Getting an Early Jump on Market Anomalies: Lessons from the Internet Stock Phenomenon

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Abstract
As measured by published indices, Internet stocks have produced an unprecedented performance in recent years. Cumulative returns exceeding 1000% in less than two years are reported. Numerous investment firms that chose not to invest in Internet stocks have badly trailed their peers in performance. This study endeavors to measure the extent of this anomaly and the risk of owning (or not owning) Internet stocks. Computing return variances around conditional means rather than sample means is explored as a method of obtaining an early warning as to the unprecedented events that unfolded.
Introduction
As measured by published indices, Internet stocks have produced unprecedented performance in recent years. Cumulative returns exceeding 1000% in less than two years have been reported. Numerous investment firms that chose not to invest in Internet stocks have badly trailed their peers in relative performance. This study endeavors to measure the extent of this anomaly and the risk of owning (or not owning) Internet stocks. We find that sophisticated but conventional risk models would not have been a sufficient warning of the extremely unusual events that have unfolded. This is because the returns associated with indices of Internet stocks have not been particularly more volatile than many established industries (such as precious metals) over the same time period. The huge risk of Internet stocks is that right from the beginning of their existence, their mean returns have been far from what most investors would have reasonably expected under our current theories of equity market behavior.

We propose computing return variances around a conditional (expected) mean rather than the conventional sample (observed) mean. This allows us to capture the notion of risk as not merely dispersion of returns about the mean, but also includes the idea of the surprises in the magnitude of the sample mean. It also allows for reasonable estimates of risk at a much earlier stage in the life of a market phenomenon, as we do not have to wait for the large number of return periods required in order to establish the magnitude of the sample mean.

Many investment managers, particularly those who consider themselves as having a “value” orientation, have entirely avoided purchasing Internet stocks. These stocks have exhibited valuations relative to their earnings and sales that are extraordinary. For example, the sample portfolio of Internet stocks used in this study had an average Price/Earnings ratio of more than 1700 for the sample period. Given the extraordinarily high returns produced by Internet stocks in recent years, investors who have avoided Internet stocks have vastly underperformed many of their manager peers and those market averages such as the NASDAQ and Russell indices that contained significant holdings in Internet stocks. The magnitude of such underperformance has been more than 2000 basis points (20%) per annum for some managers. Apparently few of these managers understood the potential of the Internet stock anomaly to produce massively large returns.

We attribute part of investors’ slow response to the Internet stock effect to a definitional problem: What is an Internet stock? Most methods for industry grouping are based on Standard Industrial Classification Codes (SIC). In the case of Internet stocks such a scheme will not work as the category includes both companies that contribute to hardware and software to the Internet infrastructure (e.g. Cisco Systems) and companies that conduct their routine business over the Internet (e.g. Amazon.com). An obvious, but
labor intensive, choice would be to qualitatively examine the business of all the thousands of companies from which an investor may choose in today’s market.

A useful alternative to qualitatively examining thousands of companies is to let someone else do the work. Numerous firms such as Dow Jones and Morgan Stanley have established Internet stock performance indices. The Dow Jones index was chosen because detailed daily information is available starting with July 1, 1997 and because the index portfolio is capitalization-weighted rather than equal-weighted as are most of the other indices. The index membership consists of thirty to forty stocks at different moments in time. For the purpose of this study, an Internet stock is defined as a member of the Dow Jones Internet Index for which financial statement data is available in commercial investment databases such as Compustat.

**Hypothesis**

However, we believe what led many investors to improperly evaluate the risk of “betting” for or against Internet stocks is the failure to cognitively or statistically recognize the difference between *volatility in return as risk*, and *surprising magnitudes of observed mean returns as risk*. Equity risk models currently available to investment professionals did not prevent many portfolio managers from vastly underperforming the markets by virtue of avoiding Internet stocks. Conventional risk models measure and predict volatility in returns, but really make no statement about the predicted magnitude of the mean. For an extensive technical discussion of risk models, see diBartolomeo. Even if we had the foresight to build a perfect foresight Internet-ready risk model at the beginning of the Internet stock phenomenon, the resultant risk estimates would have been accurate (but irrelevant) predictors of the volatility associated with active exposure to the Internet effect. Unfortunately, the real risk arises not from period to period return dispersion but rather from the cumulative wealth effect arising from the large magnitude of the mean.

There are two reasons why the wealth effect of the mean is generally ignored in portfolio risk modeling. The first is that under popular equilibrium theories of market behavior such as the Capital Asset Pricing Model (Sharpe) and the Arbitrage Pricing Theory (Chen, Roll and Ross), the expected mean return to a non-systematic factor is zero. This makes intuitive sense if we believe that markets are relatively efficient. If investors are knowledgeable and act very quickly on new information, there is no reason to think that Internet stocks should consistently produce better returns than otherwise comparable non-Internet stocks. Clearly, many market practitioners took this view and paid the consequences when expectations of a mean factor return close to zero were not realized.

The second reason that the wealth effect of the mean is not considered is that over an infinitely short instant of time, the mean return has no effect. The mean return only matters over measurable time intervals. Consider the following example: an asset has an expected return of 10% per year with a standard deviation of 20%. The coefficient of
variation is .5. Using months as a unit of time (and ignoring compounding) we get an expected return of \( \frac{10}{12} = .83\% \) and a standard deviation of \( \frac{20}{(12^{.5})} \) or 5.77\%. The coefficient of variation is now .14. Using days as the unit of time results in a ratio .04\%/1.26\% or about .03. As we continue to shorten the time interval, the ratio approaches zero. As we increase the time interval to decades, the ratio exceeds one. *The risk of underperforming over a short time interval is dominated by volatility. The risk of underperforming over long periods is dominated by the differences in the mean return.* A real life example of the latter situation might be a pension fund that bases its funding on an expected return of 9\% per annum and then invests its entire portfolio in a fixed interest annuity yielding only 5\%. There is no volatility in the rate of return to the portfolio (or the rate of change of surplus), but the pension fund will soon be unable to fulfill its obligations to pension recipients.

**Analysis & Proposals**

We begin our analysis by simply computing the returns on a capitalization-weighted portfolio of the included Internet stocks for the period from July 1 of 1997 through April 30, 1999. Portfolio weights were rebalanced monthly. For the purpose of comparison we also computed returns for the same period for the S&P 500. Details are presented in Table 1. The cumulative difference in the returns was more than 1000% percent, an effect of enormous magnitude never before seen in US financial markets.

| Table 1 Index % Returns July 1, 1997 though April 30, 1999 |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Monthly Mean    | Standard        | T-Statistic     | Cumulative      |
| Internet Index | 14.04           | 19.69           | 3.34*           | 1181            |
| S&P 500        | 2.12            | 13.34           | .75             | 54              |
| Excess         | 11.92           | 14.48           | 3.86*           | 1127            |

* indicates statistical significance at the 99% level

Our first step in trying to get some handle on the Internet returns was to try to statistically isolate how much of these huge excess returns arose from an explicit Internet effect while controlling for other influences (such as simply having a high beta portfolio during a period of highly positive returns to the market portfolio). For this purpose, we use the Northfield Fundamental Factor model. The details are presented in Appendix I. To isolate the Internet effect two modifications were made. The first was to combine the existing computer hardware and computer software industries into a single industry. A new industry of Internet stocks was then created. The model was re-estimated using data for our July of 1997 to April of 1999 sample period.
Based on this model, 1.25% per month of the excess return to the Internet portfolio could be attributed to the difference in beta relative to the S&P 500. The remaining 10.67% per month of difference, Jensen’s alpha, is detailed in Table 2.

Table 2 Alpha Component % Returns July 1, 1997 though April 30, 1999

<table>
<thead>
<tr>
<th>Component</th>
<th>Mean Monthly</th>
<th>Standard Deviation</th>
<th>T-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor Effects</td>
<td>2.97</td>
<td>9.81</td>
<td>1.42</td>
</tr>
<tr>
<td>Industry Effect</td>
<td>7.94</td>
<td>8.12</td>
<td>4.57*</td>
</tr>
<tr>
<td>Stock Specific</td>
<td>-.24</td>
<td>5.53</td>
<td>-.20</td>
</tr>
<tr>
<td>Total Alpha</td>
<td>10.67</td>
<td>13.74</td>
<td>3.64*</td>
</tr>
<tr>
<td>Pure Internet Effect</td>
<td>7.95</td>
<td>8.18</td>
<td>4.55*</td>
</tr>
</tbody>
</table>

As would be expected, industry effects accounted for a large portion of the total and are highly statistically significant. The portion of alpha attributable to stock specific effects was negative .24% per month, entirely without statistical significance. In that the stock specific effects that are residual to the model are not significant, we can be confident that our model has captured the Internet effect to an appropriate degree.

If we look at the returns attributable to “Internetness” as measured by the model’s Internet industry dummy variable, we see arithmetic mean returns of 7.95% per month (standard deviation 8.18%, T-statistic 4.55). The best month in the sample for the Internet effect was January of 1999, with a return of 25.32%. The worst month was negative 2.63% in August of 1998. It should be noted that the annualized variance of the returns to the Internet effect was far lower at 803% than many other industries (such as precious metals) over the sample period. Knowing the volatility of the pure Internet effect in advance would not have been an adequate warning to portfolio managers as to the risks associated with active Internet stock bets, since this variance value is not unusually large.

Not only would the sample variance information have been inadequate to warn investors about the massive return influence of the Internet effect, we cannot know in the real world until its too late. All our computations so far have been backward looking and unavailable for actual decision-making until May of 1999, by which time the damage was already done to portfolios.

Our proposed simple expedient for managing both instantaneous and cumulative wealth risks is to estimate variances around conditional expectations for the mean of the factor returns, rather than around the observed sample mean. Normally we compute variance as the mean of the squared differences between each data value in our sample and the mean of the sample data points. Alternatively, we can compute the squared difference between the observed data and our expectation of the mean for the sample. Let’s assume we have
a factor called X where the factor return has been 3% each time period of our sample. By computing the traditional variance, we get a variance of zero. But if our expectation of the mean was zero, the variance would be nine (3 squared for each period).

For most factors observed in equity markets, the variation around the mean is much larger than the effect of the mean itself. As such, switching to computing variance around a conditional mean of zero has little effect. However, in cases where an asset return is consistently positive (or consistently negative for long periods), the use of a conditional mean will produce a higher estimate of risk. Long periods of consistent positive performance (followed by long periods of negative performance) have been frequently observed in financial markets such as the return to the Japanese equity market over the past twenty years.

This approach brings two powerful advantages. First, it simultaneously captures both the dispersion of the return and the extent of the “surprise” in the magnitude of the observed mean. The second is that reasonable estimates of the magnitude of the variance can be obtained with far fewer data points, since we no longer need to wait for a large number of data points in order to establish the value of the sample mean, from which the squared deviations may be measured. This is particularly important when one considers that for stationary time series processes, sample variance converges to population variance at a rate proportional to the number of data points, while sample mean converges to population mean at a rate proportional to the square root of the number of data points. For non-stationary series, the class of models known as ARCH (auto-regressive conditional heteroscedasticity) pioneered by Bollerslev and Engle are suggested.

Assuming a conditional mean of zero, our new approach to our Internet problem produces risk estimates that are much higher in magnitude. The expected value for the annualized variance for the Internet factor return nearly doubles from 803%² to 1523%². If Internet stocks were to continue to consistently outperform the S&P 500 from May 1, 1999 into the future, the difference in these two risk estimates would continue to expand, as the conventional computation would produce ever lower numbers, while the computation based on conditional means would produce ever higher numbers (continuing outperformance is more and more surprising).

For the purpose of comparison, the active return risk (tracking error) of the April 30, 1999 Internet portfolio against an S&P 500 benchmark was evaluated under four different risk models. First, active volatility was estimated at 48.5% annually using the Northfield Fundamental Factor model as described in Appendix I (without any modifications). This is a commercially available model used by about a hundred institutional investment firms. It was estimated on the 60 months of data ending April 30, 1999. Using the same model modified to isolate the Internet effect and estimated over our sample period July 1997 through April 1999 gives an estimate of 65.6% annual tracking error.
Our third test was to use another model construct entirely. In this case, a “blind” factor model was estimated using 250 days of daily returns. The estimation method was principal components factor analysis, adjusted to reflect anomalies in the ratio of option implied volatility to historic volatility for stocks on which options are traded. Under the blind factor approach the estimated volatility was 65.4%, almost identical to the modified fundamental model. It is also interesting to note that almost one forth of the total risk estimated by the blind factor model came from a single factor, although substantial further testing would be needed to determine if we can infer that this factor was Internet related. Wade presents details of this model.

Finally, we used the conditional mean approach with the isolated Internet factor. For this estimation, our twenty-two month sample period was used. The expected mean return for the market risk factor (market return premium over T-Bills) was 50 basis points per month. This value, that includes both expected tracking error and the “surprise in mean” component, was 72.71% per annum.

It should be noted that these estimated risk values reflect the expected active return volatility for the period subsequent to April 30, 1999. There is no reason why these values should be similar to the historic annualized tracking error value (14.48% * 12 = 50.16%), as the portfolio composition changes substantially during the sample period. Exemplary of this change is the relative weight in the Internet portfolio of software companies, hardware companies and e-commerce companies. On average during the sample period, 86% of the portfolio is composed of software companies. At the end of the sample period, this fraction is down to only 72%.

**Conclusions**

Even if we knew in advance about the volatility associated with Internet stocks, it would not have been of much help to practitioners in terms of risk management. Even with perfect foresight, the average return to the Internet factor has been a four standard deviation event. However, the early history of Internet stocks should serve as a warning to investors that risk management over an interval of time is substantially different than risk management at a moment in time.

By isolating the Internet effect using index membership as a guide and adopting the conditional mean approach to computing variances, the estimated risk of our Internet portfolio, at the end of the sample period, was about 50% greater than was estimated using a popular commercially available model. We could also estimate the risk much sooner in the evolution of the process as a consequence of our conditional mean method.
References


End Notes

1. The start of the Internet is widely believed to have come in a 1960 paper by MIT psychology professor, J.C.R. Licklider. He stated, “The hope is that in not too many years, human brains and computing machines will be coupled…. tightly, and in a way that the resulting partnership will think as no human brain has ever thought and process data in a way not approached by the information-handling machines we know today.” Licklider went on to a key post with the Advanced Research Projects Administration, the part of the Department of Defense that oversaw a wide variety of scientific research programs. From this job, he secured and assigned the funding that led to the development of the ARPAnet, what we know today as the Internet.

2. The commercialization began in 1990 when the ARPAnet was merged with other regional computer networks to form the Internet. It has become a powerful force in the world economy in the 1990s. Although almost a decade has past, the economics of the Internet and the business practices of what became known as e-commerce continue to puzzle investment analysts, who must wrestle with entirely new models of business operations. According to McKnight and Bailey, “the lack of accepted metrics for economic analysis of Internet transactions is therefore increasingly problematic.”

3. The requirement for inclusion in financial statement databases was put in place because some of the index member companies were placed in the index shortly after their initial public offering. As a result some firms were in the index before it could be reasonably expected that investors could apply current risk measurement technology to these securities. In an average month, three or four of the Dow Jones Internet Index stocks were not analyzed for this reason.
Appendix I

Description of Fundamental Model

The Fundamental Factor Model is a multiple factor model used to explain the covariance among US stock returns. In this model, it is assumed that beta can explain some but not all of the structure of the covariances. For a detailed derivation, see Rosenberg (1974). There are sixty-seven factors (items of commonality). The sixty-seven factors consist of beta, eleven fundamental company characteristics, and fifty-five industry groups. The model can be written as:

\[ R_{it} = R_{ft} + \beta_{it} (R_{mt} - R_{ft}) + \sum_{k=1}^{66} (E_{ikt} \ast \alpha_{kt}) + e_{it} \]  

\( R_{it} \) = return on stock i during period t  
\( \beta_{it} \) = estimated beta of stock at time t  
\( R_{mt} \) = return on the market (our reference universe) during period t  
\( R_{ft} \) = risk free rate of return during period t (three month Treasury bill)  
\( E_{ikt} \) = exposure of stock i to factor k at time t  
\( \alpha_{kt} \) = Jensen’s alpha associated with factor k during period t  
\( e_{it} \) = error term associated with stock i during period t

Essentially, it is nothing more than a standard CAPM with an effort made to sub-divide the alpha term into 66 components. To the extent we can associate portions of alpha to common factors we increase the ability of the model to explain covariance, unlike the simple CAPM, which assumes that beta alone explains all covariance among securities.

The model is estimated each month in two steps. In the first step, we get preliminary estimates for the beta values \( (\beta_{it}) \) for each stock. To get the \( \beta_{it} \) values, we first run a traditional CAPM time series (60 months) regression of stock i’s return against the market to get \( B_i \).

\[ R_{it} = R_{ft} + B_i \ast (R_{mt} - R_{ft}) + \varepsilon_{it} \]  

\( B_i \) = preliminary estimate of beta on stock i  
\( \varepsilon_{it} \) = error term for stock i during period t under traditional CAPM assumptions

To improve the quality of fit of the model (\( e_{it} < \varepsilon_{it} \)), we can allow the beta values for each stock to vary over time. For example, it can be observed that highly levered companies have higher beta values. We could then imagine that a company that has just taken on a great deal of debt to finance an acquisition would have its beta increase. To capture the changes in beta values over time for a given company, we start by using a cross-sectional regression to estimate the relationships between beta values and company characteristics across the universe.
\[ B_i = \sum_{k=1}^{66} E_{ikt} \cdot \beta_{kt} + \zeta_{it} \]  
(3)

\[ \beta_{kt} = \text{sensitivity of beta values with respect to differences from stock to stock in exposure to fundamental characteristic k at time t} \]

\[ \zeta_{it} = \text{error term for the beta of stock i at time t} \]

We assume then that the \( \beta_{kt} \) values that are derived from an analysis across the universe of companies can then be applied to a single company as its characteristics change through time. Once we have the \( \beta_{kt} \) values, we estimate the contemporaneous value for \( \beta_{it} \).

\[ \beta_{it} = \sum_{k=1}^{66} E_{ikt} \cdot \beta_{kt} \]  
(4)

Incidentally, this rather complicated procedure for getting a beta has one additional benefit. We can get a reasonable estimate of beta for a stock with no return history, such as an initial public offering. Even though it has no return history, fundamental characteristics such as P/E, yield, and industry are immediately observable and equation (4) can still be used.

Once the beta values are estimated, we can substitute the \( \beta_{it} \) values into the equation (1) above and run a cross-sectional regression to estimate the \( \alpha_{kt} \) values. The observations in all cross-sectional regressions are weighted by square root of market capitalization. This weighting compensates for the skewness in the distribution of market capitalization. If the observations are equally weighted, the analysis is biased toward small capitalization names that are far more numerous. If the observations are capitalization weighted, the effective number of observations gets far too small for the large number of independent variables.

In this analysis, the return on the market (\( R_m \)) is the return on a reference universe of all US stocks with more than $250 million market capitalization. This return computation is weighted by square root of market capitalization.

The standardized fundamental variables used as factors in the model are:

- Earnings/Price
- Book/Price
- Dividend Yield
- Average Daily Volume/Shares Outstanding
- 52 Week Relative Strength
- Log of Market Capitalization
- EPS Variability
- EPS Growth Rate (blend of 5 Year historic and IBES Long Term Expected)
- Revenue/Price
- Debt/Equity
- Price Volatility ((52 Week High – 52 Week Low) / (52 Week High + 52 Week Low))

For the purpose of historic performance attribution, the usage of the model is simple. Since the factor exposures of each stock in portfolio sum to the factor exposures of the portfolio, equation (1) also holds for portfolios. Once all items in equation (1) have been estimated at the stock level we can calculate the beta and factor exposures for a given portfolio and immediately observe which “bets” paid off and which did not during a particular period.