IDIOSYNCRATIC VOLATILITY AS AN EXPLANATION OF THE SMALL FIRM EFFECT: AUSTRALIAN EVIDENCE

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Abstract

In the context of Australian stockmarkets, we examine how a company's size and stock idiosyncratic volatility relate to return performance. The paper's main conclusions may be summarized as follows. The stocks of the smallest firms markedly outperform the largest capitalized stocks, and for such small capitalized stocks, those with greater idiosyncratic volatility have markedly superior returns. It appears that the relationship of higher returns with higher idiosyncratic volatility is consistent with the mathematics of idiosyncratic volatility. In which case, the small size effect may also be interpreted as the mathematical outcome of idiosyncratic volatility. The paper further examines the condition on which the higher returns reported for either small firm size or high idiosyncratic volatility are likely to be wealth-forming. Finally, we observe that the high performances of the stocks of the smallest firms are likely irrelevant to the class of firms that are of interest to the institutional investor.

Keywords: Idiosyncratic Volatility, Size Effect
JEL Classification: G10, G12, G15

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Introduction

In separating the influences of market capitalization and idiosyncratic volatility in U.S. markets, Spiegel and Wang (2005) find that companies with high idiosyncratic volatility tend to be of small firm size, and, since stock returns are decreasing with firm size, stock returns are also increasing with idiosyncratic volatility. They conclude that while both these variables appear to bear a systematic relationship with a stock's returns, the relationship of returns with idiosyncratic volatility subsumes the relationship with firm size. Malkiel and Xu (1997, 2006) have also highlighted the intriguing possibility that the small firm size effect might actually be an idiosyncratic volatility effect. Against this, however, authors such as Ang et al. (2006, 2008) have reported that they find a negative relationship between returns and idiosyncratic volatility.

In this paper, we examine the relationship of stock returns with firm size and idiosyncratic volatility in the context of the Australian (ASX) stockmarket. The Australian stockmarket by virtue of its distinctive characteristics provides opportunities for realistic robustness tests in regard to asset pricing in other markets. The market is much smaller than U.S. markets (the 200th company is capitalized at approximately $150 US million at the time of writing) as well as being highly concentrated with around 2,000 listed companies, which are confined to a relatively small number of industries, most specifically, financials and materials dominated by mining and resource stocks (Ghrghori, Chan and Faff, 2006, provide a more extended overview of the Australian market's distinctive characteristics).

Our paper's main conclusions may be summarized as follows. Portfolios of the smallest capitalized stocks markedly outperform portfolios of the largest capitalized stocks, and for such small capitalized stocks, portfolios with greater idiosyncratic volatility generate markedly superior returns on an equally-weighted basis. Notwithstanding, for very large companies, higher idiosyncratic volatilities appear to identify decidedly lower returns. Our findings thereby provide a link with prior findings in the literature that have identified a more pronounced negative relationship of returns with idiosyncratic volatility for large companies (Ang et al., 2008; Bali and Cakici, 2008), as well as with reports in the literature of both a positive and a negative association between returns and idiosyncratic volatility (as discussed below). We show additionally how the high returns identified with high idiosyncratic volatility might be attributable to the mathematics of averaging returns that are distributed with a degree of log-symmetry. In which case, we are observing "returns created by volatility." We observe, further, that when the idiosyncratic volatility is the outcome of "fundamental" growth and decline, the returns created by idiosyncratic volatility are wealth-creating (as advocated by Dempsey, 2002); whereas when the idiosyncratic volatility is due to "noise" the process is not of itself wealth-creating (as advocated by Arnott, Hsu and Moore, 2005). Our observations thereby allow for an interpretation of Arnott et al.'s principle of "fundamental indexation" in terms of idiosyncratic volatility. Finally, we conclude that the higher returns for smaller firms – which are indeed dramatic at the lower end of firm size – are almost certainly irrelevant to the class of firms that are of interest to the institutional investor.

The portfolio analysis as adopted here calculates stock returns across compartmentalized ranges of firm size and idiosyncratic volatility. By sorting on portfolios the noise of individual stock returns created by nonsynchronous trading and measurement error is reduced (Vaihekoski, 2004). The portfolio approach is therefore simple and robust. It is the method advocated by the late Fischer Black (Black, 1993; Mehrling, 2005, see p. 112). Although it lacks statistical tests – as compared with, for example, the Fama and Macbeth (1973)/Fama and French (1992) method - Black's argument was that the method simulates the portfolios that investors might actually use, and rather than providing a "once-off" analysis, the method tends to give guidance as to where to look for the next most promising theoretical enhancements. And unlike linear regression tests, the portfolio method does not assume any specific functional form for the relations among the variables.

The rest of the paper is arranged as follows. Section 2 presents prior literature while Section 3 describes the data and the methodology employed in this paper. In section 4 we discuss the results and section 5 concludes the paper.

Background

With confirmation of the Fama and French three-factor model, a consideration of a company's market capitalization or firm size effect has become almost standard practice. Nevertheless, the evidence is not all one-sided. Banz (1981), for example, documents the size effect over a 45-year period for U.S. stocks and finds that while the effect is pronounced in the smallest firms there is no clear linear relationship between firm size and returns. Horowitz, Loughran and Savin (2000) conclude that the size effect is no longer prevalent in U.S. stocks. In the Australia market, Beedles, Dodd and Officer (1988) find that the size effect is prevalent and is robust to several methodological adjustments. They find evidence that transaction costs can explain a part of the size anomaly but that they do not appear to be the dominant factor. Other studies, however, find little or no evidence of the firm size effect in Australian markets. Brown, Kleidon and Marsh (1983) find that although the size anomaly exists, it is nevertheless not stable through time and that estimates of the size effect are subject to the historical time studied. Consistent with the findings of Banz in the U.S., they find that the relationship between firm size and returns is located in the smallest stocks. Chan and Faff (2003) report a flat regression relationship between returns and market capitalization for Australian stocks, and Gaunt (2004) finds no clear evidence of the firm size effect in Australian markets.

Malkiel and Xu (1997) show a high negative correlation between a company's size and its idiosyncratic volatility and suggest that idiosyncratic risk might explain the size effect. They consider that idiosyncratic risk is rationally priced if portfolio managers must justify (to clients) the performance of individual stocks within their portfolios, while Malkiel and Xu (2006) provide a formal model consistent with idiosyncratic risk being priced when investors (either voluntarily or non-voluntarily) are incompletely diversified. Similar to the approach adopted in the preset paper, Malkiel and Xu (1997) divide stocks into portfolios based on their idiosyncratic volatility and report their average return over the period 1963-1994. The results show a clear trend for stocks with higher idiosyncratic risk to generate higher returns. Goyal and Santa-Clara (2003) also find that equally-weighted average stock volatility is positively related to the value-weighted market returns.

Ang, Hodrick, Xing and Zhang (AHXZ) (2006, 2008), however, dispute the validity of these results and report that stocks with higher idiosyncratic volatility (calculated on one month of daily data) in relation to the three-factor Fama and French (1993) model have decidedly lower equally-weighted returns. AHXZ (2006) report that for U.S. stocks, the average return differential between the lowest and highest quintile portfolios formed on one-month lagged idiosyncratic volatilities is about -1.06% per month for the period 1963-2000; while AHXZ (2008) present evidence that the negative relation between idiosyncratic volatility and average returns is strongly significant for each of their largest seven equity markets (Canada, France, Germany, Italy, Japan, the U.S., and the U.K.), and is also observed in the larger sample of 23 developed markets, averaging 1.31% per month between the highest and lowest quintiles formed on idiosyncratic volatility. They report also that the negative volatility effect is more pronounced for larger companies than it is for very small firms.

Similarly to AHXZ (2006, 2008), Bali and Cakici (2008) use within-month daily data to calculate idiosyncratic volatility in relation to the three-factor Fama-French (1993) model, and find no robust significant relation between idiosyncratic volatility and equally-weighted expected returns. However, the value-weighted average return differential between the lowest and highest idiosyncratic volatility portfolios is about –0.93% per month and highly significant for the extended sample period of July 1963–December 2004. This result is very similar to the finding of AHXZ for equally-weighted returns (–1.06% per month) reported above. The pattern observed in their quintile portfolios is not monotonic however: average returns actually increase from quintile 1 (low idiosyncratic risk quintile) to quintile 3 and then average returns decline, so that quintile 5 experiences a substantial decrease in average returns. It is noteworthy that quintile 5 which contains 20% of stocks sorted by highest idiosyncratic volatility contains only 2% of the market, while quintile 1 (which contains 20% of stocks sorted by lowest idiosyncratic volatility) contains 54% of the market. This is consistent with a strong negative correlation between the firm's market capitalization (size) and idiosyncratic volatility.

Malkiel and Xu (2006) suggest that the AHXZ (2006) findings may be due to an errors in the variables problem when fitting their model to the short data sample; while Huang, Liu, Rhee, and Zhang (2007) argue that AHXZ's results are driven by monthly stock return reversals. After controlling for the difference in the past-month returns, Huang et al. show that the negative relation between average return and the lagged idiosyncratic volatility disappears. Fu (2008) points to a similar conclusion. He shows that idiosyncratic risk varies substantially over time and suggests that idiosyncratic volatility calculated from a single month fails to identify the expectation of idiosyncratic volatility in the subsequent month. Using rolling monthly data, Fu provides in-sample estimates of the conditional idiosyncratic variance of stock returns based on an EGARCH model and finds a significantly positive relation between stock return and idiosyncratic volatility.

Following an approach similar to Fu's (2008) EGARCH method, Brockman and Schutte (2007) estimate conditional idiosyncratic volatility and confirm that the relation between stock return and idiosyncratic volatility is positive in international data. Similarly Spiegel and Wang (2006) and Eiling (2006) adopt the EGARCH models to estimate conditional idiosyncratic volatility. Both find a positive relation stock return and idiosyncratic volatility in U.S. data. Spiegel and Wang also report that idiosyncratic volatility dominates liquidity in explaining the cross-sectional variation of average returns.

Thus we note that a degree of controversy surrounds even the direction of any idiosyncratic volatility effect for stock returns. A possible solution to the impasse is that, on the one hand, stocks are priced with the expectation that in the long run idiosyncratic volatility is rewarded, but that on the other hand, unexpected increases in stock idiosyncratic volatility of themselves presage uncertainty and subsequent falls. Supporting such conjecture, Eun and Huang (2005) find a similar result to Fu for Chinese stocks using a 24-month rolling window. However, in their updated study Eun and Huang (2007) cross over to measuring risk using daily returns for the month preceding the return calculation (as AHXZ), on which basis, they report the opposite conclusion to their earlier one, namely that of a negative relation between return performance and idiosyncratic volatility, as consistent with AHXZ.

In studies that combine the small firm size and idiosyncratic volatility effects, Bali et al. (2005) have contended that the findings of Goyal and Santa-Clara (2003) showing a relationship between market returns and prior-month levels of idiosyncratic volatility are driven largely by stocks of small firms. Consistently, Angelidis and Tessaromatis (2005) report that it is the idiosyncratic volatility of stocks of small firms that is associated with the small firm size effect. Again, Brown and Ferreira (2004) argue that it is the idiosyncratic volatilities of small firms that are significant positive predictors of stock returns.

Data, Definitions and Methodology

A. Data

We obtain the data for this study from two sources. The Australian Graduate School of Management (AGSM) equities database was used to calculate monthly returns. The Securities Industry Research Centre of Asia-Pacific (SIRCA) database, which includes daily returns for Australian equities from 1980 through 2004, was matched with the AGSM database, and used to calculate idiosyncratic volatility.

In order to be included in the sample for a given month, a stock must have been traded in 35 of the previous 60 months (to calculate the stock's beta and idiosyncratic volatility for that month). Our final sample included 190,218 monthly observations of 2,347 companies. In any month, the number of companies ranged from just less than 200 to more than 1,000. Company sizes ranged from $30,000 to $46 billion (with an average capitalization size of approximately $400 million). In the two-dimensional sorts, the minimum number of observations assigned to any portfolio was 270.

B. Definitions

The variables market capitalization and idiosyncratic variance are defined as follows.

Market capitalization (company size) (MCi,t):

The market capitalization of stock i for month t (MC i,t) is measured as the number of company i''s shares outstanding multiplied by the share price at the end of month t.

Idiosyncratic variance (volatility) (IVi,t):

We consider a market pricing model consistent with the CAPM as:

$$r_{i,t} = \alpha_i + \beta_{i,t}\left(r_{M,t}\right) + \varepsilon_{i,t} \tag{1}$$

where at each time t, ri,t is the excess return on stock i, βI,t is the beta of stock i, rM,t is the excess return on the total market of assets, M, αi is the intercept term, and $\varepsilon_{i,t}$ are the error terms. For each stock i, beta (β i,t) in each month t is calculated from the previous 60 months of historical data as:

$$\beta_{i,t} = \frac{Cov\left(r_{i,m}, r_{M,m}\right)}{Var\left(r_{M,m}\right)} \tag{2}$$

where $r_{i,m}$ and $r_{M,m}$ are, respectively, the returns for stock i and the market index M in months m = t-59 to month t. If a security did not trade for at least 35 of the previous 60 months, it is not included in month t's calculation. We estimate the total return variance for stock i in month t (TVi,t) in respect to monthly returns $r_{i,m}$ (m = t-59 -> t) as:

$$TV_{i,t} = \sum_{m=t-59}^{t} \left(r_{i,m} - \bar{r}_i\right)^2 /(N-1) \quad (3)$$

where $\bar{r}$ i is the mean monthly return for stock i over the N months of data available over the preceding 60 month period; and similarly, we calculate the market variance at time t (MVt) as:

$$MV_{M,t} = \sum_{m=t-59}^{t} \left(r_{M,m} - \bar{r}_M\right)^2 / 59 \quad (4)$$

where $\bar{r}_M$ is the mean market monthly return of the market returns rM,m over the preceding 60 months. Finally, we calculate the idiosyncratic variance of stock i for month t (IVi,t) as:

$$IV_{i,t} = TV_{i,t} - \beta_{i,t}^2 MV_t \quad (5)$$

C. Methodology

Stocks are ranked on their market capitalization (MC) in month t and partitioned as ten portfolios with the same number of stocks in each portfolio. For each portfolio constructed at month t the monthly equal-weighted and value-weighted realised returns are calculated for the following month t+1. The portfolios are rebalanced each month based on market capitalization (MC) and a time-series average of the monthly equal-weighted and value-weighted returns is calculated for each portfolio decile. The same procedure is used in relation to idiosyncratic variance (IV).

We proceed to observe the extent to which a sort of portfolios on one variable (market capitalization or idiosyncratic variance) is a sort on the other variable. Additionally, we form a set of 100 (10x10) portfolios across pairs of the variables MC and IV, which allow us to identify the pattern of returns on one variable while holding another variable constant.

A comment on the formation of the above 10x10 portfolios is warranted. In double sorts on two variables aimed at controlling for the first variable while observing the impact of the second variable, the more usual approach is to sort first on the controlled variable into say 10 portfolios before each such portfolio is sorted into say a further 10 portfolios on the second variable. The problem here is the high correlation of our explanatory variables, which implies that a sort on the first variable will also effectively be a sort on the second variable, with only a very limited range of portfolio-averaged values for portfolios formed on the second variable. For this reason, we adopt the approach of forming portfolios on the maximum spread of the values of the second variable free of the restriction that each portfolio must have an equal number of stocks. Thus we create 10x10 sorts for each pair of variables by referencing each stock to each of its decile portfolios. For example, a stock that appears in the decile 1 portfolio for the IV variable and decile 1 portfolio for the MC variable appears in the percentile portfolio (1, 1), while a stock that appears in decile portfolio 1 for the IV variable and decile 2 portfolio for the MC variable appears in the percentile portfolio (1, 2), and so on.

Analysis of Results

A) Single Sort Portfolios

Figures 1 and 2 plot the returns of portfolios constructed, respectively, on the variables of market capitalization (MC) and monthly idiosyncratic variance (IV). The relationships are plotted for equally-weighted (EW) and value-weighted (VW) returns over portfolio stocks. The corresponding values are tabulated as panels A–B of Table 1 along with the average values of idiosyncratic variance for each of the market capitalization portfolios in Panel A, and the average values of market capitalization for each of the idiosyncratic variance portfolios in Panel B. We note that the portfolios formed on increasing market capitalization are monotonically decreasing in idiosyncratic variance (Panel A) and the portfolios formed on increasing idiosyncratic variance are monotonically decreasing in market capitalization (Panel B). Our additional observations on the two relations are as follows.

(i) Portfolio Returns versus Market Capitalization (Figure 1)

In the relationship between portfolio returns and market capitalization shown in Figure 1 (equally-weighted and value-weighted returns are essentially identical for portfolios 2-10), we observe that the relationship is declining with market capitalization. Thus the graph appears to be broadly consistent with the relationship that Spiegel and Wang (2006) report for non-Australian stocks. We note, however, that this inverse relationship holds only for firms with quite low market capitalizations. We also note that Chan and Faff (2003) report a flat regression between returns and market capitalization for Australian stocks. It is possible that stocks driving the return performance of our portfolios 1 and 2 have been suppressed in Chan and Faff's linear regression analysis. Our findings, however, are consistent with Banz (1981) for the U.S. and Gaunt (2004), Brown et al. (1983) and Beedles et al. (1988) for Australia, who find that the size effect holds only for their smallest stocks.

(ii) Portfolio Returns versus Idiosyncratic Variance (Figure 2)

Figure 2 displays the relationship between portfolio returns and idiosyncratic variance. The relationship between both equally-weighted and value-weighted returns contradict each other. The equally-weighted returns are monotonically increasing (with the exception of portfolio 10) which is consistent with the findings of such as Malkiel and Xu (1997, 2006) and Fu (2008). The downward direction of the value-weighted portfolio returns from portfolio 4 onwards is precipitous. Clearly, larger capitalized stocks with higher idiosyncratic variance are somehow associated with declining returns. A possible explanation is that increases in variance for stocks of larger companies indicate apprehension and auger declines. Notwithstanding, our results are consistent with the observations of both AHXZ (2008) and Bali and Cakici (2008), who, as noted above, report that the stocks of large companies are particularly sensitive to their observed negative relationship between average returns and idiosyncratic volatility. Intriguingly, therefore, our findings cross over between previous findings in the literature of both a positive and negative correlation of idiosyncratic volatility with average stock returns.

B) Double Sort Portfolios

Pairwise sorts of variables allow the explanatory power of one variable to be examined while controlling for the explanatory power of a second variable. Figure 3 again shows the superior performances of low-capitalized stocks (as Figure 1). The graph reveals a clear relationship between returns and idiosyncratic variance for stocks of small companies that is consistent with the trend for equally-weighted portfolios in Figure 2. We note that the largest companies with high idiosyncratic variance in Figure 3 (portfolio (10,10)) have markedly negative returns (which is consistent with Figure 2 where value-weighted portfolio returns decrease with idiosyncratic variance).

Figure 3 reveals that stocks of small market capitalization with high idiosyncratic volatility provide remarkably high average returns. Although this appears as something of a phenomenon, it is possible to interpret the returns as the mathematical outcome of averaging over highly divergent returns that are bounded below by a zero return. To see this, allow for the moment that stock prices are distributed log-normally. Log-normality of returns implies:

$$P_{i,1} = P_{i,0}.\exp[\mu_i + Z.\sigma_i] \qquad (6)$$

where $P_{i,1}$ is stochastic outcome price of stock i at the end of the period, $P_{i,0}$ is price of the stock at the commencement of the period, and μ_i and σ_i are, respectively, the mean drift rate and standard deviation of the continuously compounding growth rate for the stock, and Z is the unit normally-distributed variable. If for the moment also we take it that the drift continuously compounding growth rate (μ_i) is zero, the symmetry about zero of the unit normal Z function in equation 6 implies that the outcomes $P_0 \exp(x)$ and $P_0 \exp(-x)$ are equally likely for any x. So, for example, setting x = 69.3% per period, we have the outcomes $P_0 \exp(0.693) = P_0 \times 2$ (a doubling of investment value), and $P_0 \exp(-0.693) = P_0 \times ½$ (a halving of investment value) as equally likely. And similarly, the outcomes $P_0 \times N$ and $P_0 \times 1/N$ are equally likely for any N. The intuition is that no matter how negative the decline in a share price, the share price itself cannot become negative, whereas the upside is unbounded. To illustrate, we might imagine a portfolio of a large number of identical stocks of equal value which have zero drift and zero variance. The outcome portfolio return is clearly 0%. Now consider that such stocks are subjected to idiosyncratic volatility such that half the stocks double their value and half the stocks lose half their value. The outcome portfolio return is 25%. So we note that the idiosyncratic volatility, of itself, has created a return. More generally, when a large number of identical stocks are subjected to idiosyncratic volatility in accordance with equation 6, the outcome return, R, is determined as:

$$R = \mu_i + ½\sigma_i^2 = \mu_i + ½\, IV_i \qquad (7)$$

for example, Jacquier, Kane and Marcus (2003).[1] The phenomenon of returns augmented by volatility is effective to the extent that continuously compounding returns are symmetrically distributed. The continuously-compounded returns in our sample are not normally distributed and are inclined to be negatively skewed. For this reason, equation 7 of itself will tend to overstate the relationship between idiosyncratic volatility and returns. Nevertheless, the average monthly idiosyncratic volatility for the decile portfolios in Panel B of Table 1 ranges between zero and 14.15%, indicating that if continuously compounding returns had in fact been normally distributed, the difference between the average returns for the lowest and highest idiosyncratic-ranked decile portfolios should be about ½ 14.15% = 7.07% per month. In fact, the difference is only (2.51–0.98)% = 1,65% (Panel B of Table 1).

An important issue is the extent to which the higher recorded returns reported for small firms with high idiosyncratic volatility are likely to be wealth creating. Malkiel (2004), for example, has questioned whether econometrically determined excess returns associated with either the book-to-market equity ratio or firm size can be exploited to produce real money.

To respond, we consider that idiosyncratic volatility may be interpreted as the outcome of either one or both of two distinct price-formation processes. The first process is that stocks are liable to grow or decline fundamentally through time. In other words, at each point in time, each stock has an upside and a downside potential. In this case, the phenomenon of log-symmetric outcomes leads to a real wealth outcome, as we illustrate by stocks either doubling or halving in value through successive time periods in Figure 4. The process may be conceptualized in terms of two stocks of \$100, one of which doubles to \$200, and the other which halves to \$50 over a period. The process generates a real return of 25% per period. This is the process advocated by Dempsey (2002).

The second process is that stocks are priced up and down as "noise," so that over-valued stocks have downside potential and under-valued stocks have upside potential, as advocated by Arnott et al. (2005). In this case, no real return is generated. This is illustrated in Figure 5, which may be conceptualized in terms of a portfolio of stocks each with a true value of \$100, but which with equal probability may double or half in price

[1] We note that with $\mu = 0$ and $\sigma = 0.693$ (the above binomial example), we have $½\sigma^2 = ½(0.693^2) = 0.24$ (24%), which is approximately the calculated return, 25% (above).

as noise. Such stocks may be represented as oscillating with a statistical distribution such that for each stock priced at $200 (true value $100), another stock is priced at $50 (true value $100), with two stocks priced at $100, one from a previous over-pricing of $200, and one from a previous under-pricing of $50, as depicted in Figure 5. As the stocks oscillate, a portfolio that invests in each of the representative stocks retains its value ($450 = $200 + 2 x $100 + $50). Consistently, the value-weighted return per period is calculated as zero [($50*100%+$100*100%+$200*-50%+$100*-50%)/$450 = 0%]. However the equally-weighted portfolio return calculated each period is 25% [(100%+100%-50%-50%)/4]. The outcome that when idiosyncratic volatility is generated by noise, equally-weighted returns mathematically outperform value-weighted returns suggests the possibility of a noise explanation for the Bali and Cakici (2008) observation of a more negative association between idiosyncratic volatility and value-weighted returns as compared to the association between idiosyncratic volatility and equally-weighted returns. With idiosyncratic volatility generated by noise, realization of an actual return equal to the equally-weighted return (25% in Figure 5), requires that the investor is able to rebalance the portfolio as the same amount ($100) in each stock after each price change. This is the strategy of "fundamental indexation" advocated by Arnott et al. (2005).

Conclusion

Consistent with Fama and French (1996), we report that the average stock returns for the very smallest companies are dramatically higher than for larger companies. Such size effect, however, is in evidence only for stocks of companies of less than approximately $6 million market capitalization, which are well outside the company size range expected to be held by institutions. Our findings here are roughly consistent with previous Australian findings (by Gaunt, 2004; Brown et al., 1983 and Beedles et al., 1988). Consistent with such as Malkiel and Xu (1997, 2006) and Bali et al. (2005) we find that the returns of portfolios of stocks of small firm size are strongly and positively associated with their idiosyncratic volatility. This finding suggest that the higher returns of portfolios of stocks of small firm size may be the mathematical outcome of averaging over returns that are widely distributed (high idiosyncratic volatility) but which have a degree of symmetry as log-returns. Two interesting possibilities arise. The first, allowing that the idiosyncratic volatility is the outcome of re-valuations (as opposed to "noise"), is that idiosyncratic volatility – and thereby the small firm effect - implies a real wealth creation (consistent with Dempsey's 2002 hypothesis, "risk creates its own reward"). The second possibility is that the observed idiosyncratic volatility – and thereby the small firm effect - represents "noise." In this case, taking advantage of the noise requires a continuous re-indexing of a portfolio so as to avoid over investing in the over-valued stocks, consistent with "fundamental indexing" as advocated by Arnott et al. (2005). We conclude that the phenomenon of idiosyncratic volatility suggests an area for exciting research into the fundamental nature of stock price formation.

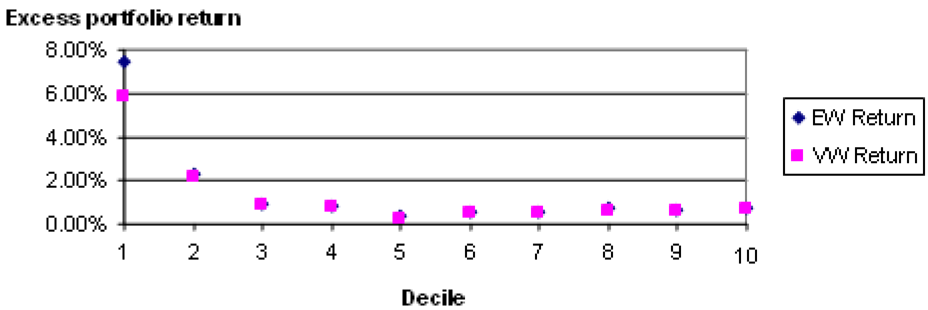

Figure 1. Average monthly returns and market capitalization

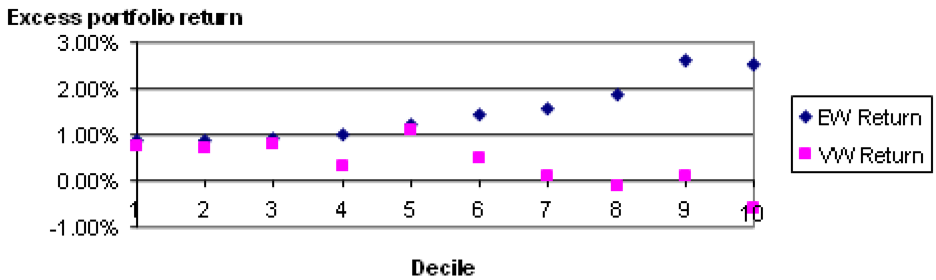

Figure 2. Average monthly returns and idiosyncratic volatility

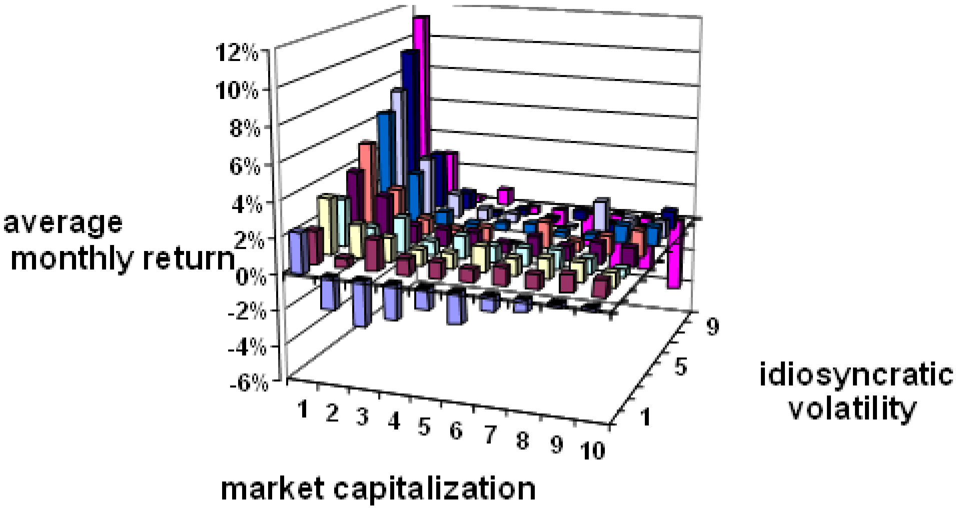

Figure 3. Average monthly returns on market capitalization and idiosyncratic volatility

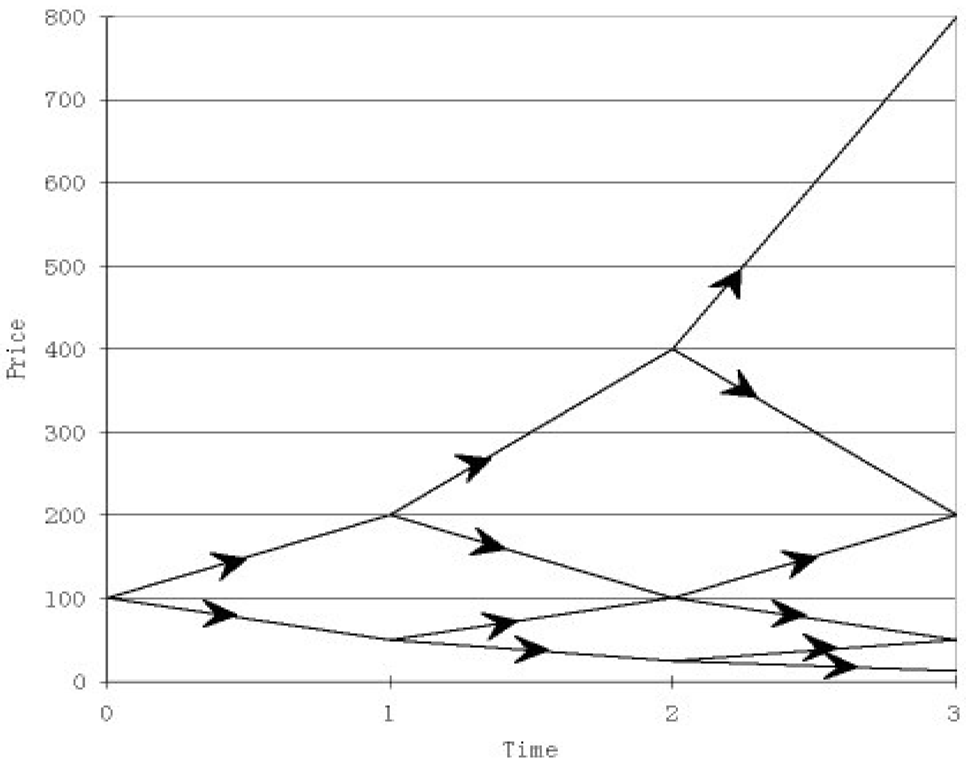

Figure 4. The outcome pattern of prices when a stock commences with a value of $100 and proceeds to either double or half its value each period as the outcome of fundamental growth or decline.

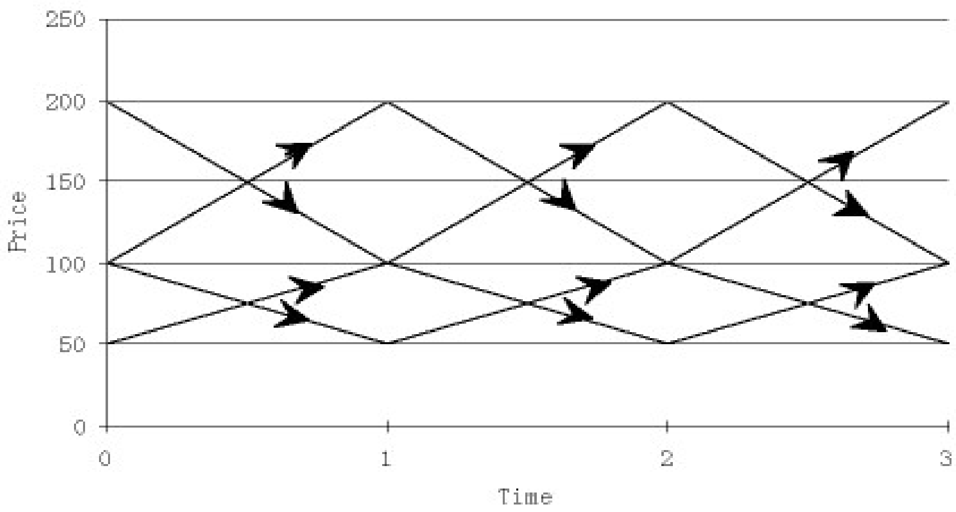

Figure 5. The outcome pattern of prices when stocks oscillate about their true value of $100 by either doubling or halving their market price each period as the outcome of "noise."

We calculate average monthly returns for portfolios formed on market capitalization (*MC*) and monthly idiosyncratic variance (*IV*). In each month, *t,* all stocks are ranked separately based on both market capitalization and idiosyncratic volatility. Both equally weighted (EW) and value-weighted (VW) average monthly returns are calculated for each portfolio. The portfolios are rebalanced monthly. The returns in the table are the average for each portfolio during the period. Panel A reports returns for portfolios formed on market capitalization. The average idiosyncratic volatility for each portfolio is tabulated in the final row. Panel B reports returns for portfolios formed on idiosyncratic volatility. The average market capitalization for each portfolio is tabulated in the final row.

Table 1: Average Monthly Returns of Portfolios Formed on Market Capitalization and Idiosyncratic Variance

Panel A: Portfolios Formed on Market Capitalization (as Figure 1)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Average MC(m)	$2	$4.2	$7.3	$11.6	$18.0	$29.4	$52.3	$106.8	$284.8	$2,074
EW Return	7.46%	2.25%	0.94%	0.81%	0.34%	0.54%	0.53%	0.69%	0.68%	0.73%
VW Return	5.84%	2.19%	0.93%	0.80%	0.32%	0.54%	0.52%	0.68%	0.66%	0.74%
Average IV	6.85%	5.64%	4.95%	4.14%	3.55%	2.81%	2.36%	1.90%	1.03%	0.53%

Panel B: Portfolios Formed on Idiosyncratic Variance (as Figure 2)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Average IV	-0.27%	0.13%	0.33%	0.59%	0.94%	1.43%	2.14%	3.21%	5.21%	14.15%
EW Return	0.86%	0.89%	0.91%	0.98%	1.20%	1.44%	1.57%	1.86%	2.63%	2.51%
VW Return	0.74%	0.68%	0.77%	0.30%	1.09%	0.49%	0.07%	-0.12%	0.07%	-0.63%
Average MC(m)	$1,041	$881	$550	$357	$219	$135	$82	$55	$37	$24

We calculate average monthly returns for portfolios formed on pairs of market capitalization (MC) and monthly idiosyncratic variance (IV)). In each month t each stock is ranked separately on the variables (MC and IV) and allocated to a decile portfolio (1-10 as in Table 1) according to its ranking on the variable. Thus, each stock is allocated to two portfolios (1-10). Portfolios 1-100 are then formed based on variable pairs according to the cross rankings of their allocations to portfolios 1-10. For example, a stock from portfolio 1 of lowest market capitalization and from portfolio 1 of lowest idiosyncratic variance is assigned to portfolio (1, 1), a stock from portfolio 1 of lowest market capitalization and from portfolio 2 of next-to-lowest idiosyncratic variance is assigned to portfolio (1, 2), and so on. Equally weighted (EW) average monthly returns are calculated for month t for each portfolio. The portfolios are rebalanced monthly. The returns in the table are the average for each portfolio over the period.

Table 2: Average Monthly Returns of Portfolios Formed on a Two-Dimensional Sort on Market Capitalization and Idiosyncratic Variance

Average monthly returns for portfolios formed on market capitalization and idiosyncratic variance										
	MC 1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**MC 10**
IV 1	2.29%	-1.80%	-2.50%	-1.97%	-1.18%	-1.73%	-0.79%	-0.64%	-0.22%	-0.17%
2	1.85%	0.50%	1.79%	0.88%	0.93%	0.73%	1.02%	0.84%	1.01%	0.94%
3	3.23%	1.92%	1.38%	0.87%	0.86%	1.43%	0.98%	1.18%	1.14%	0.78%
4	2.72%	1.25%	1.98%	0.82%	1.30%	0.91%	1.01%	1.08%	0.84%	0.46%
5	3.85%	2.58%	1.05%	1.01%	1.02%	0.58%	1.12%	0.80%	1.16%	1.04%
6	5.08%	2.56%	0.98%	0.56%	0.85%	-0.06%	1.47%	0.53%	1.03%	1.55%
7	6.40%	2.90%	0.76%	0.24%	0.48%	0.58%	0.27%	0.30%	1.04%	1.14%
8	7.42%	3.38%	1.39%	0.68%	0.55%	-0.29%	0.13%	1.77%	0.94%	0.98%
9	9.42%	3.26%	1.06%	-0.31%	0.36%	-0.24%	0.59%	-1.05%	-1.54%	1.07%
IV 10	11.29%	2.87%	0.32%	0.90%	-0.44%	-1.00%	-2.11%	-3.41%	-3.15%	-4.14%

References

1. Arnott, R.D., J. Hsu, and P. Moore (2005). Fundamental Indexation. *Financial Analysts Journal* 61, 83-99.
2. Ang, A., Hodrick, R., Xing, Y., and X. Zhang (2006). The cross-section of volatility and expected returns. *Journal of Finance* 61, 259-299.
3. Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang (2008). High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. *Journal of Financial Economics* - forthcoming.
4. Angelidis, T. and N. Tessaromatis (2005). Equity returns and idiosyncratic volatility: UK evidence. Working paper, University of Piraeus.
5. Bali, T., Cakici, N., Yan, X. and Z. Zhang (2005). Does idiosyncratic risk really matter? *Journal of finance* 60, 905-929.
6. Bali, T., and N. Cakici (2008). Idiosyncratic Volatility and the Cross-Section of Expected Returns. Journal *of Financial and Quantitative Analysis*, forthcoming.
7. Brockman, P. and M. Schutte (2007). Is idiosyncratic volatility priced? The international evidence. Working paper, University of Missouri, Colombia.
8. Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics* 9, 3-18.
9. Beedles, W., Dodd, P. and R. Officer (1988). Regularities in Australian share returns. *Australian Journal of Management* 13, 1-29.
10. Black, F. (1993). Beta and Return. *The Journal of Portfolio Management* 20, 8-18.
11. Brown, P., Kleidon, A. and T. Marsh (1983). New evidence on the nature of size-related anomalies in stock prices. *Journal of Financial Economics* 12, 33-56.
12. Brown, D. and M. Ferreira (2004). Information in the idiosyncratic volatility of small firms. Working paper, University of Wisconsin.
13. Chan, H. and R. Faff (2003). An investigation into the role of liquidity in asset pricing: Australian Evidence. *Pacific-Basin Finance Journal* 11, 555-572.
14. Dempsey. M. (2002). The Nature of Market Growth, Risk and Return. *Financial Analysts Journal* 58, 45-59.
15. Eiling, E. (2006). Can nontradable assets explain the apparent premium for idiosyncratic risk? The case of industry-specific human capital. Working paper, Tilburg University, Netherlands.
16. Eun, C.S. and W. Huang (2007). Asset pricing in China's domestic stock markets: Isthere a logic? *Pacific-Basin Finance Journal* 15, 452-480.
17. Eun, C.S. and W. Huang (2005). Asset pricing in China: Is there a logic? Working Paper, Georgia Institute of Technology..
18. Fama, E. and J. MacBeth (1973). Risk, return and equilibrium: empirical tests. *Journal of Political Economy* 81, 607-636.
19. Fama, E. and K. French (1992). The cross-section of expected stock returns. *Journal of Finance* 47, 427-465.
20. Fama, E. and K. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*, 3-56.
21. Fama, E. and K. French, K (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51, 55-84.
22. Fu, F. (2008). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics* - forthcoming.
23. Gaunt, C. (2004). Size and book to market effects and the Fama French three-factor asset pricing model: evidence from the Australian stockmarket. *Accounting and Finance* 44, 27-44.
24. Goyal, A. and P. Santa-Clara (2003). Idiosyncratic risk matters! *Journal of Finance* 58, 975-1008.
25. Gharghori, P., Chan, H. W. and R. Faff (2006). Factors or Characteristics? That Is the Question. *Pacific Accounting Review* 18, 21-46.
26. Horowitz, J., Loughran, T. and N. Savin (2000). Three analyses of the firm size premium. *Journal of Empirical Finance 7,* 143-153.
27. Huang, W., Liu, Q., Rhee, G., and L. Zhang (2007). Another look at idiosyncratic risk and expected returns. Working paper, University of Hawaii at Manoa.
28. Jacquier, E, A. Kane and A. J. Marcus (2003). Geometric or Arithmetic Mean: A Reconciliation. *Financial Analysts Journal* 59, 46-53.
29. Malkiel, B. (2004). Can Predictable patterns in Market Returns be Exploited Using Real Money? Not Likely. *Journal of Portfolio Management* 30,131-141.
30. Malkiel, B. and Y. Xu (1997). Risk and return revisited. *Journal of Portfolio Management* 23, 9-14.

31. Malkiel, B. and Y. Xu (2006). Idiosyncratic risk and security returns. Working paper, Princeton University.
32. Mehrling, P. (2005). *Fisher Black and the Revolutionary Idea of Finance*, John Wiley and Sons.
33. Spiegel, M. and X. Wang (2006). Cross-sectional variation in stock returns: liquidity and idiosyncratic risk. Working paper, Yale University.
34. Vaihekoski, M. (2004). Portfolio Construction for Tests of Asset Pricing Models. *Financial Markets, Institutions & Instruments* 13, 1-39.