Anger, Sadness and Bear Markets

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JEL classification: G12

Keywords: behavioural finance, affective states, bear markets.
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ABSTRACT

Can an understanding of mood help us understand aspects of systematic risk, volume and portfolios’ exposure to systematic risk during bear-market regimes? We hypothesize that bear markets are associated with negative emotions: either a low-arousal negative state (e.g., sadness and depression) or a high-arousal negative state (e.g., anger and stress). We define a bear market as a stock market regime where the average return is statistically significantly lower than zero and find evidence that the bear market of November 1987 to February 1988 behaved as if it was associated with a pervasive low-arousal negative state amongst investors.

1.0 Introduction

We know surprisingly little about the behaviour of investors in bear markets. Our study focuses on the negative emotions investors may feel during bears. We hypothesize that falling share prices (or low/negative returns) in bear markets evoke strong negative rather than positive affective states in investors. Negative affective states encompass a number of emotional experiences with very different psychological manifestations and very distinct influences on the decision-process. High-arousal negative moods (e.g., anger and stress) as opposed to low-arousal negative moods (e.g., sadness and depression) lead to more stereotypic judgements, promote the greater use of heuristics and generally make people more prone to impulsive and ill-considered decisions (Bodenhausen, Sheppard and Kramer, 1994; Keinan, 1987). If a high-arousal, rather than a low-arousal, negative affective state dominates investors, it is more likely that they will succumb to behavioural
biases, like representativeness, biased self-attrition and overconfidence (Bodenhausen et al., 1994).

We face a difficulty in analyzing bear markets as there is no generally accepted formal definition of what constitutes a ‘bear’ or a ‘bull’.¹ Defining bear markets as those stock market regimes² where the average returns are statistically significantly negative, we were able to detect two bear market periods in the equal-weighted stock index return series using a penalized least-squares technique to detect \( n \) unknown regimes. This analysis is reported in sub-section 4.1 of this paper. The second of these regimes - April 2000 to May 2000 – is too short a period from which significant conclusions may be drawn.³

We focus on the first of the bear regimes we detected: November 1987 to February 1988. In section 4.2 of this paper, we consider how portfolios’ sensitivity to these spanning portfolios changes in the bear regime by contrasting the behaviour in the bear regime with the regime preceding it - August 1986 to September 1987 (which we denote as the pre-bear regime). We will argue that returns observed during the bear regime of November 1987 to February 1988 are consistent with what might be expected if returns during a bear are correlated with a pervasive low-arousal negative affective state - sadness - amongst investors. When we analyze trading volume in section 4.3 of this paper, we also find patterns of behaviour we believe to be associated with a pervasive low-arousal negative affective state amongst investors. The literature underpinning our research questions is discussed in section 2 below. We discuss our data and methodology for its analysis in section 3 of the paper. Section 5 concludes the paper.

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¹ We briefly discuss competing definitions of ‘bears’ and ‘bull’ later in this paper although interested readers can find a fuller discussion of this issue, and the statistical technique we employ to detect bear markets, on an accompanying document which may be found on the corresponding author’s web page.

² We denote a regime as a period bounded by points in time where we detect a structural break in the time series of security returns. The methodology is discussed in this paper but readers interested in further information may find a more detailed discussion in an accompanying document available on the corresponding author’s web page – as referred to in footnote 1).

³ Indeed, as we suspected, the results of the analysis of this data proved to be inconclusive; interested readers may download the results from the corresponding author’s website.
2.0 High And Low-Arousal Negative Affective States

Behavioural observations and experimental data from the field of psychology suggest that the quality of decision-making is affected by emotional/mood states (Dreman, Johnson, MacGregor and Slovic, 2001; Finucane, Alhakami, Slovic and Johnson, 2000). Equity returns have also been linked to emotional/mood states (Lucey and Dowling, 2005; Kamstra, Kramer and Levi, 2000; Hirshleifer and Shumway, 2003; Boyle and Walter, 2003; Kamstra, Kramer and Levi, 2003; Goetzmann and Zhu, 2003; Cao and Wei, 2005; Dowling and Lucey, 2005; Keef and Roush, 2005, 2007).

People in negative affective states, as opposed to people in positive affective states, rely less on the use of heuristics (Bless, Bohner, Schwarz and Strack, 1990; Murray, Surjan, Hirt and Surjan, 1990), produce more logically consistent preferences (Fiedler, 1988) and form more narrow categories (Murray et al., 1990). Affective states also have a distinct influence on subjective probability judgments. Wright and Bower (1992) found that sad people have a more pessimistic view while happy people have a more optimistic view of the future. Sad subjects overestimated the probabilities of negative events and underestimated the probabilities of positive events. Happy subjects displayed the opposite tendencies. Sinclair and Mark (1995) found that positive affective states lead to non-systematic and less detailed information processing, whereas negative affective states lead to systematic and more detailed information processing.

Two accounts have been offered to explain the asymmetrical effects of negative and positive affective states on cognitive processes. First, the motivational explanation, developed by Isen (1987), postulated that negative moods are unpleasant and hence individuals are motivated to undertake activity (even if it requires considerable cognitive effort) to change to a more desirable psychological state. In contrast, positive mood is a state that individuals do not wish to change. Doing nothing requires little thinking. The

Schwarz and Bless (1991) provide a comprehensive review on the effects of positive and negative affective states on analytical reasoning.
second explanation, called the informational explanation to the differential effects of negative and positive affective states on decision-making, has been offered by Schwarz (1990). According to this account, people use mood as informational input in the judgment process. A happy mood is considered to be a sign of safety, while a sad mood is an undesirable state that one needs to escape from. Consequently, sad mood urges individuals to transform the unfriendly situation into a safe one by making logical, consistent and unbiased decisions.

In considering negative affective states, Keltner, Ellsworth and Edwards (1993) hypothesized that anger and sadness have a different effect on people’s perceptions of the causes of unrelated ambiguous and negative events. They find that sad subjects perceive situationally caused events as more likely and impersonal circumstances as more responsible for an ambiguous situation. On the other hand, angry people believe that events caused by humans are more likely, and give more weight to other people as causal agents in ambiguous situations. Bodenhausen et al. (1994) conclude that angry people are more likely to use heuristics and be affected by stereotypes when reacting to social stimuli than sad people. They proposed that the difference between the social information processing of angry versus sad subjects could stem from the differences in the physiological manifestations of these two types of negative states. Anger is primarily associated with high blood pressure, an increase in pulse and symptoms of arousal, while sadness produces none of these effects. Symptoms of arousal make angry people more prone to impulsive and ill-considered decisions and reduce their capacities for thinking.\(^5\)\(^6\)

Leith and Baumeister (1996) have argued psychological arousal leads to destructive risk-taking. Mano (1994) found that arousal, but not arousal accompanied by unpleasantness, is the most influential element in shaping individuals’ risk taking behaviours. Eisenberg, Baron and Seligman (1998) documented a direct link between low-arousal negative mood

\(^5\) Evidence of physiological states affecting social judgment and memory is presented in Bodenhausen (1990) and Wilder (1993).

\(^6\) In contrast, Sinclair and Mark (1995) find no support for the proposition that the effects of mood could be arousal-based. Their results indicated that regardless of the arousal level, students in negative affective states processed information in a similar way. Sinclair and Mark (1995) question the proposition that distinctions among negative states need to be recognized.
(in this case depression) and heightened risk-aversion. On the other hand, Raghunathan and Pham (1999) found evidence of people drawing different inferences from their mood and thus bringing different goals to the decision-making. Anxiety heightens one’s preoccupation with reducing uncertainty, while sadness heightens one’s preoccupation with increasing reward. If psychological arousal changes in bear markets, we hypothesize that investors’ required returns for exposure to risk will change in bear markets. We test this hypothesis in sub-section 4.2 of this paper.

The proposition that arousal-based negative moods lead to unsystematic information processing is supported by the findings of a large body of research conducted on the effects of stress on decision-making. It has been documented that under stress, individuals make more errors on a wide variety of tasks (Broadbent, 1957; Wilkinson, 1963), consider alternatives in a non-systematic way (Wachtel, 1967; Janis 1982), devote insufficient time to the decision problem (Fritz and Marks, 1954; Janis, 1982) and are subject to tunnel vision by neglecting peripheral cues (Easterbrook, 1959; Baddeley, 1972). Mandler (1982) argued that the unfavorable effects of stress on the quality of decision-making arise because stressors (aversive social, physical and psychological forces and pressures) produce psychological arousal in individuals, who will devote part of their attention to the threat and the reaction it generates in them. As a result, they are left with insufficient cognitive resources to meet the demands of the task at hand. Keinan’s (1987) “electric shock” experiments provide further support for the theory that arousal gives rise to self-defeating behaviour. In the absence of time constraints, stress by itself increases the incidence of premature closure and non-systematic scanning.

Lewicka (1997) concludes that the behaviour of individuals in a high-arousal negative mood can best be described as sub-optimal. Angry individuals rely on the use of heuristics, focus on salient information, devote insufficient time to the decision problem and jump to premature conclusions. On the other hand, individuals in a low-arousal negative mood seem to process information in a systematic way. According to Lewicka, the decision-making of people in a low-arousal mood can best be described as passive and uncommitted, rather than rational. She finds that while depressed people collect information in an unbiased and impartial way, it takes them a long time to weight
alternatives and arrive at their decisions. Consequently, if bear markets are dominated by sad investors, we hypothesise that the aggregate number and the dollar value of shares traded in portfolios to be lower in the bear period than in the pre-bear period. If bear markets are associated with behaviour consistent with investors being angry (investors in high-arousal negative affective states), vice versa. We examine this question in subsection 4.3 of the paper.

In conclusion, empirical research has revealed that negative affective states encompass a number of emotional experiences, with very different and distinct influences on the decision-making process. It has been demonstrated that high-arousal based negative moods such as anger and stress elicit an information processing strategy that is characterized as sub-optimal. It involves, in part, the use of heuristics, reliance on salient information, and stereotypic judgments. On the other hand, low-arousal based negative moods such as sadness and depression elicit systematic and non-biased information processing that can be viewed as either rational or passive. The differences between the two affective states regarding the quality of information processing could explain the findings that anger increases risk-seeking tendencies in individuals, while sadness and depression cause individuals to be risk-averse.

3.0 Data and methodology

As we have highlighted in the previous section, high-arousal negative moods such as anger and stress lead to increased risk-seeking tendencies in individuals (Leith and Baumeister, 1996). On the other hand, Eisenberg et al. (1998) provide evidence that low-arousal based negative moods such as sadness and depression cause individuals to be risk-averse. While the psychology literature we have discussed treat risk as a single measure, in the finance literature risk has a number of dimensions, such as total risk and, or, the systematic risk of priced factors (eg. beta, size, book to market, liquidity and momentum). Since behavioural observations are silent as to which of these risks investors are more or less sensitive, we examined the change in investors’ perceived attitude to all of these risks when stock market conditions switch from pre-bear to bear regimes. Our examination of risk focuses on two issues. Firstly, we consider how spanning portfolios currently believed to capture
the dimensions of systematic risk behave during bear episodes. To do this, we compare the behaviour of these portfolios in the bear market to the regime preceding it. The results of this analysis will be presented in sub-section 4.1 of the paper. Secondly, we consider how portfolios’ sensitivity to these spanning portfolios changes in the bear regime (once again, we do this by contrasting the behaviour in the bear regime with the regime preceding it). The results of this analysis will be presented in sub-section 4.2 of the paper.

For our measures of systematic risk, we augment Fama and French’s three-factor model (Fama and French, 1993) – denoted using the variable mnemonics RM for the equity risk premium, SMB for the small firm premium and HML for the value premium – with momentum (MOM) and liquidity (LIQ).\(^7\)

To examine the variation in the sensitivity of the variables in the bear regime, we include a dummy variable in our analysis; of the asset pricing equation below (equation 1):

\[
R_{it} = \alpha_i + b_i \cdot RM_t + s_i \cdot SMB_t + h_i \cdot HML_t + \lambda_i \cdot \text{Liquidity}_t + m_i \cdot \text{MOM}_t + \\
\text{d}_i \cdot \text{Dummy} + \text{d}_{RM,i} \cdot \text{Dummy} \cdot RM_t + \text{d}_{SMB,i} \cdot \text{Dummy} \cdot SMB_t + \text{d}_{HML,i} \cdot \text{Dummy} \cdot HML_t + \\
\text{d}_{\text{Liquidity},i} \cdot \text{ Dummy} \cdot \text{Liquidity}_t + \text{d}_{\text{MOM},i} \cdot \text{ Dummy} \cdot \text{MOM}_t + \epsilon_{it} \tag{1}
\]

where \(R_{it}\) is the excess return on portfolio \(i\) at time \(t\), \(RM\) is the excess return on the market portfolio. SMB, HML, Liquidity and MOM are spanning portfolios formed to capture the returns associated with firm size, book to market ratio, liquidity and momentum respectively.\(^8\) \(\epsilon_{it}\) is an independently and identically distributed residual term with a mean of zero. “Dummy” is a binary dummy variable that takes the value 1 in the bear period and

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\(^7\) Halliwell, Heaney and Sawicki (1999), Faff (2001), Gaunt (2004) and Durack, Durand and Maller (2004) provide evidence justifying the model with Australian data. Faff (2004) provides evidence that supports its use with daily data as we intend in this study. Chan and Faff (2003, 2005) have argued that liquidity is a priced variable in modeling the cross-section of returns. There is still debate about the role of momentum in Australia. Demir, Muthuswamy and Walter, (2004) support moment but Gaunt and Gray (2003) and Durand, Limkriangkrai and Smith (2006b) provide evidence against moment. We remain agnostic in this unresolved debate and, therefore, we have included momentum.

\(^8\) We follow Durack et al.’s methodology in forming SMB and HML. The two liquid and two illiquid portfolios include stocks that are ranked in the bottom 30% and top 30% (respectively) based on their dollar turnover and percentage of shares traded values. The winner (high momentum) and loser (low momentum) portfolios are made up of stocks in the top 30% and bottom 30% (respectively) cumulative return groups. All the portfolios are reformed monthly at the end of the last trading day of each month. The look-back period is 1 month for the size and B/M portfolios, 3 months for the liquidity portfolios and 6 months for the momentum portfolios.
zero in the pre-bear period: such a variable will capture the differences in the components of portfolio returns in the pre-bear and bear periods. Rather than fitting equation 1 individually for each equation, we recognize that the portfolios represent a system of equations and, accordingly, equation 1 is fitted via the Seemingly Unrelated Regression (SUR) technique (Zellner, 1962). Such an approach also has the advantage of facilitating the three Wald tests we discuss below as well as facilitating efficient estimation of the parameters if there are cross-correlations between the error terms. The products of the dummy variable and the four risk factors capture the magnitude and direction of the change in the factor loadings as a result of the regime switch. In order to learn more about these changes, we calculate the Chi-square values ($\chi^2$) for three different Wald tests:

I. Wald test I tests the null hypothesis that the coefficients of the dummy variable and of the product of the dummy variable and each of the risk factors are jointly equal to zero for all sample portfolios sorted on the same criteria. Wald test I enables us to determine whether the changes in the loadings on each of the risk factors and intercept term as a result of the regime switch are statistically significant for the cohort of portfolios as a whole.

II. Wald test II tests the null hypothesis that the coefficients on the interaction of the dummy variable and each of the risk factors are equal for the 10th and 1st decile portfolios. Unlike Wald test I, Wald test II focuses on the change in the loadings on each of the risk factors for the extremes of the univariate sorts rather than for the cohort as a whole. It allows us to determine whether the effect of changing stock market conditions on investors’ risk taking behaviour is influenced by the amount of risk their portfolios are exposed to.

III. Wald test III tests the null hypothesis that the sum of the coefficients on a given risk factor and on the product of the dummy variable and the same risk factor is the same for the 10th and 1st decile portfolios. While Wald test II focuses on the changes in the factor loadings (as a result of the regime switch) for the extremes of the univariate sorts, Wald test III focuses on the coefficient levels for the 10th and 1st decile portfolios after the regime switch. With Wald test III we can examine whether the compensation that investors require in the bear market for being exposed to the risk factors is influenced by the characteristics of the stocks they hold in their portfolios.
The sample portfolios in our analysis are constructed using data from the Securities Industry Research Centre of Asia-Pacific’s (SIRCA) Core Research Database and Australian Graduate School of Management’s Share Price and Price Relative Database (SPPR). In portfolio formation, we use all fully-paid non-financial stocks listed on the ASX excluding financial firms. We also require firms to remain listed over the sorting, pre-bear and bear periods. In the 1986/1988 sample period there are 587 stocks that meet the selection criteria. In the 1998/2000 sample period there are 661 stocks satisfying the above conditions. Over the 6 month period prior to the start of the pre-bear regimes, the stocks are ranked in ascending order based on their average monthly market capitalization and ten portfolios based on market capitalization are formed for our examination.9

4.0 Anger, Sadness and the Bear Market of the late 80’s

4.1 Detecting the Bear Market.

There is no generally accepted, formal definition of what constitutes a bear or a bull market. This is surprising, considering how often the terms are used to refer to stock market cycles. A typical definition is provided by the Australian Stock Exchange: a bull market occurs when “share prices are generally rising”, while a bear market occurs when “share prices are falling quite sharply and experts expect further falls”.10 One approach to determining bears is simply to compare the return on a market index and a critical threshold value to separate stock market conditions into bear and bull phases (Fabozzi and Francis, 1977; Kim and Zumwalt, 1979; Wiggins, 1992; Bhardwaj and Brooks, 1993).

Rather than imposing a possibly arbitrary structure on the data, we utilize a non-parametric perspective by focusing more on the specific features of the original data series.11 The

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9 We also conducted the analysis on portfolios formed on betas, average daily returns, cumulative returns, number of days traded, kurtosis and skewness values. The results added little to the analysis and are not reported in this paper.


pattern recognition algorithm employed is based on the works of Csörgő and Horvath (1997), Kühn (1999) and Chen and Gupta (2000). To our knowledge, our approach has not been used previously to identify stock market cycles. The method adopted in this study tests whether structural breaks have occurred somewhere in the sample and, if so, estimates the time of their occurrence. It involves calculating least squared estimates (LSE) of the location of change points in the mean of the return series and choosing those points where the LSE is minimized. Since the number of change points is unknown, we need to adopt a model selection process that ranks the alternative models and identifies the one that best fits the data. To achieve this, we use the Bayesian Information Criterion (BIC) of Schwarz (1978) to determine the optimal trade-off between model complexity and the model’s ability to accurately represent the data. The estimated optimal change points can then be used to divide the stock index return series into \( n \) sub-periods. Categorization of these sub-periods into bear, bull and ‘other’ (non-bull and non-bear) states can be done ex post (after the regimes have been identified) by comparing the mean of the stock index returns in each period to critical threshold values.

Once we have determined regimes, we analyze the data to find if any of the regimes is found to have statistically significant negative returns. Our results may be sensitive to the proxy for the market we use in the analysis. Accordingly, we analyze three different return indices: 1) SPPR equal-weighted return index (EW), 2) SPPR value-weighted return index (VW), 3) All Ordinaries Accumulation return index (XOA-A). The first two series were obtained from the SPPR. EW and VW are constructed using the stock returns of all Australian listed and previously listed companies on the Australian market from January 1974 to December 2001. The All Ordinaries Accumulation Index (a value-weighted index) covers a period beginning January 1980 and ending December 2001, and is taken from the Core Research Data; before April 1, 2000, the All-Ordinaries Index comprised only 266 of the largest Australian stocks; on this date it was broadened to include 500 stocks. As such, it may not be representative of the returns of the small stocks which make up much of the Australian market (Durand, Juricev and Smith, 2007). Differences between the sample periods of the XOA-A and the EW and VW indices imply that the results of the bear market classification procedures using these three return
indices will only be comparable from January 1980 to December 2001. Consequently, we restrict our sample period to this time frame.

[INSERT TABLE 1 ABOUT HERE]

The location of the change points identified by the penalized LSE allows us to pinpoint the start of the stock market regimes in the three return series. Table 1 presents descriptive statistics for the market regimes. Given that we do not have priors, we will assume that a bear market exists either when mean returns are statistically significantly negative or when mean returns are significantly below the risk-free rate. We use two critical threshold values as it could be argued that investors are interested in realizing not just positive returns, but returns in excess of the risk-free rate. Irrespective of the method used to assess statistical significance, we are able to detect two bear periods in the equal-weighted return series. These are the November 1987 to February 1988 and April 2000 to May 2000 market regimes. The November 1987 to February 1988 bear period lasted for 4 months, during which investors lost on average 6.88% of the value of their investment each month. We denote the period preceding this period as the pre-bear period: it begins in August 1986 and ends in September 1987. The April 2000 to May 2000 bear period had a shorter duration (2 months) but with more serious consequences for investors. Over this time window, the average monthly return in the EW index was -13.45%. As we have noted earlier, the second regime is not sufficiently long to draw valid conclusions and we do not analyse it further in this paper. The second pre-bear period starts in November 1998 and ends in March 2000.

Inspection of Table 1 reveals that no bear-regimes are found for VW and XOA-X. This suggests that the effects of bear-markets may be concentrated in the smallest stocks in the

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12 Since t-statistics cannot be calculated for regimes with a duration of 1 month, we impose the restriction of a minimum 2-month duration for bear markets.
13 However, as we note in footnote 1, the reports of the analyses of this bear market are available on the corresponding author’s web site for interested readers.
14 The October 1987 stock market crash precedes the 1987/1988 bear market and, as we report, is selected by the change-point algorithm as a regime. However, we have excluded October 1987
market. Therefore, the analysis presented in Table I suggests that using equal-weighted portfolios as independent variables, as well as equal weighted portfolios for dependent variables in the analysis, might be the clearest way of examining bear markets. Accordingly, this is the approach adopted in the following section (although it should be stressed that the results are robust to using value-weighted indices as dependent variables). Because size appears to be the dimension in which investors’ response to bear markets appears to be clearly witnessed, our analysis will utilize ten size-based portfolios as the dependent variables in the analysis. Indeed, size is a natural choice for portfolio formation in Australia. Gaunt, Gray and McIvor (2000) and Durack, Durand and Maller (2004) find a pronounced small firm effect in Australia. Exploring this phenomenon, Durand, Juricev and Smith (2007) have argued that, for Australian investors, response to stimuli is best reflected in their responses to portfolios based on market capitalization. Furthermore, while debate still rages as to which factors best capture Australian equity returns (Durand, Limkriangkrai and Smith, 2006a) size is the only dimension of risk about which there is no controversy. Forming on size reflects our contention that we should form these portfolios using a variable about which investors care.

After identifying the bear regimes using monthly data\textsuperscript{16}, we then utilize daily data to maximize the number of observations we can examine; consequently, it becomes important to identify the most likely start and end dates of the pre-bear and bear periods. Using a daily equal-weighted return series and applying the penalized LSE-approach to this index\textsuperscript{17}, we found that the first pre-bear period lasted from 12 August 1986 to 16 October 1987 and the bear regime from 12 November 1987 to 10 February 1988.

\textsuperscript{15} Analyses using value-weighted control variables may be downloaded from the corresponding author’s web page.

\textsuperscript{16} The penalized least-squares algorithm we utilize is extremely computationally intensive. Therefore, it was necessary to use monthly data for the initial scoping of the data.
4.2 Changes in Risk

Unreported summary statistics for the first bear market revealed that, while average returns for RM and the equal-weighted and value-weighted SMB spanning portfolios were lower in the bear period than in the pre-bear period, as might be expected, mean returns increased for the other spanning portfolios. It need not only be the returns on the spanning portfolios that may reflect investors’ behaviour during bear regimes; therefore, we analyse portfolios formed on size to examine how the sensitivity of portfolios formed on this criterion changes from pre-bear to bear regimes.

Table 2 reports the findings where the dependent variables are 10 portfolios formed on market capitalization. As we have noted in the previous section, size appears to be the only dimension that is indisputably priced in the Australian market. Equation 1 is estimated using equal and value-weighted spanning portfolios and two measures of liquidity. In panel A, the liquidity spanning portfolio is formed by ranking stocks based on their dollar turnovers. In panel B, liquidity is measured by the percentage of shares traded. In the pre-bear period, the coefficients on RM are positive and statistically significant at the 1% level for all size portfolios except S2 in panel B.

We hypothesized that investors’ required returns for exposure to risk will change in bear markets if psychological arousal changes in bear markets. Examination of Table 2 clearly demonstrates that our expectation of changing required returns are confirmed but the picture is complex. Where SMB is significant, there is a significant increase in the slope of the SMB from the pre-bear to bear period for all the portfolios considered together.18,19 Risk-premia, however, seem to behave differently depending on whether

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17 We do not test for multiple break points in the starting and ending months of the regimes and as a result the calculation of the BIC criterion is of no use.
18 With the exception of panel A, SMB explains time-series variations in the pre-bear portfolio returns in less than half of the regressions. The significant ‘s’ coefficients are mainly positive in panel A but not in panel B. The inferences with respect to the SMB risk factor are consistent
they invest in very large or very small market capitalization firms. Compared to the pre-bear period, in the bear period they require more (less) compensation for holding smaller (larger) stocks.\footnote{In addition, in the bear period, they are more sensitive to the size risk factor when their investment is made up of smaller rather than larger stocks.}{\cite{Durand2004}} Interpretation of this result may be assisted by considering the arguments of Durand et al. (2004) who argue that the size-premium is increased by emotional arousal and disproportionate reactions to stimuli. Investors may become less emotionally aroused in bear regimes and they will rely less on the heuristics that lead them to over and/or underreact to stimuli. Such behaviour would be expected of sadder investors. Accordingly, they will prefer larger to smaller stocks.

In both panels of Table 2, the intercept term is statistically significant and positive only for the smallest and/or the largest of the size portfolios. These results imply that our multifactor model cannot fully capture the pre-bear returns accrued to portfolios comprising very small and/or very large firms. If we follow Garber (2004, p. 4) and define a bubble as “…that part of asset price movement that is unexplainable based on what we call fundamentals”, a significant intercept term may mean that the pre-bear

\footnote{Inspection of Table 3 reveals that the $\chi^2$ values of Wald test I for SMB are statistically significant at the 1\% level in both panels. Wald test I tests the null hypothesis that the coefficients on the dummy variables and on the product of the dummy variable and each of the risk factors are jointly equal to zero for all size portfolios. The average direction of the change in the loadings on SMB is positive, implying that investors systematically become more sensitive to being exposed to the size risk factor as the stock market switches from the pre-bear to bear regime.}{
Wald test II tests the null hypothesis that the coefficients on the interaction of the dummy variable and spanning portfolios are the same for the 10th and 1st decile portfolios. Unlike Wald test I, Wald test II focuses on the change in the loadings on the risk factors for the extremes of the size decile portfolios, rather than for the cohort as a whole. It helps us to determine whether the effect of the regime switch on investors’ sensitivity toward the risk factors is amplified when investors hold very large or very small market capitalization stocks. The $\chi^2$ values of Wald test II are statistically significant (at the 1\% level) in all 4 panels for the size spanning portfolio. The coefficients on the product of the dummy variable and SMB are negative for the biggest portfolios (S10) and positive for the smallest portfolios (S1). These results imply that as stock market conditions change, investors’ sensitivity to the size risk factor increases (decreases) when their investment comprises smaller (larger) stocks.}{\cite{Wald2004}}

\footnote{The $\chi^2$ values of Wald test III can be rejected for SMB in all 4 panels. The slope of SMB in the bear period is positive for the S1 portfolio and negative for the S10 portfolio. These results imply that compared to larger stocks, investors require more compensation for holding smaller stocks in the bear period.}{
regardless of the method that was used to compute spanning portfolio returns and the proxy that was used to measure liquidity.
regime might be characterized as a bubble. If so, the average direction of change for the intercept term is negative in the bear period; this may indicate that the bear regime represents a return to “normal” market condition. Such an interpretation is consistent with our analysis of the change in the distribution of the returns of the equal weighted market portfolio and spanning portfolios discussed in the previous sub-section.

Table 2 reports mixed findings for the loadings on other spanning portfolios. Thus, we are inclined to infer that the transitions from pre-bear to bear periods had no systematic impact on investors’ attitudes toward these risk factors.

4.3 Changes in Volume.

Following our review of the psychology literature, we hypothesized that if bear markets are correlated with investors being in a low-arousal negative affective state, such investors will be more cautious with their buy/sell decisions and we would expect to see that the volume of shares traded in portfolios and their dollar values would be lower in the bear period than in the pre-bear period. An examination of average portfolio trading volumes in both of the periods we study reveals that volumes are lower in the bear regime than the pre-bear regime and such a finding is consistent with market behaviour that is correlated with a pervasive low-arousal negative affective state amongst market participants during this bear market.

Table 3 presents descriptive statistics for the (daily) trading volumes for each portfolio in the bear market of the 1980’s. Trading volumes are measured by the number of times the shares in the portfolios trade. In all but the portfolio of largest stocks, the average portfolio trading volumes are lower in the bear period than in the pre-bear period. This is consistent with our expectation that the bear market would be associated with investors in predominately low-arousal negative affective states.
The null hypothesis that the distributions of the trading volumes are normal is rejected in both periods for the majority of the portfolios. Even though the trading volume distributions are ‘non-normal’ in both periods, the results of the 2-sample Kolmogorov-Smirnov Z tests reveal that they are statistically significantly different from each other; the null hypothesis (tested by the Mann-Whitney U test) that the trading volumes come from the same population is rejected with confidence in all but one instance. We are unable to find a theoretical basis to allow us to discuss the distribution of volume and simply report the results for completeness.

5.0 Conclusion

Our study has focused on the negative emotions investors may feel during bears. We hypothesized that falling share prices (or low/negative returns) in bear markets evoke strong negative, rather than positive, affective states in investors. High-arousal based negative moods such as anger and stress involve, in part, the use of heuristics, reliance on salient information, and can lead to increased risk-seeking. Low-arousal based negative moods such as sadness and depression elicit systematic and non-biased information processing that can be viewed as either rational or passive.

This bear regime, lasting from 12 November 1987 to 10 February 1988, provides evidence that is consistent with a low-arousal affective state predominating among investors. In other words, the market was driven by sad and depressed investors. Investors appear to have required a higher return to compensate them for their exposure to a variety of dimensions of risk and they were more sensitive to the size risk factor when their investment comprised smaller rather than larger stocks. Volume in this bear market was lower, compared with the preceding regime, and this is also to be expected if a low-arousal affective state pervaded the market.
References


Broadbent, K. E. 1957, “Effects of noises of high and low frequency on behavior”, Ergonomics, 1, 21-29.


Kühn, C. 1999, “An estimator of the number of change points based on a weak invariance principle”, Munich University of Technology, Centre for Mathematical Sciences.


**Table 1: Stock Market Regimes in the Return Series.**

This table presents descriptive statistics for the stock market regimes identified in the equal-weighted (EW), value-weighted (VW) and the All Ordinaries Accumulation (XOA-X) monthly return series. The starting months of the regimes are the optimal change points identified by the penalised LSE approach described in Appendix A. The duration of the regimes is expressed in months, while the mean monthly returns and standard deviations are in percentages. The table also presents two t-statistics for each regime. The conventional t-statistics (t) is computed by dividing the mean (monthly) returns of the regimes (Column 4) by the corresponding standard deviations (Column 5). It tests whether the mean returns of the regimes are statistically significantly different from zero. t* is computed by subtracting the average 1-month risk free rate (R_f) over the regimes’ duration (Column 6) from the mean returns of the regimes (Column 4), before dividing it by the corresponding standard deviations (Column 5). It tests whether the mean returns of the regimes are statistically significantly different from the risk-free rate. The risk-free rate is proxied by the monthly rates on the 13 week Treasury notes and is obtained from the SPPR Database.

<table>
<thead>
<tr>
<th>Series</th>
<th>Market Regimes</th>
<th>Duration (months)</th>
<th>Mean (%</th>
<th>Std. Dev.</th>
<th>R_f</th>
<th>t</th>
<th>t*</th>
</tr>
</thead>
<tbody>
<tr>
<td>EW</td>
<td>Jan. 80 – Jun. 82</td>
<td>30</td>
<td>1.76</td>
<td>6.47</td>
<td>1.01</td>
<td>0.27</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>Jul. 82 - Jul. 86</td>
<td>49</td>
<td>3.28</td>
<td>4.88</td>
<td>1.01</td>
<td>0.67</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>Aug. 86 - Sep. 87</td>
<td>14</td>
<td>6.46</td>
<td>4.6</td>
<td>1.14</td>
<td>1.4</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>Oct. 87</td>
<td>1</td>
<td>-29.33</td>
<td>-</td>
<td>0.83</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Nov. 87 - Feb. 88</td>
<td>4</td>
<td>-6.88</td>
<td>1.64</td>
<td>0.81</td>
<td>-4.2***</td>
<td>-4.69***</td>
</tr>
<tr>
<td></td>
<td>Mar. 88 - Jun. 89</td>
<td>16</td>
<td>0.14</td>
<td>3.84</td>
<td>1.09</td>
<td>0.04</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>Jul. 89 - Aug. 89</td>
<td>2</td>
<td>11.89</td>
<td>2.77</td>
<td>1.31</td>
<td>4.29***</td>
<td>3.82***</td>
</tr>
<tr>
<td></td>
<td>Sep. 89 – Jan. 91</td>
<td>17</td>
<td>-1.84</td>
<td>2.79</td>
<td>1.16</td>
<td>-0.66</td>
<td>-1.08</td>
</tr>
<tr>
<td></td>
<td>Feb. 91 - Feb. 92</td>
<td>13</td>
<td>6.7</td>
<td>4.59</td>
<td>0.75</td>
<td>1.46</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>Mar. 92 – Nov. 92</td>
<td>9</td>
<td>0.25</td>
<td>2.52</td>
<td>0.49</td>
<td>0.1</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>Dec. 92 – Feb. 94</td>
<td>15</td>
<td>8.04</td>
<td>5.42</td>
<td>0.41</td>
<td>1.48</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>Mar. 94 – Jun. 95</td>
<td>16</td>
<td>-1.72</td>
<td>3.36</td>
<td>0.54</td>
<td>-0.51</td>
<td>-0.67</td>
</tr>
<tr>
<td></td>
<td>Jul. 95 – Oct. 98</td>
<td>40</td>
<td>0.98</td>
<td>5.12</td>
<td>0.49</td>
<td>0.19</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Nov. 98 – Mar. 00</td>
<td>16</td>
<td>5.59</td>
<td>4.7</td>
<td>0.4</td>
<td>1.19</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>Apr. 00 – May 00</td>
<td>2</td>
<td>-13.45</td>
<td>3.8</td>
<td>0.48</td>
<td>-3.54***</td>
<td>-3.67***</td>
</tr>
<tr>
<td></td>
<td>Jun. 00 – Sep. 01</td>
<td>16</td>
<td>-1.21</td>
<td>5.66</td>
<td>0.45</td>
<td>-0.21</td>
<td>-0.29</td>
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<tr>
<td>VW</td>
<td>Jan. 80 – May 87</td>
<td>89</td>
<td>1.99</td>
<td>5.7</td>
<td>1.03</td>
<td>0.35</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>Jun. 87 – Sep. 87</td>
<td>4</td>
<td>5.73</td>
<td>6.25</td>
<td>0.94</td>
<td>0.92</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Oct-87</td>
<td>1</td>
<td>-39.54</td>
<td>-</td>
<td>0.83</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Nov. 87 – Dec. 01</td>
<td>170</td>
<td>0.9</td>
<td>3.59</td>
<td>0.63</td>
<td>0.25</td>
<td>0.08</td>
</tr>
<tr>
<td>XOA-X</td>
<td>Jan. 80 – Sep. 87</td>
<td>93</td>
<td>2.11</td>
<td>5.18</td>
<td>1.03</td>
<td>0.41</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>Oct-87</td>
<td>1</td>
<td>-15.55</td>
<td>-</td>
<td>0.83</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Nov-87</td>
<td>1</td>
<td>-31.98</td>
<td>-</td>
<td>0.82</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Dec 87 – Jan. 94</td>
<td>74</td>
<td>1.21</td>
<td>3.86</td>
<td>0.84</td>
<td>0.31</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>Feb 94 – Jan. 95</td>
<td>12</td>
<td>-1.11</td>
<td>1.92</td>
<td>0.49</td>
<td>0.58</td>
<td>-0.83</td>
</tr>
<tr>
<td></td>
<td>Feb. 95 – Dec. 01</td>
<td>83</td>
<td>1.04</td>
<td>2.83</td>
<td>0.47</td>
<td>0.37</td>
<td>0.2</td>
</tr>
</tbody>
</table>

*, ** and *** denote significance at the 10%, 5% and 1% significance level, respectively.
Table 2: Modeling Time-Series Variation in Size Portfolio Returns in the 1986/1988 Sample Period

This table presents the results when estimating the following seemingly unrelated regression (SURE) equation for the period 12 August 1986 to 9 February 1988, after deleting the crash period 19 October 1987 to 11 November 1987:

\[ R_t = a + bRM_t + sSMB_t + \lambda LIQ_t + nMOM_t + dDummy_t + RMSBM_t + dDummy_t^2 + Liq Dummy_t + Liquidity_t + \sigma_t \]

\( R_t \) is the daily excess return on the size portfolios and \( \text{RM}_t \) is the daily excess return on the All Ordinaries Accumulation Index. Excess returns are calculated using the daily cash rate. SMB_t is the daily return on a portfolio of small minus big stocks. Liquidity is the daily returns on a portfolio of low minus high liquidity stocks. The low minus high liquidity portfolio is formed upon ranking stocks on dollar turnover and percentage of shares traded. \( \text{MOM}_t \) is the daily return on a portfolio of high minus low momentum stocks. All the spanning portfolios are reformed monthly. The Dummy variable takes the value 1 in the bear period (12 November 1987 to 9 February 1988) and zero in the pre-bear period (12 August 1986 to 16 October 1987). Columns 2 to 11 present the coefficient values along with the \( R^2 \) and F-statistics values for each size portfolio. The corresponding two-tailed t-statistics are in italics. In Panel A, the spanning portfolios are equal-weighted and liquidity is measured by turnover in dollars while, in Panel B, liquidity is measured by the percentage of shares traded. Columns 12 to 14 report the Chi-square values for Wald Test I, II and III. Wald Test I tests the null hypothesis that the coefficient on the product of the dummy variable and spanning portfolio is jointly equal to zero for all decile portfolios. Wald Test II tests the null hypothesis that the coefficient on the product of the dummy variable and spanning portfolio is the same for the 10th and 1st decile portfolios. Wald test III tests the null hypothesis that the sum of the coefficient on the spanning portfolio and the coefficient on the product of the dummy variable and the same spanning portfolio is the same for the 10th and 1st decile portfolios.

<table>
<thead>
<tr>
<th>Panel A: Spanning Portfolios are equal-weighted and liquidity is measured by turnover in dollars</th>
<th>Wald Tests</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Big</td>
</tr>
<tr>
<td></td>
<td>S10</td>
</tr>
<tr>
<td>a</td>
<td>-0.028</td>
</tr>
<tr>
<td>b</td>
<td>0.889</td>
</tr>
<tr>
<td>s</td>
<td>-0.022</td>
</tr>
<tr>
<td>m</td>
<td>-0.012</td>
</tr>
<tr>
<td>d</td>
<td>0.010</td>
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<tr>
<td>( \rho_{\text{BM}} )</td>
<td>-0.029</td>
</tr>
<tr>
<td>( \rho_{\text{BM}} )</td>
<td>-0.050</td>
</tr>
<tr>
<td>( \rho_{\text{BM}} )</td>
<td>0.046</td>
</tr>
<tr>
<td>( \rho_{\text{BM}} )</td>
<td>-0.101</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.859</td>
</tr>
<tr>
<td>F-stat</td>
<td>236.61***</td>
</tr>
</tbody>
</table>

24
Panel B: Spanning portfolios are equal-weighted and liquidity is measured by the percentage of shares traded

<table>
<thead>
<tr>
<th>(Reg)</th>
<th>S10</th>
<th>S9</th>
<th>S8</th>
<th>S7</th>
<th>S6</th>
<th>S5</th>
<th>S4</th>
<th>S3</th>
<th>S2</th>
<th>S1</th>
<th>I</th>
<th>II</th>
<th>III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
<td>Coeff.</td>
<td>t</td>
</tr>
<tr>
<td>a</td>
<td>-0.025</td>
<td>-1.05</td>
<td>0.009</td>
<td>0.28</td>
<td>-0.002</td>
<td>-0.06</td>
<td>-0.033</td>
<td>-0.85</td>
<td>0.054</td>
<td>0.68</td>
<td>0.046</td>
<td>0.40</td>
<td>0.188</td>
</tr>
<tr>
<td>b</td>
<td>0.859</td>
<td>25.02***</td>
<td>0.395</td>
<td>6.67***</td>
<td>0.577</td>
<td>6.61***</td>
<td>0.403</td>
<td>7.08***</td>
<td>0.311</td>
<td>2.65***</td>
<td>0.469</td>
<td>4.01***</td>
<td>0.464</td>
</tr>
<tr>
<td>s</td>
<td>-0.041</td>
<td>-2.07**</td>
<td>-0.121</td>
<td>-4.65***</td>
<td>-0.085</td>
<td>-2.61***</td>
<td>-0.003</td>
<td>-0.08</td>
<td>-0.016</td>
<td>-0.23</td>
<td>-0.024</td>
<td>-0.36</td>
<td>0.133</td>
</tr>
<tr>
<td>λ</td>
<td>-0.056</td>
<td>-1.64*</td>
<td>-0.119</td>
<td>-5.59***</td>
<td>-0.161</td>
<td>-6.02***</td>
<td>-0.056</td>
<td>-2.12***</td>
<td>-0.123</td>
<td>-2.24***</td>
<td>-0.152</td>
<td>-2.77***</td>
<td>-0.283</td>
</tr>
<tr>
<td>m</td>
<td>0.015</td>
<td>-1.33</td>
<td>0.020</td>
<td>1.37</td>
<td>0.061</td>
<td>3.33***</td>
<td>0.077</td>
<td>4.22***</td>
<td>0.067</td>
<td>1.79*</td>
<td>0.095</td>
<td>2.51***</td>
<td>0.090</td>
</tr>
<tr>
<td>d</td>
<td>0.157</td>
<td>2.69***</td>
<td>0.015</td>
<td>-0.20</td>
<td>-0.061</td>
<td>-0.63</td>
<td>-0.039</td>
<td>-0.40</td>
<td>-0.136</td>
<td>-0.68</td>
<td>-0.164</td>
<td>-0.82</td>
<td>-0.364</td>
</tr>
<tr>
<td>δ_{US}</td>
<td>-0.019</td>
<td>-0.31</td>
<td>-0.031</td>
<td>-0.39</td>
<td>-0.056</td>
<td>-0.57</td>
<td>-0.134</td>
<td>-1.38</td>
<td>-0.234</td>
<td>-1.15</td>
<td>-0.049</td>
<td>-0.24</td>
<td>-0.335</td>
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<tr>
<td>δ_{J}</td>
<td>-0.003</td>
<td>-1.14</td>
<td>-0.041</td>
<td>-0.67</td>
<td>0.005</td>
<td>0.06</td>
<td>0.082</td>
<td>1.06</td>
<td>-0.102</td>
<td>-0.64</td>
<td>-0.028</td>
<td>-0.18</td>
<td>-0.284</td>
</tr>
<tr>
<td>δ_{USM}</td>
<td>-0.011</td>
<td>-0.23</td>
<td>-0.125</td>
<td>-2.08**</td>
<td>-0.181</td>
<td>-2.40***</td>
<td>-0.129</td>
<td>-1.71*</td>
<td>-0.153</td>
<td>-0.99</td>
<td>-0.067</td>
<td>-0.96</td>
<td>-0.238</td>
</tr>
<tr>
<td>2D</td>
<td>0.080</td>
<td>0.588</td>
<td>0.521</td>
<td>0.390</td>
<td>0.137</td>
<td>0.247</td>
<td>0.452</td>
<td>0.246</td>
<td>0.085</td>
<td>0.310</td>
<td>0.432</td>
<td>0.228</td>
<td>0.257</td>
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<tr>
<td>F-stat</td>
<td>238.34***</td>
<td>56.63***</td>
<td>42.31***</td>
<td>24.60***</td>
<td>6.18***</td>
<td>12.79***</td>
<td>32.69***</td>
<td>12.66***</td>
<td>3.61***</td>
<td>14.47***</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* ** *** denote significance at the 10%, 5% and 1% significance level, respectively
Table 3: Trading Volumes of the Sample Portfolios in the 1986/1987 Pre-Bear and 1987/1988 Bear Periods

This table presents descriptive statistics for the trading volume of the sample portfolios in the pre-bear and bear periods. The pre-bear period spans from 12 August 1986 to 16 October 1987. The bear period spans from 12 November 1987 to 9 February 1988. Trading volumes for the sample portfolios were calculated by summing the total number of shares traded each day for each stock belonging to the same portfolio together. S10Vol and S1Vol are the trading volumes for the biggest and smallest size portfolios respectively. For each sample portfolio, the table reports average daily trading volumes and standard deviations, maximum and minimum daily trading volumes, skewness and excess kurtosis values and 1-sample Kolmogorov-Smirnov (K-S) Z-scores for the pre-bear (Panel A) and bear (Panel B) periods. The 1-sample K-S test tests the null hypothesis that trading volumes are normally distributed. Panel C reports the F-statistics for the Levene test and the Z-scores for the non-parametric Mann-Whitney (M-W) U test and the 2-sample K-S Z-test. The Levene test tests the null hypothesis of equal variances in the two periods. The M-W U test tests the null hypothesis that the volume observations in the two periods come from the same population. The 2-sample K-S Z test tests the null hypothesis that both pre-bear and bear volumes have the same distribution (same location and shape).

<table>
<thead>
<tr>
<th>Portfolio Volumes</th>
<th>Panel A: Pre-Bear Period</th>
<th>Panel B: Bear Period</th>
<th>Panel C</th>
</tr>
</thead>
<tbody>
<tr>
<td>S10Vol</td>
<td>19,717,577</td>
<td>10,390,908</td>
<td>3,476,779</td>
</tr>
<tr>
<td>S9Vol</td>
<td>6,343,172</td>
<td>5,190,907</td>
<td>3,476,779</td>
</tr>
<tr>
<td>S8Vol</td>
<td>4,944,302</td>
<td>3,886,964</td>
<td>33,875,428</td>
</tr>
<tr>
<td>S6Vol</td>
<td>4,383,164</td>
<td>3,284,432</td>
<td>30,075,260</td>
</tr>
<tr>
<td>S5Vol</td>
<td>4,445,666</td>
<td>2,409,834</td>
<td>17,772,018</td>
</tr>
<tr>
<td>S4Vol</td>
<td>4,708,208</td>
<td>2,434,127</td>
<td>13,925,216</td>
</tr>
<tr>
<td>S3Vol</td>
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<td>2,529,943</td>
<td>21,181,838</td>
</tr>
<tr>
<td>S2Vol</td>
<td>5,000,740</td>
<td>2,544,098</td>
<td>25,518,196</td>
</tr>
<tr>
<td>S1Vol</td>
<td>3,048,017</td>
<td>1,506,959</td>
<td>10,379,645</td>
</tr>
</tbody>
</table>

*,**,*** denote significance at the 10%, 5% and 1% significance level, respectively.