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Stochastic Dominance and Behavior towards Risk: The Market for Internet Stocks

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Abstract

Internet stocks registered large gains in the late 1990s, followed by large losses from early 2000. Using stochastic dominance theory, we infer how investor risk preferences have changed over this cycle, and relate our findings to utility theory and behavioral finance. Our major findings are as follows. First, risk averters and risk seekers show a distinct difference in preference for internet versus “old economy” stocks. This difference is most evident during the bull market period (1998-2000) where internet stocks stochastically dominate old economy stocks for risk seekers but not risk averters. In the bear market, risk averters show an increased preference for old economy stocks, while risk seekers show a reduced preference for Internet stocks. These results are inconsistent with prospect theory and indicate that investors exhibit reverse S-shaped utility functions.

Key words: Stochastic dominance, prospect theory, utility functions, gambles.

1. Introduction

This paper uses stochastic dominance theory (Hadar and Russell 1969 and Hanoch and Levy 1969) to identify dominant types of risk preferences over the Internet bull and bear market of the late 1990s. We argue that Internet stocks provide lottery-like payoffs which appeal to risk seekers or gamblers (Friedman and Savage 1948, Markowitz 1952, Hartley and Farrell 2002). We also use the implied risk preferences to test two competing theories of choice under risk. The first is the prospect theory of Kahnemann and Tversky (1979), which has been applied recently to behavioral finance e.g. Barberis, Huang and Santos (2001). The second theory, which stems from the experimental work of Thaler and Johnson (1990), indicates that contrary to prospect theory, investors may be risk seeking over gains and risk averse over losses i.e., investors have reverse S-shaped utility functions. The Internet episode provides an ideal setting for such a test since the bull and bear market define regimes of gains and losses of a substantial magnitude. Furthermore, these market regimes reveal strong preferences by investors for Internet and non-Internet stocks respectively.

Stochastic dominance theory is appealing because of its non-parametric orientation. Stochastic dominance criteria require minimal assumptions about returns distribution and preferences. For example, returns can display time series dependence and conform to any distribution. The underlying utility functions can be standard linear utility functions satisfying von-Neumann-Morgenstern axioms or as Fishburn (1989) shows, they can include a variety of nonlinear utility functions based on substantially weaker axioms. Machina (1982) and Starmer (2002) show that stochastic dominance criteria are also meaningful for a range of non-expected utility theories of choice under uncertainty.

We apply a recent test of stochastic dominance developed by Davidson and Duclos (2000), hereafter, DD. The DD test allows for mutually dependent observations and has simple asymptotic properties. Like most traditional stochastic dominance test, however, the DD test takes the viewpoint of risk averters. We show that it is straightforward to adapt the test for risk seekers since orderings for convex utility functions are simply the dual of orderings for concave utility functions (Li and Wong 1999). Incorporating this result leads to a complete test framework that can be used to infer risk averse and risk seeking behavior. We apply this framework to test for the dominant type of risk preferences associated with different types of stocks during the Internet bubble and post-bubble period.

The rest of this paper is organized as follows. Section 2 revisits the Internet stock market episode of the late 1990's. Section 3 reviews theories of decision making under risk that incorporates risk aversion as well as risk seeking. Section 4 describes the dataset and presents descriptive statistics for our stock returns series. The theory of stochastic dominance for risk averters and risk seekers is discussed in Section 5. Section 6 introduces the Davidson-Duclos (2000) test for stochastic dominance, and discusses test implementation issues. Section 7 reports the results of the DD test for the bull and bear market and what these results imply for prospect theory and the Thaler-Johnson hypothesis. In Section 8, we interpret our results by drawing on the utility analysis of gambling (Hartley and Farrell 2002) and related results from behavioral finance. Section 9 concludes.

2. The Internet Stock Episode

From 1998 to early March 2000, prices of Internet stocks rose six-fold, outperforming the S&P 500 by a whopping 482%¹. Technology stocks in general showed a similar trend, as evident from NASDAQ 100 Index which quadrupled over the same period, and outperformed the S&P 500 index by 268%. Following the peak of the bull market, prices of Internet stocks fell by more than 80% through the end of December 2003. This spectacular rise and fall of Internet stocks has spurred research into the causes of the Internet stock “bubble”.

Ofek and Richardson (2003) provide circumstantial evidence that Internet stocks attract mostly retail investors who are more prone to be overconfident about their ability to predict future stock prices than institutional investors. They add that this investor clientele, along with short sale constraints and lockup agreements forced pessimistic investors out of the market, leaving only investors with most optimistic beliefs. Baker and Stein (2004) develop a model of market sentiment with irrationally overconfident investors and short sale constraints, and show that the model’s predictions are consistent with the high trading volume and liquidity of Internet stocks during the boom period. Cochrane (2002) finds similar correlations between stock prices and turnover during the Internet bubble period and the 1929 stock market boom and crash. Hong, Scheinkman and Xiong (2005) explain that the bubble was caused by a combination of factors such as investor overconfidence, short sale constraints and limited asset float. These papers all point to investor irrationality as the most probable cause of the Internet boom and crash.

¹ We use the Amex Inter@active Index (more commonly known as the @Net Index) as our proxy for stocks in the internet sector. The @Net index is a popular benchmark for internet-related firms. We also use the Nasdaq 100 Index as a broader proxy for “new economy” or technology-related firms. Our main proxy for “old economy” stocks is the S&P 500.

Whether or not the bubble is due to investor irrationality is hard to resolve given our imperfect knowledge of correct asset pricing benchmarks. These models also assume that investors are globally risk averse, and that risk aversion is time-invariant. The first assumption is inconsistent with the possibility that people may be both risk averse and risk seeking as Friedman and Savage (1948) pointed out long ago. The second assumption is inconsistent with evidence that people's risk aversion changes with prior experience (Thaler and Johnson 1990) and is conditional on contemporaneous market states (Shive and Shumway 2004). The ability of standard asset pricing models to explain market "anomalies" are constrained by both assumptions.

3. Theories of Risk Preferences

As mentioned, expected utility is the predominant approach used in asset pricing and within this framework, global risk aversion is the standard assumption. However, expected utility theory is primarily normative, and has been criticized for not describing how investors actually behave. Several alternative theories have been proposed to provide more realistic descriptions of individual risk preferences. Seminal contributions are Friedman and Savage (1948), Markowitz (1952), Kahnemann and Tversky (1979).

Friedman and Savage (1948) make the important point that people might be both risk averse as well as risk loving. In particular, people who buy insurance might also buy lottery tickets, which are unfair games. They propose an utility function with concave and convex segments to account for insurance and lottery purchase. The Friedman-Savage utility function is defined over absolute wealth and comprises two concave segments separating a convex segment in the middle-wealth region.

Although innovative, this utility function implies counterfactually that only middle-wealth people buy lotteries. Markowitz (1952) extends Friedman and Savage's analysis to accommodate insurance and lottery purchase by all individuals, rich and poor. He proposed that the utility function be centered around "customary wealth", which is usually interpreted as current wealth, denoted here as W_0 . This utility function is assumed to be convex, then concave in the region $W - W_0 > 0$, implying that the individual is initially willing to gamble in the hope of improving his current wealth, and then become risk averse as higher levels of wealth are attained. Conversely, the utility function is assumed to be concave, then convex in the region $W - W_0 < 0$ so that he is risk averse over small losses but is willing to gamble over large losses, perhaps in a bid to recover from large cumulative losses. Figure 1 depicts the Markowitz utility function. It is interesting to note that the utility function has a reverse S-shaped in the neighborhood of W_0 , but is overall S-shaped in each of the two domains.

[Figure 1 about here]

Markowitz's work forms the basis of prospect theory (Kahneman and Tversky 1979). In prospect theory, the emphasis is on wealth changes rather than levels of wealth. Based on a series of lottery experiments, Kahneman and Tversky show that people are risk averse in the domain of gains and risk seeking in the domain of losses. In other words, the utility function is S-shaped around the reference point separating gains from losses. Unlike Markowitz, the reference point in prospect theory is context specific, and need not necessarily be current wealth. For example, following the purchase of an asset, the purchase price may form a natural reference point.

The theories just described provide fundamental insights into behavior that is absent in expected utility theory, namely that people are motivated by hopes for riches as well as protection from poverty. Of the three theories that incorporate risk aversion and risk seeking, prospect theory has emerged as the most popular alternative to expected utility theory in describing how individuals make decisions under risk.

Although prospect theory has received experimental support, it should be noted that the theory was developed based on experimental evidence of one-shot gambles. Therefore, prospect theory has little to say about the dynamics of choice under risk e.g. how people make decisions after a sequence of gambles. Experimental evidence based on sequential gambles (Thaler and Johnson 1990) show that prior outcomes affect subsequent behavior in a way that may be contrary to the static version of prospect theory. In particular, subjects are more risk seeking following gains and more risk averse following losses, suggesting that in a dynamic context, a reverse S-shaped utility function may be more descriptive of actual behavior. Recent research using market data provides additional evidence that supports this view. For example, Barberis et al. (2001) find that investor risk aversion increases after loss but decreases after gains, and that these shifts in risk preferences can account for the equity risk premium. Post and Levy (2005) find that risk aversion over losses and risk seeking over gains can capture the cross section of expected stock returns, whereas S-shaped risk preferences cannot. Shive and Shumway (2004) find that contrary to the fundamental assumption of standard asset pricing models, pricing kernels (marginal utilities) are positively sloped instead of negatively sloped over regions of moderate to large market returns. A positively sloped pricing kernel is consistent with risk seeking during good states, and implies that investors are willing to purchase

securities with high variance and low expected returns. They do so because these securities offer lottery-like payoffs (see Shefrin and Statman 2000).

In this study, we take prospect theory as our null hypothesis and use Internet stock returns data to test its implications that investors were risk averse during the bull market period (domain of gains) and risk seeking during the bear market period (domain of loss). Our alternative hypothesis is that investors' utility functions are reverse S-shaped as suggested by Thaler and Johnson (1990) and Shive and Shumway (2004).

4. Data

The data for this study consists of daily returns on three stock indices: the S&P 500, the Amex Inter@active Internet index and the Nasdaq 100 index. We use the S&P 500 index to represent non-technology or "old economy" firms.

Our proxies for the Internet and technology sectors are the Amex Inter@active Internet index (also known as the @Net index) index and the Nasdaq 100 index. The @Net index is a popular index benchmark for the Internet-related firms. Component firms in this index include Internet infrastructure and service providers and firms that market Internet content, software and e-commerce. Among the prominent stocks in the index are Cisco Systems, American Online, Yahoo!, Amazon.com and Ebay.

The Nasdaq 100 index comprises one hundred of the largest domestic and international technology firms on the Nasdaq stock market. Firms represented in the Nasdaq 100 include those in the computer hardware and software, telecommunications and biotechnology sectors. Like the @Net index, the Nasdaq 100 index is value-weighted.

Our sample period is from January 1, 1998 through December 31, 2003 and comprises 1,564 return observations. We start from January 1998 because a clear upward trend in technology stock prices emerged from around that period (Ofek and Richardson 2003). This sample period spans a period of intense IPO and secondary market activities for Internet stocks. Schultz and Zaman (2001) reported that 321 Internet firms went public between January 1999 and March 2000, accounting for 76% of all new Internet issues since the first wave of Internet IPOs began in 1996. Ofek and Richardson (2003) find that the extraordinary high valuations of internet stocks between early 1998 and February 2000 was accompanied by very high trading volume and liquidity. Schwert (2001) shows that the rise in trading volume and volatility over this period is not confined to internet stocks, but is also present in the computer, biotechnology, and telecommunications sectors. The unusually high volatility of technology stocks is only partially explained by the rise in overall market volatility.

Our interest centers on two distinct periods: the bull market period from 1998 through March 9, 2000 (the peak of the Internet bubble), and the subsequent bear market period. The number of daily return observations in these sub-periods is 570 and 994 respectively. All data for this study are from Datastream.

Figure 2 shows the cumulative daily excess returns of the two technology stock indices relative to the S&P 500 index during this bull period. The continuous out-performance of technology stocks is clearly evident.

[Figure 2 about here]

The bursting of the Internet bubble on March 9, 2000 was followed by a prolonged bear period. From March 10, 2000 through end of December 2003, the @Net index lost 87% of its value and underperformed the S&P 500 by 60% while the Nasdaq 100 declined by 79%, and underperformed the S&P 500 by 51%. Figure 3 charts the cumulative excess returns of these two indices relative to the S&P 500 during this bear period. The performance of technology stocks over the entire bull-bear cycle from 1998 to 2003 is summarized in Table 1.

[Figure 3 about here]

[Table 1 about here]

5. Stochastic Dominance and Risk Preferences

5.1 First Order Stochastic Dominance

Stochastic dominance theory provides a general framework for ranking risky prospects based on utility theory. Hadar and Russell (1969), Hanoch and Levy (1969), Rothschild and Stiglitz (1970, 1971) and Whitmore (1970) lay the utility foundations of stochastic dominance analysis. Fishburn (1989) shows that stochastic dominance rules extend to nonlinear utility functions based on substantially weaker axioms than von Neumann-Morgenstern linear utility theory. Machina (1982) and Starmer (2002) show that stochastic dominance criteria also apply for a range of non-expected utility theories of choice under uncertainty.

For this study, the main advantage for using stochastic dominance is that it enables us to infer the shape of investors' utility functions based on preference rankings of technology and non-technology stocks. In addition, stochastic dominance

is attractive because of its non-parametric orientation. In contrast to mean variance analysis, which is valid only for quadratic utility functions or normal returns distributions, stochastic dominance rules do not restrict distributions and requires minimal assumptions about preferences.

The most common rules of stochastic dominance literature are first, second and third order stochastic dominance. First order stochastic dominance is the most intuitive of the three criteria since it only assumes non-satiation. Let F and G be the cumulative distributions of two risky assets, x be the uncertain return and U be an utility function. Suppose all investors are non-satiated i.e. $U'(x) \geq 0$. Then, all such investors will agree that F is preferred to G if

$$F(x) \leq G(x) \text{ for all } x. \quad (1)$$

Intuitively, F dominates G because the probability that returns $\leq x$ will be realized is always higher for G than for F .

5.2 Higher Order Stochastic Dominance: Risk Averters

Consider the case of a risk averter. We say that F dominates G at the second order for all risk averse investors with utility functions $U'(x) \geq 0$ and $U''(x) \leq 0$ if and only if

$$\int_{-\infty}^{\infty} [G(z) - F(z)] dz \geq 0 \text{ for all } x \quad (2)$$

It is well known that when distributions are normal, rankings by second order stochastic dominance and rankings by mean-variance criterion are identical.

Third order stochastic dominance adds to risk aversion, the assumption of skewness preference. We say that F dominates G at the third order for all risk averse

investors with $U'(x) \geq 0$, $U''(x) \leq 0$ and $U'''(x) \geq 0$ if and only if $\mu_F > \mu_G$ where μ denotes expected return and

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [G(z) - F(z)] dz dv \geq 0 \text{ for all } x \quad (3)$$

Roughly speaking, investors who prefer positive skewness assign larger weight to upside potential and will hold a less diversified portfolio with large upside potential. Empirical evidence indicates that investors indeed prefer more positively skewed returns distributions (Arditti 1967, Kraus and Litzenberger 1976, Friend and Westerfield 1980 and Harvey and Siddique 2000).

5.3 Higher Order Stochastic Dominance: Risk Seekers

Li and Wong (1999) show that stochastic dominance rules apply to risk seekers, with the preferences reversed. Specifically, let Λ denote an n -tuple of convex coefficients:

$$\Lambda = \{(\lambda_1, \dots, \lambda_n) : \lambda_i \geq 0 \text{ for } i = 1, \dots, n \text{ and } \sum_{i=1}^n \lambda_i = 1\}. \quad (4)$$

Then risk seekers will prefer F to G if there exists an Λ such that

$$\sum_{i=1}^n \lambda_i F(x_i) \geq \sum_{i=1}^n G(x_i) \quad (5)$$

This is satisfied if and only if the utility function is convex.

Consider a risk seeking investor with utility function satisfying $U'(x) \geq 0$ and $U''(x) \geq 0$. Then F dominates G at the second order if and only if

$$\int_{-\infty}^{\infty} [G(z) - F(z)] dz \leq 0 \text{ for all } x \quad (6)$$

If distributions are normal and short sales are restricted, then second order stochastic dominance for this investor implies the following: between two assets with identical expected returns, he will choose the asset with higher variance. This is of course a

dominated asset in mean-variance space, and the high variance does provide the potential for large upside gains. More generally, this indicates that higher order dominance incorporating positive skewness preference is even more suited to modeling risk seeking than risk aversion. This is captured by third order stochastic dominance for risk seekers which we define next.

We say that F dominates G at the third order for all risk seekers with $U'(x) \geq 0$, $U''(x) \geq 0$ and $U'''(x) \geq 0$ if and only if $\mu_F > \mu_G$ where μ denotes expected return and

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [G(z) - F(z)] dz dv \leq 0 \text{ for all } x \quad (7)$$

Third order stochastic dominance thus allows a risk seeker to trade off risk for positive skewness. Extending this to the market level implies that there should be evidence of skewness preference during periods when risk seeking predominates. Evidence based on the three-moment CAPM of Kraus and Litzenberger (1976) confirms this hypothesis (Post and van Vliet 2004).

6. Econometric Tests of Stochastic Dominance

6.1 The Davidson-Duclos Test

Several methods for testing stochastic dominance have been used in the econometrics literature. An early test for stochastic dominance was proposed by McFadden (1989). This is a Kolmogorov-Smirnov type test for first-order stochastic dominance for independent samples with equal number of observations. The asymptotic distribution of the test statistic for $s \geq 2$ is analytically intractable. Davidson and Duclos propose a test that is more general and computationally simpler test than the Kolmogorov-Smirnov test. The DD test simplifies by comparing cumulative distribution functions over an arbitrary grid of points. An advantage of this test is that it can be applied to

dependent samples drawn from a joint distribution, in contrast to earlier tests. As the DD test is relatively new, we briefly describe the test set-up.

Let $\{I_i\}$, $i = 1, 2, \dots, T$ be sample of returns to Internet stocks, drawn from a population with cumulative distribution function (CDF), $F_I(x)$. Without loss of generality, assume that all CDFs have common support $[a, b]$ where $a \leq x \leq b$. Define $D_I^s(x)$ as the function that integrates F_I to order $s - 1$. That is,

$$D_I^1(x) = F_I(x)$$

$$D_I^2(x) = \int_a^x F_I(u) du = \int_a^x D_I^1(u) du$$

$$D_I^3(x) = \int_a^x \int_a^y F_I(v) dv du = \int_a^x D_I^2(u) du$$

Let $\{N_i\}$, $i = 1, 2, \dots, T$ be a sample of returns to non-Internet stocks, with cumulative distribution function, $F_N(x)$ Define $D_N^s(x)$ analogously.

We test the following null and alternative hypotheses:

1. $H_0: D_I^s(x_k) = D_N^s(x_k) \forall x_k, k = 1, \dots, K$
2. $H_A: D_I^s(x_k) \neq D_N^s(x_k)$ for some x_k
3. $H_{A1}: D_N^s(x_k) > D_I^s(x_k)$
4. $H_{A2}: D_N^s(x_k) < D_I^s(x_k)$

where s is the order of stochastic dominance. The null hypothesis implies that neither Internet nor non-Internet stocks dominate each other. Alternative hypothesis A1 implies that the integrated distribution function for internet stocks (roughly speaking, the cumulative probabilities of bad outcomes over grid points) is significantly less than that for non-Internet stocks. Thus, if A1 holds, all risk averters would prefer Internet to non-Internet stocks. Alternate hypothesis A2 implies the reverse.

The following the statistic can be used to test the null hypothesis:

$$T^s(x) = \frac{\hat{D}_I^s(x) - \hat{D}_N^s(x)}{\sqrt{\hat{V}^s(x)}} \quad (8)$$

where

$$\hat{D}_I^s(x) = \frac{1}{T(s-1)!} \sum_{i=1}^T (x_k - I_i)_+^{s-1}$$

$$\hat{D}_N^s(x) = \frac{1}{T(s-1)!} \sum_{i=1}^T (x_k - N_i)_+^{s-1}$$

and

$V^s(x)$, the variance of the integrals of the cumulative distribution functions is computed as follows:

$$\hat{V}_I^s(x) = \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (x_k - I_i)_+^{2(s-1)} - \hat{D}_I^s(x)^2 \right]$$

$$\hat{V}_N^s(x) = \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (x_k - N_i)_+^{2(s-1)} - \hat{D}_N^s(x)^2 \right]$$

$$\hat{V}_{I,N}^s(x) = \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (x_k - I_i)_+^{s-1} (x_k - N_i)_+^{s-1} - \hat{D}_I^s(x) \hat{D}_N^s(x) \right]$$

$$\hat{V}^s(x) = \hat{V}_I^s(x) + \hat{V}_N^s(x) - 2\hat{V}_{I,N}^s(x)$$

Under the null hypothesis, Davidson and Duclos show that $T^s(x)$ is asymptotically distributed as a standard normal variate. Thus, statistical inference can be based either on the normal distribution or the Studentized Maximum Modulus (SMM) distribution (Richmond 1982) to account for joint test size. A significantly positive $T^s(x)$ statistic implies that risk averters prefer non-Internet stocks over Internet stocks, and vice versa.

For risk seekers, the null and alternative hypotheses are the same as above, but the DD statistic is computed with CDFs integrated in the reverse direction:

$$\begin{aligned}\hat{D}_I^s(x) &= \frac{1}{T(s-1)!} \sum_{i=1}^T (I_i - x)_+^{s-1}, \\ \hat{D}_N^s(x) &= \frac{1}{T(s-1)!} \sum_{i=1}^T (N_i - x)_+^{s-1}, \\ \hat{V}_I^s(x) &= \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (I_i - x)_+^{2(s-1)} - \hat{D}_I^s(x)^2 \right], \\ \hat{V}_N^s(x) &= \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (N_i - x)_+^{2(s-1)} - \hat{D}_N^s(x)^2 \right], \\ \hat{V}_{I,N}^s(x) &= \frac{1}{T} \left[\frac{1}{T((s-1)!)^2} \sum_{i=1}^T (I_i - x)_+^{s-1} (N_i - x)_+^{s-1} - \hat{D}_I^s(x) \hat{D}_N^s(x) \right],\end{aligned}$$

A significantly positive $T^s(x)$ statistic implies that risk seekers prefer Internet over non-Internet stocks, and vice versa. These preferences are the opposite of those for risk averters.

6.3 Implementation Issues

The DD test is implemented over a grid of pre-selected points, x_k , $k = 1, \dots, K$ and the null hypothesis is rejected only if the *largest* t-statistic across these grid points is significant. Our choice of K is guided by the results of various simulation studies. Barrett and Donald (2003) and Tse and Zhang (2004) show that for reasonably large samples (> 500 observations), the DD test works well for $K = 10$. Actual applications may require a finer grid because as Barrett and Donald (2003, pp. 91) point out, a coarse grid may miss out important differences in the distributions. To mitigate this, we partition the data equally by using 10 major grids. Each major interval is in turn partitioned into 10 equal sub-intervals. The DD statistic is then calculated using the 10 grids within each sub-interval. To control for joint test size, statistical inference is

based on the SMM distribution for $K = 10$ and infinite degrees of freedom. The 5% asymptotic critical value of the SMM distribution is 3.254 from Stoline and Ury (1979).

7. Stochastic Dominance Results

Results for first order stochastic dominance are summarized by Figures 4 and 5. These plots show the cumulative distribution functions of the @Net and the S&P 500 indices. If the @Net index dominates the S&P 500 index at first order, then the population CDF of the S&P 500 index should lie everywhere below that of the @Net index.

[Insert Figures 4 and 5 about here]

The CDF plots suggest show that there is no first order stochastic dominance between the @Net and S&P 500 stock indices. To verify this more formally, we apply the DD test for first order stochastic dominance to the two series. The results are shown in Table 2. If Internet stocks dominate the S&P 500, we should find a high proportion of significantly negative DD statistics and no significantly positive DD statistics. The reverse holds if the S&P dominates over internet stocks. To minimize type 2 errors, we use a 50% threshold for the DD statistics in our inference. That is, we reject the null hypothesis and conclude that the @Net index dominates over the S&P 500 index if at least 50% of DD statistics are significantly negative and none are significantly positive. Table 2 shows that neither index dominates the other at first order. This result is robust across all three sample periods.

[Table 2 about here]

Although the first order stochastic dominance results appear ambiguous, they actually answer the question of whether the Internet bubble was a market anomaly. If the @Net index dominates the S&P 500 index at first order, then *all* investors (regardless of their utility functions) would prefer internet stocks to non-internet stocks. This implies that no asset pricing models would be able to rationalize the exceptionally high returns of internet stocks in terms of risk compensation. Our results do not justify such a conclusion. Thus, the internet bubble may not be entirely due to investor irrationality as suggested in some recent studies. In Section 6, we provide an alternative explanation for the bubble based on risk preference arguments.

We now turn to test results for second and third order stochastic dominance. Results for the bull market period are reported in Table 3. For risk averters (seekers) a high proportion of negative (positive) DD statistics indicate that investors prefer internet to non-internet stocks.

[Table 3 about here]

Results for second-order stochastic dominance (left-hand panel) shows that risk averters are indifferent to internet and non-internet stocks, while risk seekers strongly prefer internet stocks. Similar results are obtained using third-order stochastic dominance (right-hand panel) and the Nasdaq 100 index. Thus, the evidence shows that only risk seekers were strongly attracted to internet stocks during the bull period.

Table 4 presents results for the bear period. This period is marked by a sharp decline in stock prices and increased volatility of Internet stock returns². The distribution of returns also became more negatively skewed, exposing investors to substantial downside risks. As shown in Figure 3, buy-and-hold investors of Internet stocks underperformed the S&P 500 index throughout the bear period. Given these distribution changes, we would expect to see an increase in risk aversion for all investors, especially for risk averters. Our results bear this out. Compared to the bull period, the percentage of significantly positive DD statistics is much higher for risk averters and lower for risk seekers. This implies a general shift in preferences away from volatile internet stocks towards non-Internet stocks. This preference shift is most clearly seen in the third-order stochastic dominance results, where 77% of DD statistics for the @Net index are positive and none negative for risk averters. The corresponding percentage for risk seekers is 47%. Results for the Nasdaq 100 (Panel B) are very similar.

[Table 4 about here]

These differences in risk preferences also have interesting implications for theories of investment decisions under risk. Prospect theory implies that investors are risk averse over gains and risk seeking over losses. The results in Tables 3 and 4 do not support this prediction. They are, however, consistent with the analysis of Thaler and Johnson (1990). That is, investors appear to be risk seeking in the domain of gains but risk averse in the domain of losses.

² The daily standard deviation of @Net returns rose to 52% per annum from 45% per annum in the bull period.

It may be argued that the Internet bubble is an extreme event, and hence our results may not hold under normal conditions. Even if this were true, the economic impact of the Internet episode makes it an important counter-example to the predictions of prospect theory³. Moreover, as Thaler and Johnson notes, it does not require very high stakes to induce reverse S-shape preferences, at least among the subjects in their experiments. This suggests that reverse S-shaped preferences may not be that atypical.

One way to see if our results hold for extreme comparisons is to pair internet stocks with diversified portfolios consisting of both internet and non-internet stocks. Table 5 shows the results of this test by comparing the S&P 500 index with portfolios combining the S&P 500 and the @Net or Nasdaq 100 indices. Table 5 only reports results based on the more powerful third order stochastic test. The numbers in the body of the table are the percentage of DD statistics for third order stochastic dominance which are significantly positive.

[Table 5 about here]

Panel A shows that consistent with earlier results, risk averters never prefer Internet stocks in the bull market period. Their aversion to Internet stocks, however, decreases monotonically with the weight of Internet stocks in the portfolio. On the other hand, risk seekers show a consistent preference for Internet stocks. This preference is strongest for a pure Internet portfolio, but remains even with portfolios that contain a small percentage of Internet stocks.

³ Ofek and Richardson (2003) document that by February 2000, the Internet sector accounted for 6% of the market capitalization of all U.S. public companies and 20% of all publicly traded equity volume.

Panel B shows results for the bear market. Risk averters show a consistent preference for non-Internet stocks. Their aversion to Internet stocks is strongest when forced to hold a pure Internet portfolio but remains even with portfolios that contain a small proportion of Internet stocks. While risk seekers still prefer Internet stocks during the bear period, this preference is clearly weaker than in the bull period.

In summary, the results of Table 5 are consistent with our previous results without diversification: the domain of gain (bull period) induced risk seeking behavior, which led investors to gravitate towards Internet stocks, while the domain of loss (bear period) induced risk aversion, causing investors to switch to the relative safety of non-Internet stocks.

8. What Draws Risk Seekers to Internet Stocks?

An intriguing question is why risk seekers find Internet stocks so attractive in the bull market period. We argue that Internet stocks are attractive because risk seekers have high financial aspirations, and seek securities with lottery-like payoffs to fulfill their aspirations (Shefrin and Statman 2000)⁴. Internet stocks feature lottery-like payoffs due to call options embedded in their stock prices. Firstly, strategic growth options are of critical importance in the technology business. Sagi and Seasholes (2005) show that if a firm's near-term cash flows are derived mainly from growth options, then a rise in firm value will lead to higher expected returns (and volatility) since growth options form a larger component of the firm's total cash flows. This may explain why risk seekers remained net buyers of Internet stocks throughout the bull market period.

⁴ Shefrin and Statman (2000) show that when an individual's aspiration level is sufficiently high, the only efficient portfolio is one that resemble a lottery ticket. In Gul's (1991) theory of disappointment aversion, an individual will be risk loving with regards to gambles involving winning large gains with small probabilities if his initial wealth is low.

Several authors argue that Internet stock prices also reflect a bubble component which they term as a speculative resale option (see Hong et al. 2005, Cao and Yang 2005). The idea is that when investors have different beliefs about a stock's payoff and short selling is constrained, some investors will be willing to pay a high stock price today because they anticipate selling to other investors who are willing to pay an even higher price in the future. Since their model emphasizes investor overconfidence as the main source of heterogeneous beliefs, the resulting asset price bubble is interpreted as "non fundamental" i.e., irrational. Clearly, not every bubble must be irrational. As shown in early work by Harrison and Kreps (1978) and more recently by Cao and Yang (2005), bubbles can arise simply because investors hold genuinely different opinions about fundamentals. This might be the case for Internet stocks given the highly uncertain value of growth options embedded in such firms. Nonetheless, from a risk seeker's perspective, it is precisely such growth options which give Internet stocks a lottery-like appeal.

As we have shown, Internet stocks were very rewarding gambles indeed especially during the bull market period. Of course, ex-ante, the downside risks were unknown, and it is difficult to account for this uncertainty in econometric tests, including those used in this paper. However, we believe that incorporating ex-ante risks is unlikely to change our findings in substantial way for the following reasons. Firstly, sophisticated investors may have superior ability in predicting both the extent and timing of the Internet price bubble. Brunnermeier and Nagel (2004) examine the market timing ability of 53 hedge funds during the Internet "bubble" period of 1998-2000. Using data for actual portfolio holdings, they find that far from correcting the bubble, the funds significantly increased their holdings of technology stocks until about six months before the crash. It is interesting to note that this period coincided

with the dramatic rise in lock-up expirations, which was followed by a wave of insider sales and new issues (Ofek and Richardson 2003). The near-perfect market timing of hedge funds suggests that these sophisticated investors were confident that limited float and investor enthusiasm would keep prices of technology stocks high at least until around the peak of lock-up expirations. Their results, as Brunnermeier and Nagel put it, “suggests that the technology exposure of hedge funds cannot simply be explained by unawareness of the bubble” (p. 2015)

Second, while less sophisticated investors may not have the same forecasting skills as hedge funds, they can trade in the direction of recent price trends established by more informed traders. Empirical evidence by Dhar and Kumar (2001) indicate that less informed investors tend to be momentum traders.

Third, since even gamblers diversify (Statman 2002, Statman and Shefrin 2000), investment in Internet stocks is likely to comprise only a small part of an investor’s portfolio. Diversification limits overall downside risk, which increases the risk seeking propensity of Internet stock investors.

Fourth, the results of Johnson and Thaler (1990) and Shive and Shumway (2004) show that investors become less risk averse following prior gains. Our result indicating reverse S-shaped risk preferences is consistent with this effect.

In sum, the above arguments suggest that investors have good reasons to be optimistic during the bull market period. We do not wish to imply, however, that market sentiments do not play a role in explaining the behavior of internet stock prices. After all, Internet stocks attract primarily retail investors, who are more prone to behavioral biases such as overconfidence that lead to overly optimistic beliefs (Shiller and Pound 1998, Moore, Kurtzberg, Fox and Bazerman 1999, and Barber and Odean 2000). Baker and Stein (2004) show how investor sentiment driven by

overconfidence can capture some stylized features of the Internet bubble such as high trading volume and liquidity during the bullish period, followed by low returns and reduced liquidity in the bearish period.

While these behavioral models may explain some aspects of the Internet bubble, they typically assume that investors are risk averse, and that risk aversion remains constant over time. These assumptions are limiting. An implication of this study is that endogenizing risk tolerance can also produce similar stylized facts without putting the burden of the explanation entirely on market sentiment or investor irrationality.

9. Conclusion

Several papers have focused on the role of market sentiment and investor overconfidence in explaining the Internet stock bubble. This paper argues that the behavior of Internet stock prices is also consistent with changing risk preferences of investors. In particular, the rise of Internet stock prices during the “bubble” period may be due to the lottery-like appeal of Internet stocks to risk seekers. Using stochastic dominance methodology, we test and confirm that risk seeking was indeed dominant during the Internet bull market period. This provides an alternative perspective to “irrationality” as the cause of the Internet stock bubble.

Our results also bear on theories of choice under risk. Prospect theory posits that individuals have S-shaped utility functions and risk seeking over losses. However, experimental evidence by Thaler and Johnson (1990) and market evidence by Shive and Shumway (2004) suggests that investors may be risk seeking following gains and risk averse following losses. The Internet episode provides an interesting setting to test these competing theories since the bull and bear markets represent

regimes of sizeable gains and losses for Internet stock investors. Our results do not support the predictions of prospect theory that investors are risk averse over gains and risk seeking over losses. On the contrary, we find that Internet stocks attracted mainly risk seekers during the bull market, and risk averters during the bear market. These results also hold for technology stocks in general and are robust to diversification. Overall, our findings are consistent with the Thaler-Johnson hypothesis that reverse S-shape utility functions may be more descriptive of actual investor behavior.

References:

Arditti, F., 1967. Risk and the required return on equity. *Journal of Finance* 22, 19-36.

Baker, M., Stein, J.C., 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7, 271-300,

Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55, 773-806.

Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. *Quarterly Journal of Economics* 116, 1-54.

Barrett, G., Donald, S., 2003. Consistent tests for stochastic dominance. *Econometrica* 71, 71-104.

Brunnermeier, M., Nagel, S., 2004. Hedge funds and the technology bubble. *Journal of Finance* 59, 2013-2040.

Cao, H., Yang, H.O., 2005. Bubbles and panics in a frictionless market with heterogeneous expectations. Working paper. Graduate School of Business. Beijing.

Cochrane, J., 2002. Stocks as money: convenience yield and the tech-stock bubble. Working paper, University of Chicago.

Dhar, R., Kumar, A., 2001. A non-random walk down main street: impact of price trends in trading decisions of individual investors. Working paper, Yale University.

Davidson, R., Duclos, J-Y., 2000. Statistical inference for stochastic dominance and for the measurement of poverty and inequality. *Econometrica* 68, 1435-1464.

Fishburn, P.C., 1989. Stochastic dominance in nonlinear utility theory. In: Fomby, T.B., Seo, T.K., (Eds.), *Studies in the Economics of Uncertainty*. Springer-Verlag, New York.

Friedman, M., Savage, L.J., 1948. The utility analysis of choices involving risk. *Journal of Political Economy* 56, 279-304.

Friend, I., Westerfield, R., 1980. Co-skewness and capital asset pricing. *Journal of Finance* 35, 897-913.

Gul, F., 1991. A theory of disappointment aversion. *Econometrica* 59, 667-686.

Hadar, J., Russell, W.R., 1969. Rules for ordering uncertain prospects. *American Economic Review* 59, 25-34.

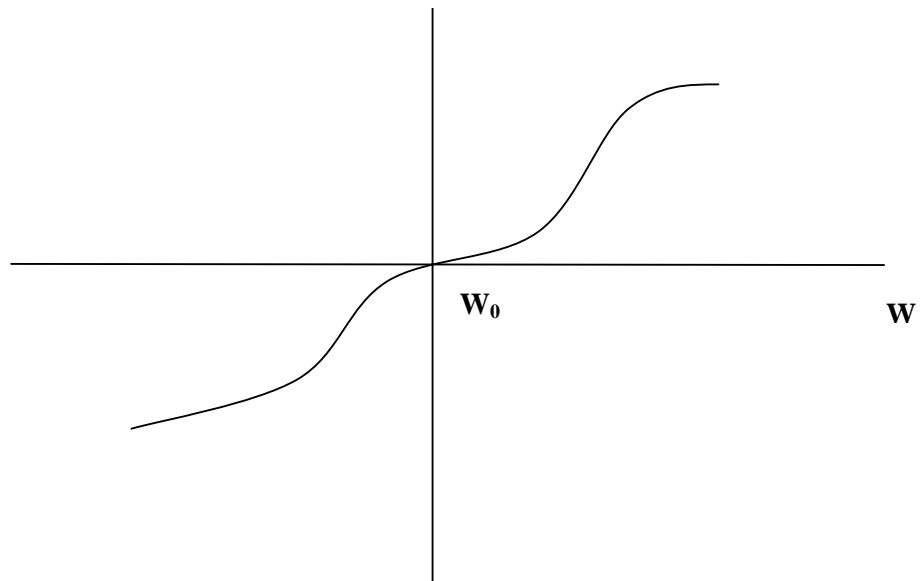
Hanoch, G. Levy, H., 1969. The efficiency analysis of choices involving risk. *Review of Economic Studies* 36, 335-346.

- Hartley, R., Farrell, L., 2002. Can expected utility theory explain gambling?. *American Economic Review* 92, 613-624.
- Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. *Journal of Finance* 55, 1263-1295.
- Hong, H., Scheinkman, J., Xiong, W., 2005. Asset float and speculative bubbles. *Journal of Finance*, forthcoming.
- Kahneman, D., Tversky, A., 1979. Prospect theory of decisions under risk, *Econometrica* 47, 263-291.
- Kimball, M.S., 1990. Precautionary saving in the small and in the large. *Econometrica* 58, 53-73.
- Kraus, A., Litzenberger, R., 1976. Skewness preference and the valuation of risk assets. *Journal of Finance* 31, 1085-1099.
- Levy, H., 1998. *Stochastic Dominance: Investment Decision Making Under Uncertainty*. Kluwer, Boston.
- Levy, H., Weiner, Z., 1998. Stochastic dominance and prospect dominance with subjective weighting functions. *Journal of Risk and Uncertainty* 16, 147-163.
- Li, C.K., Wong, W.K., 1999. A note on convex stochastic dominance theory. *Economics Letters* 62, 293-300.
- Machina, M.J., 1982. Expected utility theory without the independence axiom. *Econometrica* 50, 277-323.
- McFadden, D., 1989. Testing for stochastic dominance. In: Fomby, T.B., Seo, T.K., (Eds.), *Studies in the Economics of Uncertainty*. Springer-Verlag, New York.
- Moore, D.A., Kurtzberg, T.R., Fox, C.R., Bazerman, M.H., 1999. Positive illusions and forecasting errors in mutual fund investment decisions. *Organization Behavior and Human Decision Processes* 79, 95-114.
- Ofek, E., Richardson, M., 2003. DotCom mania: A survey of market efficiency in the Internet sector. *Journal of Finance* 58, 1113-1138.
- Perkins, A.B., Perkins, M.C., 1999. *The Internet Bubble: Inside the Overvalued World of High-Tech Stocks*. Harper Business, New York.
- Post, T., Levy, H., 2005. Does risk seeking drive stock prices? A stochastic dominance analysis of aggregate preferences and beliefs. *Review of Financial Studies* 18, 925-953.
- Post, T., van Vliet, P., 2004. Conditional downside risk and the CAPM. Working paper, Erasmus University.

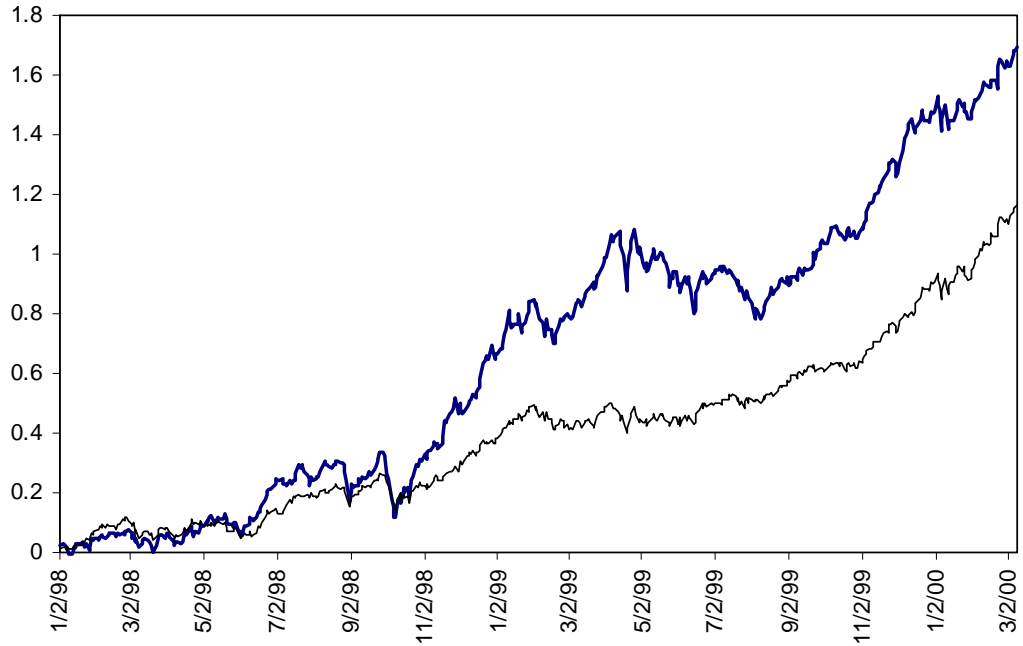
- Richmond, J., 1982. A general method for constructing simultaneous confidence intervals. *Journal of the American Statistical Association* 77, 455-460.
- Rothschild, M., Stiglitz, J., 1970. Increasing risk I: A definition. *Journal of Economic Theory* 2, 225-243.
- Rothschild, M., Stiglitz, J., 1971. Increasing risk II: Its economic consequences. *Journal of Economic Theory* 3, 66-84.
- Schultz, P., Zaman, M., 2001. Do the individuals closest to internet firms believe they are overvalued? *Journal of Financial Economics* 59, 347-381.
- Schwert, G.W., 2001. Stock volatility in the new millennium: how wacky is Nasdaq? Working paper, University of Rochester.
- Shefrin, H., Statman, M., 2000. Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis* 35, 127-151.
- Shive, S., Shumway, T., 2004. A non-decreasing pricing kernel: evidence and implications. Working paper, University of Michigan, Ann Arbor.
- Shiller, R., Pound, J.R., 1989. Survey evidence on diffusion of investment among institutional investors. *Journal of Economic Behavior and Organization* 12, 47-66.
- Starmer, C., 2000. Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature* 38, 332-382.
- Statman, M., 2002. Lottery players/stock traders. *Journal of Financial Planning* 58, 14-21.
- Stoline, M.R., Ury, H.K., 1979. Tables of the studentized maximum modulus distribution and an application to multiple comparisons among means. *Technometrics* 21, 87-93.
- Thaler, R.H., Johnson, E.J., 1990. Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science* 36, 643-660.
- Tse, Y.K., Zhang, X.B., 2004. A Monte Carlo investigation of some tests for stochastic dominance. *Journal of Statistical Computation and Simulation* 74, 361-378.
- Tversky, A., Kahneman, D., 1992. Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5, 297-323.
- Whitmore, G.A., 1970. Third degree stochastic dominance. *American Economic Review* 60, 457-459.

Figures and Tables

Figure 1. Markowitz Utility Function



**Figure 2. Cumulative Excess Returns of Technology Stocks
January 1, 1998 – March 9, 2000**



**Figure 3. Cumulative Excess Returns of Technology Stocks
March 10, 2000 – December 31, 2003**

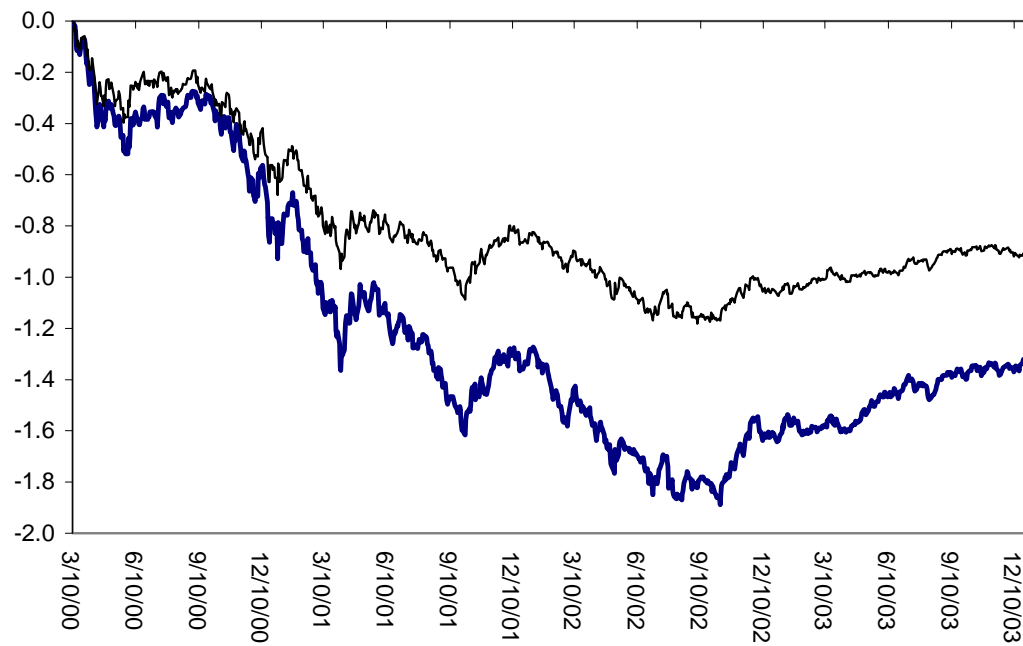


Figure 4. CDF of S&P 500 and @Net Index (Bull Market)

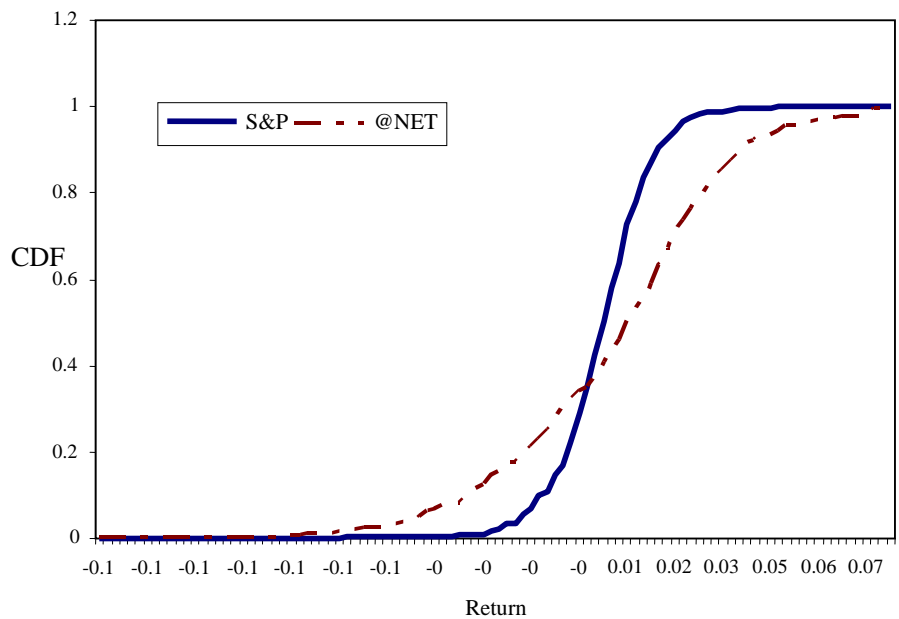


Figure 5. CDF of S&P 500 and @NET Index (Bear Market)

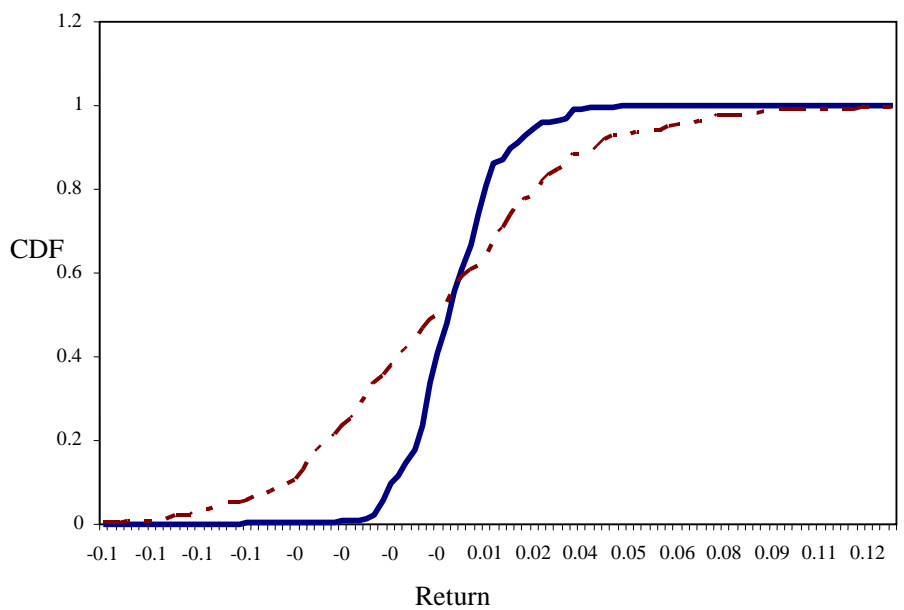


Table 1. Holding Period Returns (January 1998 – December 2003)

Holding period returns are reported for the @Net, Nasdaq 100 and S&P 500 stock indices for two sample periods. The bull market period is from January 1, 1998 to March 9, 2000 and the bear market period is from March 10, 2000 to December 31, 2003. The last row shows the number of days within each sample period in which the holding period return of the @Net or Nasdaq 100 index exceeds that of the S&P 500.

A. Bull Market: Jan 1, 1998 – March 9, 2000		
	@Net	Nasdaq 100
No. of days	570	570
HPR (@Net/Nasdaq 100)	520.1%	306.3%
HPR (S&P 500)	38.5%	38.5%
Excess HPR	481.6%	267.8%
No. of days with positive excess returns	570	570

B. Bear Market: March 10, 2000 – Dec 31, 2003		
	@Net	Nasdaq 100
No. of days	994	994
HPR (@Net/Nasdaq 100)	-87.4%	-79.9%
HPR (S&P 500)	-27.5%	-27.5%
Excess HPR	-51.4%	-59.9%
No. of days with negative excess returns	994	993

Table 2: DD Test Results for First Order Stochastic Dominance

Results of the David-Duclos (DD) test for first order stochastic dominance between the @Net and the S&P 500 indices. The full sample period is from January 1, 1998 to December 31, 2003 (1564 daily return observations). % DD - (+) denote the percentage of DD statistics which are significantly negative (positive) at the 5% significance level, based on the asymptotic critical value of 3.254 of the Studentized Maximum Modulus (SMM) distribution.

Period	DD Statistic	Percent of DD statistics significant at 5%
Full Sample (Jan 1, 1998 – Dec 31, 2003)	% DD -	28
	% DD +	26
Bull Market (January 1, 1998 – March 9, 2000)	% DD -	28
	% DD +	23
Bear Market (March 10, 2000 – Dec 31, 2003)	% DD -	27
	% DD +	27

Table 3. DD Test Results: Bull Market (Jan 1998- March 2000)

Results of the Davidson-Duclos (DD) test for second order stochastic dominance (SSD) and third order stochastic dominance (TSD). The sample period is from January 1, 1998 to March 9, 2000 (570 daily return observations). Panel A (B) compares the @Net (Nasdaq 100) index with the S&P 500 index. %DD- (+) denote the percentage of DD statistics which are significantly negative (positive) at the 5% significance level, based on the asymptotic critical value of 3.254 of the Studentized Maximum Modulus (SMM) distribution.

A. S&P vs @Net	SDD		TSD	
	Risk Averters	Risk Seekers	Risk Averters	Risk Seekers
% DD -	7	0	0	0
% DD+	27	85	32	84

B. S&P 500 vs Nasdaq 100				
% DD -	17	0	0	0
% DD+	30	87	36	82

Table 4. DD Test Results: Bear Market (March 2000 – December 2003)

Results of the Davidson-Duclos (DD) test for second order stochastic dominance (SSD) and third order stochastic dominance (TSD). The sample period is from March 10, 2000 to December 31, 2003 (994 daily return observations). Panel A (B) compares the @Net (Nasdaq 100) index with the S&P 500 index. %DD– (+) denote the percentage of DD statistics which are significantly negative (positive) at the 5% significance level, based on the asymptotic critical value of 3.254 of the Studentized Maximum Modulus (SMM) distribution.

A. S&P vs @Net	SDD		TSD	
	Risk Averters	Risk Seekers	Risk Averters	Risk Seekers
% DD-	0	0	0	0
% DD+	40	30	77	47

B. S&P 500 vs Nasdaq 100				
% DD-	0	0	0	0
% DD+	42	32	83	50

Table 5. DD Test Results: Diversified Portfolios

Results of the DD test for third order stochastic dominance of the S&P500 index against two portfolios. The first portfolio comprises the S&P500 and the @Net indices and the second portfolio comprises the S&P500 and the Nasdaq 100 indices. The weight of technology indices (@Net or Nasdaq 100) in the portfolios are shown in the first column. The body of the table shows the percentage of DD statistics which are significantly positive at the 5% level based on the asymptotic critical value of 3.254 of the Studentized Maximum Modulus (SMM) distribution. Panel A shows results for the bull market period from January 1, 1998 to March 9, 2000. Panel B shows results for the bear market period from March 10, 2000 to December 31, 2003.

A. Bull Market		@Net		Nasdaq 100	
% in tech stocks	Risk Averters	Risk Seekers	Risk Averters	Risk Seekers	
100%	32	85	36	82	
75%	32	86	33	80	
50%	29	81	29	78	
25%	24	77	25	77	
5%	17	76	20	75	
B. Bear Market		@Net		Nasdaq 100	
% in tech stocks	Risk Averters	Risk Seekers	Risk Averters	Risk Seekers	
100%	78	45	83	51	
75%	77	49	80	53	
50%	77	52	75	56	
25%	73	54	70	59	
5%	67	55	65	61	