGARCH through the window rolling. This performance regression is not cross-sectional but it is run for each portfolio. For each country, we will have results for 20 portfolios where we can draw an inference of relation between α, expected idiosyncratic volatility and β.[2]

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