Idiosyncratic Volatility and Equity Returns: UK Evidence

Timotheos Angelidis*

Department of Economics, University of Crete,

Gallos Campus,74100 Rethymno, Greece

and

ALBA Graduate Business School. Athinas Ave. & 2a Areos street,

16671 Vouliagmeni, Greece

Nikolaos Tessaromatis**

ALBA Graduate Business School. Athinas Ave. & 2a Areos street,

16671 Vouliagmeni, Greece

Abstract

The proposition that idiosyncratic volatility may matter in asset pricing is currently a topic of research and controversy. Using data from the UK market we examine the predictive ability of various measures of idiosyncratic risk and provide evidence which suggests that: (a) it is the idiosyncratic volatility of small capitalization stocks that matters for asset pricing and (b) that small stocks idiosyncratic volatility predicts the small capitalization premium component of market returns and is unrelated to either the market or the value premium. The predictive power of the aggregate idiosyncratic volatility of small stocks remains intact even after we control for the possible proxying effects of business cycle fluctuations and liquidity and is robust across time and different econometric specifications.

Keywords: Idiosyncratic Risk, Stock Market Volatility and Stock Return Predictability

JEL: G10, G11, C13

---

*Corresponding Author.
Tel.: +30-210-8964-736.
E-mail address: taggelid@alba.edu.gr.
** Tel.: +30-210-8964-736.
E-mail address: ntessaro@alba.edu.gr.
We thank seminar participants at Fourth Conference On Research on Economic Theory and Econometrics, Syros, July, 11-14, 2005, at the 8th Conference of the Swiss Society for Financial Market Research, Zurich, April 8, 2005 and at the 3rd conference of the Hellenic Finance and Accounting Association, Athens, December 4, 2004. We would also like to thank an anonymous referee for the instructive suggestions that helped to improve an early version of the paper. All errors remain our responsibility.

1. Introduction

Standard asset pricing models predict that only systematic risk is priced in equilibrium. Accordingly most of the empirical work on the validity of asset pricing models was focused on whether one or multiple systematic factors are incorporated in asset prices and command a risk premium. The possibility that idiosyncratic risk (which in theory can be eliminated through diversification) maybe priced in equilibrium and therefore investors might demand a systematic risk premium to bear it, has been largely neglected[1].

The recent paper by Campbell et al. (2001) on the statistical properties of idiosyncratic volatility has rekindled interest in the role of idiosyncratic volatility in asset pricing and stock return prediction. Campbell et al. (2001), using monthly data over the 1962-1997 period, show that average idiosyncratic risk is the most important component of total volatility, has increased noticeably over the period (while market volatility shows no significant trend), is countercyclical and helps forecast future economic activity.

The possibility that idiosyncratic risk might be priced in equilibrium has been studied in two recent papers. Xu and Malkiel (2001) build an equilibrium model, on the assumption that some investors might not be able to hold the market portfolio, which includes idiosyncratic risk as one of the systematic determinants of future stock returns. They study empirically the cross sectional relation between idiosyncratic volatility and firm returns and find a positive relation between idiosyncratic risk and future returns. Ang et al. (2006) reach the opposite conclusion; stocks with high idiosyncratic risk deliver abysmally low returns.

The other strand of the literature, more relevant for this paper, studies the inter-temporal relationship between lagged aggregate idiosyncratic volatility and market stock returns. Goyal and Santa-Clara (2003) find that the equally-weighted stock volatility is a significant predictor of subsequent returns of the value-weighted market portfolio. This result persists even after controlling for other variables that are known to predict future equity returns. Bali et al. (2005) argue that the positive relation uncovered by Goyal and

---

[1] Early papers by Lintner (1965) and Douglas (1969) suggested that idiosyncratic risk measured as the standard deviation of the error term from the market model explains the cross sectional average of stock returns. This finding was criticized by Miller and Scholes (1972) and Fama and McBeth (1973) for inappropriate econometric methodology. Later Tinic and West (1986) and Lehman (1990) in a careful econometric study, reaffirmed the significance of idiosyncratic risk.

Santa-Clara (2003) is not robust across different stock portfolios, disappears if the sample includes the more recent history of returns[2] and is partially driven by a liquidity premium. Guo and Savickas (2003), using quarterly data to measure volatility, reach the conclusion that value weighted idiosyncratic stock volatility is negatively related to future stock returns. Finally, Brown and Ferreira (2004) create two measures of idiosyncratic risk: one based on large capitalization stocks and another based on small capitalization stocks. Their evidence suggest that only the small capitalization based measure of idiosyncratic risk is significantly and positively related to future returns of the market portfolio as well as portfolios of large and small stocks.

The existing evidence on the relationship between idiosyncratic volatility and future stock returns based on US data are conflicting and confusing. On the one hand the evidence by Goyal and Santa-Clara (2003) point to a positive relation between market returns and the lagged equally weighted idiosyncratic volatility. On the other hand Wei and Zhang (2004) and Bali et al. (2005) argue that the results are driven by small stocks traded on the Nasdaq and disappear in the extended sample, while Guo and Savickas (2003) find a negative relation between idiosyncratic risk and returns. The evidence in Brown and Ferreira (2004) point to a special role for idiosyncratic volatility based only on small capitalization stocks.

The purpose of this paper is to examine the properties and forecasting ability of idiosyncratic volatility of the UK stock market. Given that most of the research on idiosyncratic volatility is based on USA data, using data from another major stock market minimizes the biases that arise due to data snooping (Lo and MacKinley, 1990) and offers an independent assessment of the empirical findings. In addition to the value weighted measures of idiosyncratic volatility, we also study idiosyncratic volatility measures based on large and small capitalization stocks. Consistent with the evidence presented in Brown and Ferreira (2004) we also find that idiosyncratic risk based on small capitalization stocks is different from either the value weighted volatility used in the previous studies or from the volatility measures based on large cap stocks. The idiosyncratic volatility of small capitalization stocks is highly correlated with the aggregate equally weighted idiosyncratic

[2] Wei and Zhang (2004) also find that the relation between returns and idiosyncratic risk disappears if the sample used by Goyal and Santa-Clara (2003) is extended by three years to 2002.

measure used by Goyal and Santa-Clara (2003). The predictive power of the aggregate idiosyncratic volatility of small and large stocks remains intact even after we control for the possible proxying effects of business cycle fluctuations and liquidity. The evidence on the predictive power of idiosyncratic risk (and especially the idiosyncratic volatility of small capitalization stocks) is robust across time and remains significant after we control for possible persistence in idiosyncratic volatilities.

The structure of the paper is as follows. The second section describes the measures of idiosyncratic risk, while the third presents the data and summary statistics. Section 4 investigates the forecasting ability of the idiosyncratic risk. Section 5 examines whether the relation between idiosyncratic risk and expected returns is attributed to either business cycle or illiquidity variables. Section 6 performs several robustness tests, while the last section concludes the paper.

2. *Measures of Idiosyncratic Risk*

Goyal and Santa-Clara (2003), Wei and Zhang (2004) and Bali et al. (2005) implemented the indirect method that was proposed by Campbell et al. (2001) in order to calculate the idiosyncratic risk. This technique uses the market model under the assumption that the betas of all securities are one and calculates idiosyncratic risk as the difference between stock and market variance.

Following Goyal and Santa-Clara (2003), we define the monthly variance of stock i based on daily returns as:

$$V_{i,t} = \sum_{d=1}^{D_t} r_{i,d}^2 + 2\sum_{d=2}^{D_t} r_{i,d} r_{i,d-1}, \qquad \text{Eq. 1}$$

where D_t is the number of trading days in month t and $r_{i,d}$ is the return of stock i in day d. Note that this measure does not compute the stock variance accurately, since it does not demean the returns. However, for daily data this effect is not important, as French et al. (1987), Schwert (1989) and Goyal and Santa-Clara (2003) pointed out. The second term of equation 1 adjusts the variance to the autocorrelation of stock returns, by employing the French et al. (1987) procedure. Similar to Goyal and Santa-Clara (2003) and Guo and Savickas (2003b), we exclude stocks with less than 5 observations during month *t*, while we drop the $2\sum_{d=2}^{D_t} r_{i,d} r_{i,d-1}$ term from equation 1 if $V_{i,t} < 0$. Under this framework, the equally weighted total variance, TV_t^{Equal} is calculated as:

$$TV_t^{Equal} = \frac{1}{N}\sum_{i=1}^{N} V_{i,t}, \qquad \text{Eq. 2}$$

while the value-weighted total variance, TV_t^{Value} is expressed as:

$$TV_t^{Value} = \sum_{i=1}^{N} \omega_{i,t} V_{i,t} \text{ and } \omega_{i,t} = \frac{v_{i,d_{t-1}}}{\sum_{i=1}^{N} v_{i,d_{t-1}}}, \qquad \text{Eq. 3}$$

where N is the number of stocks during month t, while $v_{i,d_{t-1}}$ is the market capitalization of stock i in day d in month t-1.

Using the market model under the assumption that the betas of all securities against the market is one, (see also Xu and Malkiel, 2001), the variance of stock i at time t, $V_{i,t}$ t, can be decomposed in two parts: a systematic part that equals to the variance of the market, MV_t and an idiosyncratic part that equals to the variance of the idiosyncratic return.

$$V_{i,t} = MV_t + IV_{i,t} \qquad \text{Eq. 4}$$

Therefore, the aggregate idiosyncratic variance is calculated as:

$$IV_t = TV_t - \mathrm{M}V_t \qquad \text{Eq. 5}$$

where TV_t is the aggregate total volatility calculated from individual stock's variance, (equations 2 or 3) and MV_t is the variance of the market. The equally weighted idiosyncratic variance is defined as:

$$IV_t^{Equal} = TV_t^{Equal} - MV_t^{Equal} \qquad \text{Eq. 6}$$

and the value weighted idiosyncratic variance as:

$$IV_t^{Value} = TV_t^{Value} - MV_t^{Value} \qquad \text{Eq. 7}$$

Using equations 6 and 7 we construct three measures of volatility: a measure based on all the stocks in the sample (denoted with the subscript ALL), a measure based on 80% of the largest stocks in the sample (denoted with the subscript LARGE) and a measure based on 20% of the smallest by market capitalization stocks in the sample (denoted with the subscript SMALL).

The advantage of using, in addition to idiosyncratic volatility based on ALL stocks in the sample, the idiosyncratic volatilities of LARGE and SMALL stocks is that we can examine the differences between stock returns and SMALL and LARGE volatilities and yet interpret our evidence in the light of previous research using volatility measures based on ALL stocks.

3. *Dataset*

The data is obtained from Datastream and covers all listed stocks that either currently trade or were traded in the London Stock Exchange Market from 31/12/1979 to 30/9/2003. According to Nagel (2001), Datastream's stock coverage prior to 1979 was relatively poor compared to the total population of the listed stocks. Datastream's coverage after 1979 is far more comprehensive and free from survivorship bias. From the database we exclude all the foreign companies and the investment trusts.

We follow closely the Fama and French (1993) methodology to construct the HML and SMB portfolios. However, following Dimson et al. (2003), we adjust the portfolio formation mechanism to account for peculiarities of the UK data. For the creation of size portfolios we use the 80th percentile of the market value instead of the median used by Fama and French (1993), while for the book to market portfolios we set the breakpoints at the 40th and 60th percentiles. By employing a larger breakpoint for the size portfolios we ensure that corner portfolios are well diversified and that the distribution of aggregate market value across portfolios is relatively similar to the distribution in Fama and French (1993). Using these portfolio construction rules, the small-cap portfolio represents on average 8% of total market value, a percentage close to the 10% of total capitalization represented by the Hoare Govett Smaller Companies Index.

At the end of June of each year, we form the 6 portfolios of Fama and French (1993) and calculate the value-weighted monthly returns for the next 12 months. Table 1 reports the average return and the standard deviation of SMB and HML portfolios over the 1979-2003 period. For comparison purposes we also present the return and the standard deviation reported by Dimson et al. (2003). As table 1 shows, over the 1979-2003 period small stocks outperformed large stocks and value stocks outperformed growth stocks. Compared to the longer period (1951-2001) used by Dimson et al. (2003), the small cap and the value premia are smaller in the more recent period.

3.1 Descriptive Statistics and Graphical Analysis for Idiosyncratic Volatility

Panel A of table 2 presents descriptive statistics for the monthly equally and value weighted idiosyncratic variances based on ALL stocks, only on LARGE stocks and only on SMALL stocks. In panel B, it also shows descriptive statistics for size weighted volatility of the market portfolio. Panel C of table 2 reports the correlations between the various risk measures.

Table 1. Fama and French (1993) portfolios in the U.K.		
	SMB	HML
	Panel A. 1979 -2003	
Average Monthly Return	0.06%	0.33%
Standard Deviation	3.23%	2.82%
	Panel B. 1955 -2001	
Average Monthly Return	0.15%	0.49%
Standard Deviation	3.40%	2.17%

This table presents summary statistics for the Fama and French (1993) HML and SMB factors. Panel A shows the average monthly return and the corresponding standard deviation for the period from 1979 to 2003. Panel B shows the average monthly return and standard deviation reported in Dimson et al. (2003) for the period from 1955 to 2001.

Table 2. Descriptive Statistics

	Mean	Median	Maximum	Minimum	S.D.	Skew	Kurt.	J.B	AR1	AR6	AR12
Panel A. Idiosyncratic Volatilities											
IV_{All}^{Equal}	0.016	0.013	0.056	0.006	0.008	1.926	7.854	456	0.820	0.445	0.415
IV_{All}^{Size}	0.007	0.005	0.038	0.001	0.005	2.995	16.022	2440	0.814	0.441	0.401
IV_{Large}^{Size}	0.007	0.005	0.039	0.001	0.005	3.080	16.555	2633	0.821	0.451	0.415
IV_{Small}^{Size}	0.026	0.022	0.121	0.007	0.017	2.473	10.964	1044	0.658	0.320	0.265
Panel B. Market Volatilities											
MV_{All}^{Size}	0.002	0.001	0.040	0.00012	0.333%	7.223	71.591	58348	0.270	0.033	0.002

Panel C. Correlation Matrix

	IV_{All}^{Equal}	IV_{All}^{Size}	IV_{Large}^{Size}	IV_{Small}^{Size}	MV_{All}^{Size}
IV_{All}^{Equal}	1				
IV_{All}^{Size}	0.68	1			
IV_{Large}^{Size}	0.71	0.98	1		
IV_{Small}^{Size}	0.90	0.48	0.51	1	
MV_{All}^{Size}	0.38	0.40	0.39	0.21	1

In panels A and B we present the descriptive statistics of Idiosyncratic and Market Volatilities, respectively. IV is the idiosyncratic risk, while MV is the variance of the market. “SD” is the standard Deviation, “Skew” is the skewness, “Kurt” is the kurtosis. “J.B” is the Jarque-Bera statistic. AR1, AR6 and AR12 are the autoregressive coefficients of order 1, 6 and 12 respectively. Panel C reports the bivariate correlation between the various variance measures, which are log-transformed. The sample period is from 31/12/1979 to 30/9/2003.

The monthly average value (equally) weighted measure of idiosyncratic variance equals 0.007 (0.016), a standard deviation of 8.37% (12.65%) per month. Consistent with the results reported by Goyal and Santa-Clara (2003) and Campbell et al. (2001), idiosyncratic risk is highly persistent with first order autoregressive coefficients ranging from 0.65 to 0.82[3]. High (low) idiosyncratic risk in one period is likely to be followed by higher (lower) than average idiosyncratic risk for many subsequent periods, especially for the large capitalization securities. In contrast market volatility is much less persistent with AR(1) coefficient close to 0.3, while the AR(12) coefficient is close to zero.

Idiosyncratic volatility represents the largest component of total volatility whether we look at volatilities based on ALL, LARGE or SMALL stocks and irrespective of the employed weighting scheme. Idiosyncratic volatility represents between 75% and 97% of total average volatility and therefore market variance is only a faction of the total variance[4]. The equally weighted variance is almost double than that of the value weighted, a finding consistent with other research using US data and not surprising given the heavier weight of smaller and more volatile securities under the equal weighting scheme.

Volatility based only on LARGE stocks is similar to the volatility calculated using ALL stocks, as the correlation between these risk measures is close to 1. On the other hand, the variance of the SMALL stocks exhibits a different behaviour, as the average volatility of SMALL stocks is more than three times than that of the volatility of LARGE stocks.

Finally, as figure 1 shows, the monthly value weighted idiosyncratic volatility of ALL stocks and the corresponding volatility of LARGE stocks show little trend until the end of 1997 but increase noticeably during the 1998-2002 period. The spike in volatility lasts until the end of 2002 when both volatilities measures return to their long term average[5]. In contrast, the equally weighted idiosyncratic volatility of ALL and the capitalization weighted volatility of SMALL stocks show a smooth upward trend while the spike in volatility that started in 1998 seems to persist until the end of the sample period.

---

[3] Campbell and Yogo (2006, abstract) argued that "Conventional tests of the predictability of stock returns could be invalid, that is reject the null too frequently, when the predictor variable is persistent and its innovations are highly correlated with returns.". This issue is addressed in section 6.

[4] Due to space limitations, we do not report the results for total volatility, but they are available upon request.

[5] In order to investigate more formally whether idiosyncratic volatility in the UK market increased during the 1979-2003 period, we compute the PS-statistic described by Vogelsang's (1998) and the implied 90% confidence interval for the trend coefficient. Based on Vogelsang's (1998) confidence intervals, the trend coefficient is not statistically different from zero. The absence of a trend in volatility in the UK market is in contrast to the evidence of a positive and significant trend found in the US market but in line with the evidence presented by Frazzini and Marsh (2003) and Guo and Savickas (2004).

The 1998-2002 period spike which is common for all volatility measures, begins with the Asian crisis which took place in the middle of 1997.

4. *Empirical Investigation of the Forecasting Ability of Idiosyncratic Risk*

According to capital asset pricing theories, expected stock returns should be a function of the systematic factors that affect stock prices. Idiosyncratic risk, which can be eliminated through diversification, should play no role in the pricing of stocks. The evidence that asset specific risk is a significant predictor of future stock returns or that it is priced cross sectional can be reconciled if idiosyncratic volatility is a proxy for systematic risk factors. Goyal and Santa-Clara (2003) speculate that idiosyncratic volatility is a proxy for either background risk or lack of diversification. Bali et al. (2005) and Brown and Fereiras (2003), in addition, discuss the possibility that idiosyncratic risk proxies for liquidity or business cycle risk, while Drew et al. (2004) argue that idiosyncratic volatility is priced and that firm size and idiosyncratic volatility may serve as proxies for systematic risk.

4.1. Forecasting the Market Portfolio

We explore the relationship between volatility and subsequent stock returns by regressing capitalization and equally weighted monthly market stock returns on various measures of lagged volatility.

$$r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}, \qquad \text{Eq. 8}$$

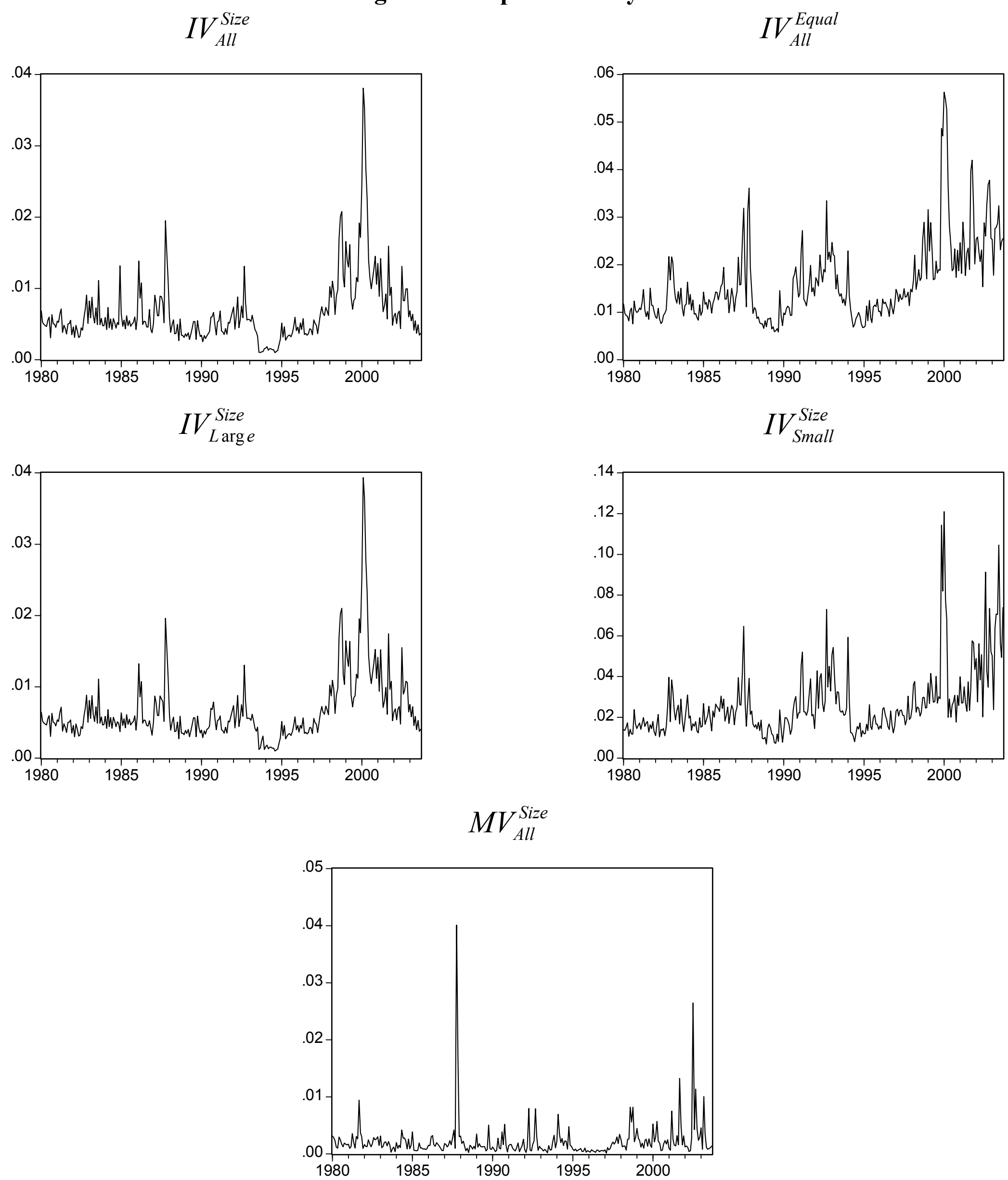
where r_{t+1} is the log monthly return of the market portfolio at month $t+1$ and X_t includes different combinations of market and idiosyncratic volatilities[6]. Given the evidence presented in panel A of table 2 that volatility displays non-zero skewness and excess kurtosis relative to that of the standard normal distribution, we follow the suggestion of Goyal and Santa-Clara (2003) and log transform the variance measures. The log transformation reduces both skewness and kurtosis and brings the distribution closer to the normal.

Panel A of table 3 present the regressions results of the monthly value weighted market return on lagged measures of market and idiosyncratic volatility. Consistent with

[6] Based on the Dickey and Fuller (1979) and the Phillips and Peron (1988) tests, the hypothesis of the presence of a unit root for all volatility measures is rejected at 5% confidence level, whether we include a trend or not.

previous US studies we also find that the coefficient of the market volatility is insignificant. Equal or value weighted idiosyncratic volatility based on ALL stocks is insignificantly related to market returns, a result contradicting the significant positive relationship found by Goyal and Santa-Clara (2003) using US data. Using idiosyncratic volatility measures based on either LARGE or SMALL stocks gives similar results: idiosyncratic volatility is not related to stock returns.

Figure 1. Graphical Analysis



This figure plots the monthly value and equally weighted idiosyncratic variances of ALL, LARGE and SMALL stocks, as well as the corresponding of the market. The sample covers the period from 1980-2003.

Table 3. Panel A. Forecasts of the Capitalization Weighted Market Return

Equation	Constant.	IV_{All}^{Size}	IV_{All}^{Equal}	IV_{Small}^{Size}	IV_{Large}^{Size}	MV_{All}^{Size}	R^2 Ad.
1	0.0239	0.0026					-0.26%
p-value	0.26	0.53					
2	-0.0023		-0.0030				-0.28%
p-value	0.91		0.54				
3	-0.0089			-0.0051			-0.07%
p-value	0.69			0.38			
4	0.0188				0.0016		-0.32%
p-value	0.40				0.71		
5	0.0236					0.0020	-0.24%
p-value	0.24					0.50	
6	0.0299	0.0018				0.0015	-0.55%
p-value	0.17	0.72				0.67	
7	0.0087		-0.0052			0.0031	-0.40%
p-value	0.72		0.35			0.36	
8	0.0057			-0.0061		0.0028	-0.21%
p-value	0.84			0.31		0.37	
9	0.0255				0.0006	0.0018	-0.59%
p-value	0.24				0.92	0.63	
10	0.0070			-0.0083	0.0054		-0.12%
p-value	0.76			0.29	0.36		
11	0.0138			-0.0083	0.0043	0.0019	-0.39%
p-value	0.57			0.30	0.55	0.61	

Panel B. Forecasts of the Equally Weighted Market Return

Equation	Constant	IV_{All}^{Size}	IV_{All}^{Equal}	IV_{Small}^{Size}	IV_{Large}^{Size}	MV_{All}^{Size}	R^2 Ad.
1	0.0355	0.0043					-0.07%
p-value	0.15	0.35					
2	0.0583		0.0106				0.65%
p-value	0.04		0.09				
3	0.0581			0.0119			1.24%
p-value	0.03			0.07			
4	0.0289				0.0030		-0.22%
p-value	0.24				0.50		
5	0.0310					0.0027	-0.13%
p-value	0.20					0.45	
6	0.0428	0.0034				0.0019	-0.34%
p-value	0.17	0.47				0.62	
7	0.0605		0.0102			0.0006	0.31%
p-value	0.05		0.14			0.88	
8	0.0647			0.0114		0.0013	0.93%
p-value	0.04			0.10		0.74	
9	0.0370				0.0018	0.0023	-0.45%
p-value	0.23				0.71	0.56	
10	0.0485			0.0138	-0.0032		1.00%
p-value	0.06			0.09	0.56		
11	0.0564			0.0138	-0.0044	0.0022	0.76%
p-value	0.07			0.10	0.45	0.57	

Panel A (B) presents results from the one-month-ahead predictive regressions of the capitalization (equally) weighted market return on the lagged volatility measures. The predictive regression is defined as $r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where r_{t+1} is the log monthly return of the capitalization (equally) weighted market return at month $t+1$ and X_t includes different combinations of market and idiosyncratic variances. The second row for each regression gives the Newey-West (1987) adjusted p-values. The last column reports the adjusted R^2 values.

The results from the regressions of the monthly equally weighted market return on the lagged measures of the market and idiosyncratic volatility are presented in panel B of table 3. While both value and equal weighted volatility are positively related to future market returns, none of the coefficients is statistically significantly different from zero. When we use the volatility measures based on large and small stocks only the coefficient for that small stock based volatility is positive and significant at the 10% level[7]. In summary our findings suggest a positive, albeit weak, relationship between market returns and lagged idiosyncratic risk based on the volatility of small stocks and no relation with the other volatility measures.

4.2 Forecasting the SMB and HML Portfolios.

According to the ICAPM of Merton (1973), the demand for a risky asset depends partly on the asset's ability to hedge uncertainties about future consumption opportunities. In an ICAPM world, where s state variables describe time-variations in the investment opportunity set, the expected return on an asset is a function of the covariance between the asset's return and the market portfolio and the covariance between the asset's return and the return on the s-th hedge portfolio. As the ICAPM does not specify the identity of the state variables, various authors use different variables as proxies. Fama (1996) for example argues that the SMB and HML portfolios used in Fama and French (1992, 1993) could be thought of as mimicking portfolios that are correlated with the relevant state variables. Empirical evidence consistent with the view that SMB and HML are correlated with future economic activity is provided by Liew and Vassalou (2000) who show that the Fama and French (1993) factors can forecast GDP growth in several countries. Their findings support the hypothesis of Fama and French (1992, 1993, 1995, 1998) that SMB and HML act as state variables in the context of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). In a multifactor world it is possible that idiosyncratic volatility might be related to one or all the risk factors.

[7] The evidence is consistent with the findings of Bali et al. (2005) for the US market. According to Bali et al. (2005) the positive relation between idiosyncratic volatility and equally weighted market returns uncovered by Goyal and Santa-Clara (2003), is due to the small stock component of market returns (NASDAQ stocks).

Table 4 presents the results from regressing value weighted monthly returns of SMB and HML portfolios on market volatility and various combinations of idiosyncratic volatilities[8].

Panel A of table 4 shows the results from the estimation of the relation between returns on the SMB portfolio returns and lagged idiosyncratic volatility. The return of the SMB portfolio is positively related to the lagged value and equally weighted idiosyncratic volatility but the coefficient is statistically significant only when idiosyncratic volatility is equally weighted. The estimated coefficients for both LARGE and SMALL idiosyncratic volatility (line 10) are statistically significantly different from zero[9]. The coefficient for LARGE volatility is negative suggesting that a higher than average idiosyncratic volatility of LARGE stocks predicts a negative SMB return (i.e. large stocks outperform small stocks). The coefficient for SMALL volatility is positive indicating that when idiosyncratic volatility based only on SMALL capitalization stocks is above average, the return difference between SMALL and LARGE stocks tends to be positive. The adjusted R-squared suggests that SMALL and LARGE idiosyncratic volatility capture 6.48% of future SMB return variability.

Finally, the results in panel B of table 4 show that none of the idiosyncratic volatility measures is related to the return spread between value and growth stocks[10].

---

[8] Guo and Savickas (2003b), using quarterly data, also examined whether idiosyncratic risk has significant forecasting ability on SMB, HML and momentum (Jegadeesh and Titman, 1993) momentum strategy of buying past winners and selling past losers portfolios. They argued that idiosyncratic risk is a strong predictor of HML but has no explanatory power for SMB.

[9] To check whether the results are robust to the 80-20 rule used to construct LARGE and SMALL idiosyncratic variance, we re-calculated LARGE and SMALL idiosyncratic volatility based on 90% and 10% of the number of stocks in the sample. The new idiosyncratic volatilities of SMALL and LARGE stocks had a correlation of 0.33. Using the new measures of SMALL and LARGE, we obtained the following coefficients (p-values in parentheses): for SMALL idiosyncratic volatility 0.014 (0.00) and for LARGE idiosyncratic volatility -0.007 (0.15).

[10] We also created 10 size-based and 10 book to price based portfolios and re-estimated equation 8 for each portfolio. The Newey-West t-statistic was 1.83 (-0.96) when we forecasted the returns of the smallest (largest) portfolio with the idiosyncratic risk of the smallest stocks. The forecasting ability of LARGE idiosyncratic volatility was insignificant. The same procedure was used to test the forecasting ability of idiosyncratic risk for value-growth portfolios, but no significant relation was uncovered. The detailed results are available from the authors upon request.

Table 4. Panel A. Forecasts of the SMB portfolio

Equation	Const.	IV_{All}^{Size}	IV_{All}^{Equal}	IV_{Small}^{Size}	IV_{Large}^{Size}	MV_{All}^{Size}	R^2 Ad.
1	0.0057	0.0011					-0.32%
p-value	0.81	0.81					
2	0.0438		0.0103				1.72%
p-value	0.09		0.08				
3	0.0559			0.0148			5.04%
p-value	0.00			0.00			
4	0.0021				0.0004		-0.36%
p-value	0.93				0.93		
5	-0.0143					-0.0022	-0.04%
p-value	0.37					0.35	
6	-0.0055	0.0025				-0.0029	-0.22%
p-value	0.83	0.58				0.22	
7	0.0257		0.0140			-0.0052	2.86%
p-value	0.34		0.02			0.04	
8	0.0332			0.0163		-0.0044	5.91%
p-value	0.13			0.00		0.07	
9	-0.0078				0.0019	-0.0027	-0.30%
p-value	0.77				0.69	0.25	
10	0.0306			0.0200	-0.0087		6.48%
p-value	0.21			0.00	0.06		
11	0.0201			0.0201	-0.0071	-0.0029	6.63%
p-value	0.44			0.00	0.13	0.23	

Panel B. Forecasts of the HML portfolio

Equation	Const.	IV_{All}^{Size}	IV_{All}^{Equal}	IV_{Small}^{Size}	IV_{Large}^{Size}	MV_{All}^{Size}	R^2 Ad.
1	0.0206	0.0034					0.15%
p-value	0.48	0.52					
2	0.0133		0.0024				-0.21%
p-value	0.65		0.71				
3	-0.0016			-0.0012			-0.32%
p-value	0.95			0.84			
4	0.0191				0.0031		0.06%
p-value	0.53				0.57		
5	0.0060					0.0005	-0.34%
p-value	0.65					0.81	
6	0.0188	0.0036				-0.0005	-0.19%
p-value	0.51	0.51				0.80	
7	0.0131		0.0025			0.0000	-0.57%
p-value	0.65		0.73			0.98	
8	0.0019			-0.0014		0.0007	-0.64%
p-value	0.94			0.81		0.74	
9	0.0174				0.0034	-0.0005	-0.29%
p-value	0.55				0.57	0.82	
10	0.0131			-0.0042	0.0050		0.11%
p-value	0.69			0.51	0.37		
11	0.0116			-0.0042	0.0052	-0.0004	-0.24%
p-value	0.71			0.51	0.37	0.84	

Panel A (B) presents results from the one-month-ahead predictive regressions of the capitalization-weighted return of the SMB (HML) portfolio on the lagged volatility measures. The predictive regression is defined as $r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where r_{t+1} is the capitalization-weighted return of the SMB (HML) portfolio at month $t+1$ and X_t includes different combinations of market and idiosyncratic variances. The second row for each regression gives the Newey-West (1987) adjusted p-values. The last column reports the adjusted R^2 values.

5. Controlling for Business Cycle and Liquidity

5.1 Business Cycle

Campbell et al. (2001) provide strong evidence which suggest that idiosyncratic risk tends to be 1.5 times higher during economic contractions than during economic expansions. These authors also find that idiosyncratic risk leads future GDP growth and its forecasting power for future GDP remains after controlling for past GDP growth and stock returns. There is also substantial evidence which suggest that variables related to the business cycle can forecast future stock returns[11]. Liew and Vassalou (2000) also report that the returns on SMB and HML are positively related to future growth in the macro-economy. It is therefore possible that idiosyncratic risk might be a proxy for business cycle variations. We follow Goyal and Santa-Clara (2003) and Brown and Fereira (2004) and include in equation 8 the UK market dividend yield, the default premium and the one month interest rate[12] as controls variables for business fluctuations. We also include the lagged return on the value weighted market portfolio, a variable found to have strong predictive power for the small-large spread.

The results of equation 8 with SMB as the dependent variable are shown in table 5. Future SMB returns are negatively and statistically significantly related with the dividend yield and the stochastically detrended one month interest rate (line 2). Past market returns are positively and statistically significantly related with the future small cap premium. There is no statistically significant relation between the SMB returns and the default premium. The four variables explain 15.76% of future SMB variability. Adding the idiosyncratic risk for SMALL and LARGE stocks (line 3) increases the adjusted R-squared to 19.88%. Both coefficients of the idiosyncratic risk variables remain statistically significant and with the same signs as in panel A of table 4, while the significance of the idiosyncratic risk of LARGE stocks has increased noticeably. The evidence suggests that idiosyncratic risk provides additional information to the business cycle variables.

---

[11] See for example, Campbell and Shiller (1988), Fama and French (1988, 1989).

[12] The dividend yield is the yield of the Financial Times All Share Index, the default premium is measured as the difference between the corporate bond yield and the government bond yield. The stochastically detrended one month interest rate is the difference between the one month London Interbank Rate and its twelve month moving average.

5.2 Illiquidity Ratio

Bali et al. (2005) claim that part of the positive relation between stock returns and idiosyncratic risk found in Goyal and Santa-Clara (2003) is due to the proxying effects of idiosyncratic risk for liquidity. The authors argue that in an environment of poor liquidity, the bid-ask bounce will result in spurious volatility of the equally weighted measure of idiosyncratic risk. Once they control for expected and unexpected liquidity they find that idiosyncratic risk is no longer significant. Liquidity risk will be negatively related with volatility if the bid-ask spread set by market makers will be higher for more volatile stocks.

We use the liquidity measure proposed by Amihud (2002) to test whether idiosyncratic risk is a proxy for liquidity risk. Hasbrouck (2005) and Acharya and Pedersen (2004), argue that Amihud's (2002) liquidity measure based on daily volume and absolute returns is the best proxy for measuring liquidity risk and is highly correlated with alternatives measures based on microstructure data. Amihud (2002) defines illiquidity (I) as the average ratio of the daily absolute return to the daily dollar trading volume:

$$I_{i,t} = \sum_{t=1}^{n} \left\{ \left| r_{i,d} \right| / Vol_{i,t} \right\} / n \qquad \text{Eq. 9}$$

where $Vol_{i,t}$ and $\left| r_{i,d} \right|$ is the trading dollar volume and the absolute return on stock i on day t respectively, while the summation is over the total sample observations n. A stock is illiquid if significant price changes occur simultaneously with insignificant volume. Daily stocks returns and trading volume were obtained from Datastream and cover the period from January 1987 to September 2003[13]. The average market wide illiquidity variable is constructed by averaging the illiquidity measures for individual stocks within the month as follows:

$$ILLIQ_t = \frac{1}{N_t} \sum_{1}^{N_t} I_{i,t} \qquad \text{Eq. 10}$$

According to the liquidity hypothesis, (Amihud, 2002), expected stock returns are positively related to expected illiquidity and negatively related to unexpected illiquidity.

[13] The period is shorter because daily trading volume data were not available from Datastream before January 1987.

We obtain expected and unexpected illiquidity measures by estimating the following autoregressive model:

$$\begin{array}{lllll} Ln(ILLIQ_t) = & -2.831 + & 0.7333 Ln(ILLIQ_{t-1}) & + \text{residual} & \\ (t =) & (-4.39) & (11.66) & R^2_{\text{Adjusted}} = 0.58 & \end{array} \qquad \text{Eq. 11}$$

The sum of the two first terms in equation 11 measure expected illiquidity, while the residual measures the unexpected illiquidity.

To examine whether idiosyncratic risk is a proxy for illiquidity risk, we re-estimate equation 8 including the idiosyncratic risk variables, the business cycle variables and expected and unexpected illiquidity. Line 4 in table 5 presents the estimation results. The coefficient of expected illiquidity is negative but statistically insignificantly different from zero. The coefficient of unexpected illiquidity, as in Amihud (2002), is negative and statistically significant. Consistent with theory, an increase in unexpected illiquidity is associated with a fall in stock prices. Contrary to the findings of Bali et al. (2005), who find that the coefficient of idiosyncratic risk becomes insignificant after the inclusion of the illiquidity variables; the coefficients of idiosyncratic risk of the SMALL and LARGE securities remain statistically significant. Therefore idiosyncratic risk is not a proxy for liquidity risk.

Table 5. Forecasts of the SMB portfolio :
Controlling for the Business Cycle and Market Liquidity.

Equation	Const.	IV^{Size}_{Small}	IV^{Size}_{Large}	DY	Default	TB	Market Lag	$Illq^E$	$Illq^U$	R^2 Ad.
1	0.031	0.020	-0.009							6.48%
p-value	0.21	0.00	0.06							
2	-0.065			-0.018	0.130	-0.386	0.240			15.76%
p-value	0.06			0.07	0.68	0.03	0.00			
3	-0.077	0.016	-0.012	-0.021	0.463	-0.242	0.233			19.88%
p-value	0.20	0.00	0.03	0.05	0.11	0.18	0.00			
4	-0.142	0.017	-0.013	-0.032	0.347	-0.652	0.259	-0.002	-0.005	26.24%
p-value	0.03	0.00	0.02	0.01	0.41	0.01	0.00	0.16	0.03	

This table presents results from the one-month-ahead predictive regressions of the capitalization-weighted return of the SMB portfolio on the lagged volatility measures and Business Cycle and Illiquidity variables. The sample covers the period 1980:01-2003:09. The description of idiosyncratic risk measures is given in table 2. The dividend yield (DY) is the yield of the Financial Times All Share Index, the default premium (Default) is measured as the difference between the corporate bond yield and the government bond yield. The stochastically detrended (TB) one month interest rate is the difference between the one month London Interbank Rate and its twelve month moving average. The expected ($Illq^E$) and the unexpected illiquidity ($Illq^U$) measures are defined in equation 11. All the variables are log-transformed. Due to the unavailability of daily turnover before 1987, the regression in line 4 covers the period from 1987:01 to 2003:09. The second row for each regression gives the Newey-West (1987) adjusted p-values. The last column reports the adjusted R^2 values.

6. *Robustness Tests*

The recent papers of Bali et al. (2005) and Wei and Zhang (2004) have raised questions about the robustness of the relation between idiosyncratic risk and expected returns reported in Goyal and Santa-Clara (2003). In particular Wei and Zhang (2004) argue that the significant positive relation between market returns and average idiosyncratic volatility is mainly driven by the data in the 1990's and that it disappears during sub-periods. Therefore, it is important to examine whether the relation between SMB returns and the idiosyncratic risk of the SMALL and the LARGE stocks reported in sections 4 and 5 is robust across time. We address this issue by examining sub-period results. Figure 2 shows the Newey-West (1987) adjusted t-statistics of the regression coefficients of SMALL and LARGE idiosyncratic volatility regressed against the future return of the SMB portfolio. The first observation on the graph is estimated using data from the beginning of the period (12/1979) to the month marked on the horizontal axis. Subsequent observations are generated by adding one month of data to the sample. As the graph shows, for SMALL stock idiosyncratic volatility the t-statistic remains positive and greater than 2 for most of the sample and especially after 1994. The spike in volatility during the 1998-2002 period observed earlier makes little difference in the estimated t-statistics. In contrast, the estimated t-statistics for idiosyncratic volatility based only on LARGE capitalization stocks is statistically insignificant for most of the sample. The coefficient of LARGE idiosyncratic volatility becomes statistically significant at 10% level of confidence only after 2000. These results suggest that the relation between SMB returns and SMALL stock idiosyncratic volatility is robust across time and casts doubt on the power and significance of LARGE stock idiosyncratic volatility. SMALL stock idiosyncratic volatility is special and different than LARGE stock idiosyncratic volatility.

To further examine the relation between idiosyncratic volatility and SMB returns during the 2000-2003 period we split the full sample in two sub-samples. The first sample runs from 1980:01 to 1999:12, while the second covers the period from 2000:01 to 2003:09. Bali et al. (2005) and Wei and Zhang (2004) claim that when data after 2000 are added up to the US sample used by Goyal and Santa-Clara (2003), the positive relation between return and idiosyncratic risk disappears. The 2000-2003 period is also unusual in the UK market since idiosyncratic volatility is significantly higher than other periods (see Figure 1). Panel A of table 6 presents the predictive equations for the two samples. For both samples the coefficient of the SMALL idiosyncratic risk is positive and statistically significant at 10% level of confidence. The only difference between the pre-1999 and the post-1999 samples is that the absolute value of the coefficient of SMALL stock idiosyncratic volatility after 1999 is about twice to that before 1999. On the other hand, the coefficient of LARGE stock idiosyncratic volatility, although negative in both sub-periods, is statistically insignificant.

Table 6. Robustness Check

Panel A. Sub sample analysis

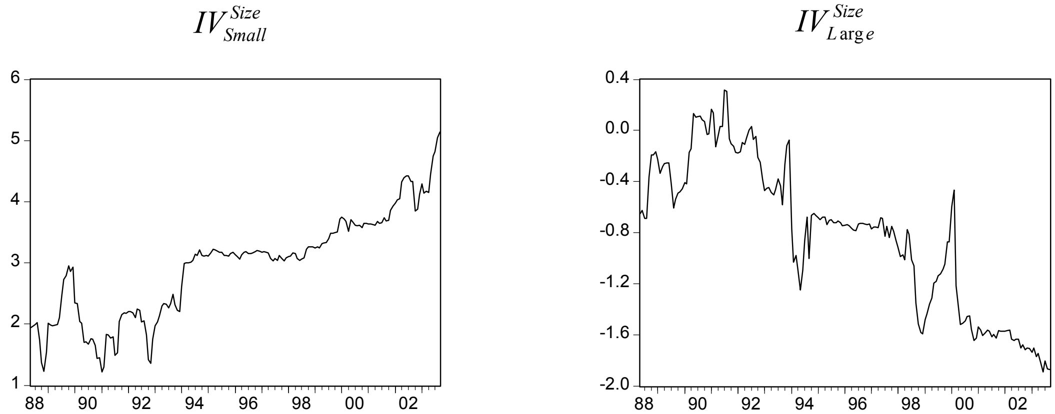
	Const.	IV^{Size}_{Small}	IV^{Size}_{Large}	R^2 Ad.
Equation	Sample Period: 1980:01 – 1999:12			
1	0.0439	0.0167	-0.0039	4.51%
p-value	0.06	0.00	0.38	
	Sample Period: 2000:01 – 2003:09			
2	0.0168	0.0302	-0.0181	8.90%
p-value	0.89	0.06	0.32	

Panel B. On the dynamic relation between returns and risk

		Coefficient	p-value.
	Constant	0.0001	0.94
SMALL (Lag)	1	0.0281	0.00
	2	0.0050	0.49
	3	0.0131	0.01
	4	0.0068	0.43
	5	-0.0006	0.93
LARGE (Lag)	1	-0.0180	0.02
	2	-0.0018	0.77
	3	-0.0082	0.19
	4	0.0012	0.82
	5	-0.0047	0.42
R^2 Ad.		6.53%	

Panel A presents results from the one-month-ahead predictive regressions of the capitalization-weighted return of the SMB portfolio on the lagged volatility measures, based on two sub samples. The first sample runs from 1980:01 to 1999:12, while the second covers the period from 2000:01 to 2003:09. The predictive regression is defined as $r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where r_{t+1} is the capitalization-weighted return of the SMB portfolio at month $t+1$ and X_t includes different combinations of market and idiosyncratic variances. The second row for each regression gives the Newey-West (1987) adjusted p-values. The last column reports the adjusted R^2 values. Panel B presents results from the one-month-ahead predictive regressions of the capitalization-weighted return of the SMB portfolio on the lagged volatility innovations. The predictive regression is defined as $r_{t+1} = \alpha + \sum_{q=0}^{4} \hat{u}_{t-q} + \varepsilon_{t+1}$, where r_{t+1} is the capitalization-weighted return of the SMB portfolio at month $t+1$ and $\hat{u}_t$ is the innovation in volatility. The innovation is estimated as the residual from a second order autoregressive model for the idiosyncratic risk of LARGE and SMALL stocks. The last row for each regression gives the Newey-West (1987) adjusted p-values. The last row reports the adjusted R^2 values.

Figure 2. Time Series of Newey-West (1987) adjusted t-Statistics.



This figure shows the Newey-West (1987) adjusted t-statistics of the regression coefficients of SMALL and LARGE stocks idiosyncratic volatility regressed against the future return of the SMB portfolio. Each observation shows the Newey-West (1987) adjusted t-statistic estimated using data from the start of the period (12/1979) to the month marked on the horizontal axis.

Finally, Jiang and Lee (2004**)** argue that the power of the one-step predictive regressions methodology used to study the relationship between future returns and volatility depends critically on whether the explanatory variable is persistent or not[14]. Specifically, they argued that, if idiosyncratic risk is persistent, instead of the raw idiosyncratic measures, the serially uncorrelated innovations in idiosyncratic volatility must be used as regressor. Given the evidence presented in table 2 showing that the idiosyncratic variances are persistent we use the modelling approach suggested by Jiang and Lee (2004). Specifically we estimate the following model:

$$r_{t+1} = \alpha + \sum_{q=0}^{4} \hat{u}_{t-q} + \varepsilon_{t+1}, \qquad \text{Eq. 12}$$

where $\hat{u}_t$ is the innovation in volatility. The innovation is estimated as the residual of a second order autoregressive model for the idiosyncratic risk of LARGE and SMALL stocks. Panel B of table 6 reports the estimation results of equation 12. The coefficients for the first lag remain statistically significant with correct sign for SMALL and LARGE stocks. The coefficients for lags 2 to 5 are statistically insignificantly different from zero,

[14] The issue of small sample bias when the regressor is persistent has been studied by Stambaugh (1999) and Campbell and Yogo (2006).

except in the case of the third lag of the SMALL stocks. Therefore, the persistence in idiosyncratic volatility does not alter the results reported earlier.

7. Conclusions

The behaviour, properties and pricing of idiosyncratic volatility has become a hot issue in the literature. This is perhaps not surprising given the importance of idiosyncratic risk for portfolio management. Evidence that idiosyncratic volatility is a priced factor in asset pricing and that it can be used to forecast future stock returns are currently a topic of research and debate.

This paper uses data from the UK market to study the properties of average idiosyncratic volatility and its predictive power for future stock market returns. We report convincing evidence that the idiosyncratic volatility of small stocks predicts the small capitalization premium but has no forecasting power for market risk or the value/growth spread. The predictive power of idiosyncratic volatility is unrelated to either business cycle or liquidity variables. These conclusions are robust across time and remain intact after we take into account the possibility that volatility is persistent.

The possibility that small stock idiosyncratic volatility is a proxy for non traded risk like human and entrepreneurial capital or that it reflects the inability of investors to hold undiversified portfolios due to transaction costs, taxes or other institutional restrictions, should be a topic for further research. The evidence presented in this paper suggests that the relevant variable of interest is the idiosyncratic volatility of small capitalization stocks and the research question is why it has predictive power for the small capitalization premium and not the other risk factors.

8. References

Acharya, V. V., and Pedersen, L. H. 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. Journal of Financial Markets 5, 31-56.

Ang, A., Hodrick, R., Xing, Y., and Zhang, X. 2006. The Cross Section of Volatility and Expected Returns. Journal of Finance 61(1), 259 – 299.

Bali, T., Cakici, N., Yan, X., and Zhang, Z. 2005. Does Idiosyncratic Risk Really Matter? Journal of Finance 60(2), 905-929.

Brown, D. P. and Ferreira, M. A. 2004. Information in the Idiosyncratic Volatility of Small Firms. EFA 2004 Maastricht Meetings Paper

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. Journal of Finance, 56, 1 –43.

Campbell, J. Y., and Shiller, R. 1988. Stock Prices, Earnings and Expected Dividends. Journal of Finance, 43, 3, 661-676.

Campbell, J. Y., and Yogo, M. 2006. Efficient Tests of Stock Return Predictability. Forthcoming in Journal of Financial Economics.

Dickey, D.A. and Fuller, W. A. 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74, 427-431.

Dimson, E., Nagel, S., and Quigley, G. 2003, Capturing the value premium in the U.K. 1955-2001. Financial Analysts Journal, Nov/Dec.

Drew, M.E., Naughton, T., and Veeraraghavan, M. 2004. Is idiosyncratic volatility priced?: Evidence from the Shanghai Stock Exchange International Review of Financial Analysis, 13 (3), 349-366.

Douglas, E. 1969. Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency. Yale Economic Essays, 9, 3-45.

Fama, E. F. 1996. Multifactor Portfolio Efficiency and Multifactor Asset Pricing. Journal of Financial and Quantitative Analysis, 31(4), 441-65.

Fama, E. F., and French, K. R. 1988. Dividend Yields and Expected Stock Returns. Journal of Financial Economics, 22(1), 3-25.

Fama, E. F., and French, K. R. 1989. Business Conditions and Expected Returns on Stocks and Bonds, Journal of Financial Economics, 25(1), 23-49.

Fama, E. F., and French, K. R. 1992. The Cross-Section of Expected Stock Returns. Journal of Finance 47(2), 427-65.

Fama, E. F., and French, K. R. 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3-56.

Fama, E. F., and French, K. R. 1995. Size and Book-to-Market Factors in Earnings and Returns. Journal of Finance, 50(1), 131-55.

Fama, E. F., and French, K. R. 1998. Value versus Growth: The International Evidence. Journal of Finance, 53(6), 975-99.

Fama, E. F., and MacBeth, J. 1973. Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy, 81, 607-636.

Frazzini, A. and Marsh, I. 2003. Idiosyncratic Volatility in the US and UK Equity Markets. Working Paper. Yale University.

French, K. R., Schwert, W., and Stambaugh, F. R. 1987. Expected Stock Returns and Volatility. Journal of Financial Economics 19, 3-29.

Goyal, A., and Santa-Clara, P. 2003. Idiosyncratic risk matters!, Journal of Finance 58, 975-1008.

Guo, H., and Savickas, R. 2003. Does Idiosyncratic Risk Matter: Another Look. Working paper. Federal Reserve Bank of St. Louis.

Guo, H., and Savickas, R. 2003b. Idiosyncratic Volatility, Stock Market Volatility, and Expected Stock Returns, Working paper. Federal Reserve Bank of St. Louis.

Guo, H., and Savickas, R. 2004. Aggregate Idiosyncratic Volatility in G7 Countries, Working paper, Federal Reserve Bank of St. Louis.

Hasbrouck, J. 2005. Trading Costs and Returns for US Equities: The Evidence from Daily Data. Working Paper. Stern School of Business.

Jegadeesh, N., and Titman, S. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance, 48, 65-91.

Jiang, X., and Lee, B-S. 2004. On the Dynamic Relation Between Returns and Idiosyncratic Volatility, Sixty Fifth Annual Meeting American Finance Association.

Lehmann, B. 1990. Residual Risk Revisited. Journal of Econometrics, Vol. 45, 71-97.

Liew, J., and Vassalou, M. 2000. Can Book-to-Market, Size, and Momentum Be Risk Factors That Predict Economic Growth? Journal of Financial Economics, 57, 221-245.

Lintner, J. 1965. The valuation of risky assets and the selection of risky investment in stock portfolio and capital budgets. Review of Economics and Statistics, Vol. 47, 13-37.

Lo, A, and MacKinlay, A. 1990. Data-snooping Biases in Tests of Financial Asset Pricing Models. Review of Financial Studies, 3 (3), 431-467.

Merton, R. 1973. An Intertemporal Capital Asset Pricing Model. Econometrica 41 867 - 887.

Miller, M., and Scholes, M. 1972. Rates and Returns in Relation to Risk: A Re-examination of Some Recent Findings. In Michael Jensen, ed: Studies in the Theory of Capital Markets, Praeger: New York, 47-78.

Nagel, S. 2001. Accounting Information Free of Selection Bias: a New UK Database 1953-1999. Working Paper, London Business School.

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

Phillips, P.C.B., and Perron, P. 1988. Testing for a Unit Root in Time Series Regression. Biometrika, 75, 335-346.

Schwert, W. G. 1989. Why Does Stock Market Volatility Change Over Time?, Journal of Finance 44, 1115-1153.

Stambaugh, R. 1999. Predictive Regressions. Journal of Financial Economics, 54, 375-421.

Tinic, S and West, R. 1986. Risk, Return and Equilibrium: A Revisit. Journal of Political Economy, 94, 1, 126-147.

Vogelsang, T. 1998. Trend function hypothesis testing in the presence of serial correlation. Econometrica 66, 123-148.

Wei, X. S., and Zhang, C. 2004. Idiosyncratic Risk Does Not Matter: A Re-examination of the Relationship Between Average Returns and Average Volatilities. Forthcoming in Journal of Banking and Finance.

Xu, Y., and Malkiel, B. G. 2001. Idiosyncratic Risk and Security Returns. AFA 2001 New Orleans Meetings.