Investment Analytics

QN ECM/10914
February 2006

QUANTNOTES™

PREDICTING MARKET DIRECTION

SUMMARY

- Although asset returns are essentially unforecastable, the same is not true for asset return signs (i.e. the direction-of-change).
- As long as expected returns are nonzero one should expect sign dependence, given the overwhelming evidence of volatility dependence.
- Even in assets where expected returns are zero, sign dependence may be induced by skewness in the asset returns process.
- Hence market timing ability is a very real possibility, depending on the relationship between the mean of the asset returns process and its higher moments.
- The highly nonlinear nature of the relationship means that conditional sign dependence is not likely to be found by traditional measures such as signs autocorrelations, runs tests or traditional market timing tests.
- Sign dependence is likely to be strongest at intermediate horizons of 1-3 months, and unlikely to be important at very low or high frequencies.
- A simple logit regression model captures the essentials of the relationship very successfully.
- Empirical tests demonstrate that sign dependence is very much present in actual US equity returns, with probabilities of positive returns rising to 65% or higher at various points over the last 20 years.

APPLICATIONS

- **Investment Strategy:** Optimization of balanced funds and other market timing investment strategies based on direction-of-change forecasts.
- **Portfolio Construction:** Portfolio rebalancing strategy based on sign predictions and forecasts of asset variance-covariance matrix.
- **Asset Allocation:** Tactical asset allocation strategy based on logit market timing model.
- **Derivatives Valuation & Trading:** Valuation and trading of digital options based on asset return sign forecasts.
- **Risk Management:** Adjustments to portfolio Value-at-Risk estimates based on direction-of-change forecasts.

RESOURCES WITH THIS QUANTNOTE

- **MatLab:** workspace with algorithms for logit model estimation
- **Excel:** workbook containing data and logit models
- **Mathematica:** notebook containing key mathematical derivations
- **Source journal article:** Christofferson, P. F., Diebold F. X., *Financial Asset Returns, Direction-of-Change Forecasting and Volatility Dynamics,* Penn Institute for Economic Research, Working Paper 04-009.

IN THIS QUANTNOTE:

Editor:

Jonathan Kinlay, PhD
Partner
Investment Analytics

Adjunct Professor
NYU Stern School

Sign Dynamics & Volatility Dynamics

"... despite having the same, constant expected return, the process has a greater chance of generating a positive return in the first case than in the second.

Thus volatility dynamics drive sign dynamics."

(Continued from page 1)
Asset return forecasting is central to active asset allocation. Short-run return forecasting, however, is viewed as difficult and perhaps even impossible. Consequently, conditional mean independence is viewed as a reasonable working approximation to asset return dynamics, although there is evidence of conditional mean dependence at very short (see Lo and MacKinlay, 1999) and at very long (e.g. Fama and Franch, 1988) time horizons.

Now consider dependence and hence forecastability in the sign of asset returns, or, equivalently, the direction-of-change. It may be possible to develop profitable trading strategies if one can successfully time the market, regardless of whether or not one is able to forecast the returns themselves.

There is substantial evidence that sign forecasting can often be done successfully. Relevant research on this topic includes Breen, Glosten and Jaganathan (1989), Leitch and Tanner (1991), Wagner, Shellans and Paul (1992), Pesaran and Timmerman (1995), Kuan and Liu (1995), Larsen and Wozniak (10050, Womack (1996), Gencay (1998), Leung Daouk and Chen (1999), Elliott and Ito (1999) White (2000), Pesaran and Timmerman (2000), and Cheung, Chinn and Pascual (2003).

There is also a huge body of empirical research pointing to the conditional dependence and forecastability of asset volatility. Bollerslev, Chou and Kramer (1992) review evidence in the GARCH framework, Ghysels, Harvey and Renault (1996) survey results from stochastic volatility modeling, while Andersen, Bollerslev and Diebold (2003) survey results from realized volatility modeling.

Sign Dynamics Driven By Volatility Dynamics

Let the returns process R_t be Normally distributed with mean μ and conditional volatility σ_t.

$$f = \frac{1}{\sigma_{t+1|t}\sqrt{2\pi}} \text{Exp}\left[-\frac{(R_{t+1}-\mu)^2}{2\sigma^2_{t+1|t}}\right];$$

The probability of a positive return $\Pr[R_{t+1} > 0]$ is given by the Normal CDF F=1-Prob[0,f]

$$F = \frac{1}{2}\left(1 + \text{Erf}\left[\frac{\mu}{\sqrt{2}\,\sigma_{t+1|t}}\right]\right)$$

For a given mean return, μ, the probability of a positive return is a function of conditional volatility σ_t. As the conditional volatility increases, the probability of a positive return falls, as illustrated in Figure 1 below with μ = 10% and σ_t = 5% and 15%. In the for-

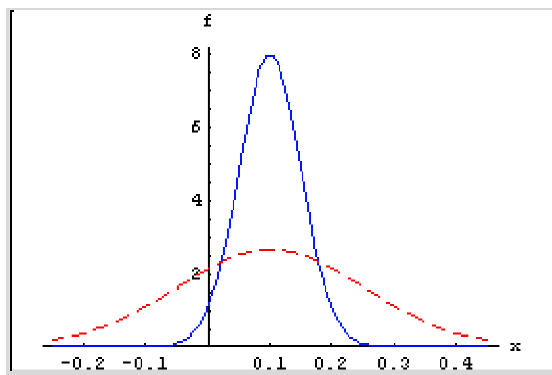


Figure 1: The Dependence of Sign Probability on Volatility

(Continued on page 3)

Asset Return Decomposition

We decompose the returns process R_t as follows:

$$R_{t+1} = sign\,(R_{t+1}) \bullet |R_{t+1}|$$

While the left hand side of the equation is essentially unforecastable, both of the right-hand-side components of returns display persistent dynamics and hence are forecastable. Both the signs of returns and magnitude of returns are conditional mean dependent and hence forecastable, but their product is conditional mean independent and hence unforecastable. This is an example of a nonlinear "common feature" in the sense of Engle and Kozicki (1993).

Sign Forecast Responsiveness

mer case, the probability of a positive return is greater because more of the probability mass lies to the right of the origin. Despite having the same, constant expected return of 10%, the process has a greater chance of generating a positive return in the first case than in the second. Thus volatility dynamics drive sign dynamics.

Responsiveness of Sign Forecasts to Changes in Volatility

The probability of a positive return, F, is not monotonic in σ_t as can bee seen by taking the derivative:

```
∂σ F // FullSimplify
```

$$-\frac{e^{-\frac{\mu^2}{2\sigma^2_{t+1|r}}}\,\mu}{\sqrt{2\pi}\,\sigma^2_{t+1|r}}$$

Let us denote this measure of 'responsiveness' by ξ_t .

Sign responsiveness is not monotonic in σ_t but attains an interior minimum. Figure 2 illustrates the case with μ = 10% .

The plots in Figures 3 and 4 give a more general indication of the location of the minima in the responsiveness curves for different drift and volatility levels.

More generally,

$$\xi_t = -\frac{e^{-\frac{\mu^2}{2\sigma^2_{t+1|r}}}\,\mu}{\sqrt{2\pi}\,\sigma^2_{t+1|r}};$$

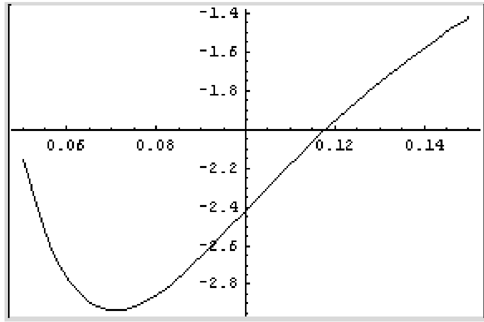


Figure 2: Responsiveness of Sign probability to Changes in Volatility

We can locate the maximum value of ξ_t by taking the derivative with respect to σ :

$$\partial_\sigma \xi_t$$

$$-\frac{e^{-\frac{\mu^2}{2\sigma^2}}\,\mu^3}{\sqrt{2\pi}\,\sigma^5} + \frac{e^{-\frac{\mu^2}{2\sigma^2}}\sqrt{\frac{2}{\pi}}\,\mu}{\sigma^3}$$

Solving for σ gives the solution :

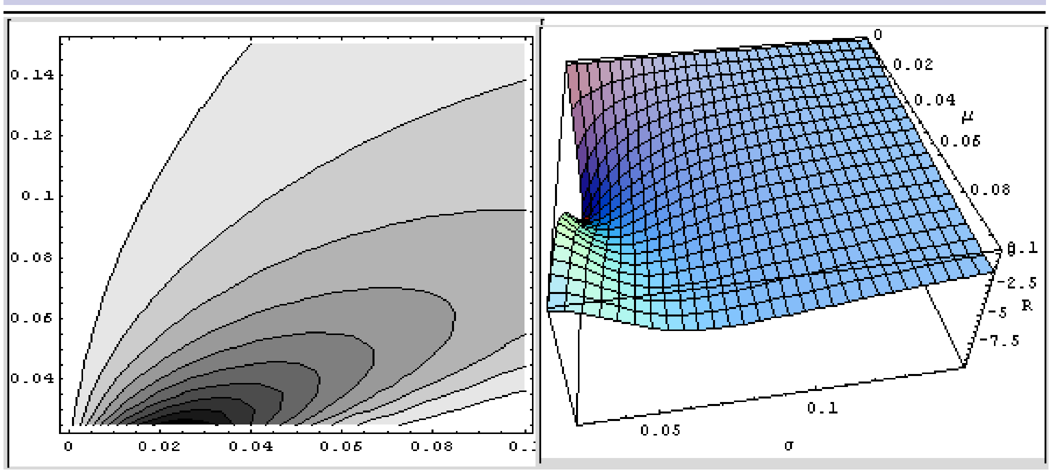
$$\sigma = \frac{\mu}{\sqrt{2}}$$

What this tells us is that for very small values of

(Continued on page 4)

" What this tells us is that for very small values of σ responsiveness is low because the probability of a positive return cannot deviate much from 1. Similarly, for large values of σ, the probability must remain close to 1/2. It is at intermediate values of s that responsiveness is greatest and forecastability is maximized when s is low, but not too low, in relation to μ. "

Figures 3&4: Contour and 3-D Plots of Sign Prediction Responsiveness



MEASURING SIGN FORECASTABILITY

“. . . there is no information contained in the number of runs that is not also in the first-order autocorrelation of the sequence.

So runs tests are no more likely to find evidence of sign predictability than autocorrelation tests. ”

(Continued from page 3)

σ responsiveness is low because the probability of a positive return cannot deviate much from 1. Similarly, for large values of σ, the probability must remain close to 1/2. It is at intermediate values of σ that responsiveness is greatest and forecastability is maximized when σ is low, but not too low, in relation to μ. With an expected return μ of 10%, $\sigma_{t+1|t}$ of 7.1% implies quite a high conditional information ratio $\mu / \sigma_{t+1|t}$.
As the researchers point out, the frequency with which conditional volatility hits the “sweet spot” depends on the volatility of volatility of the process.

Correlation Between Sign Forecasts and Realizations

It is easy to show that the correlation between I_{t+1}, the indicator variable of an ex-post realized positive return and $P_{t+1|t}$, the conditional probability of a positive return, is given by the expression:

$$Corr\left(I_{t+1},\ P_{t+1|t}\right) = \frac{Std\left(P_{t+1|t}\right)}{\sqrt{P\,(1-P)}}$$

Where P is the unconditional probability of a positive return.
Hence the correlation between sign forecasts and realizations depends only on the standard deviation of the forecast. A high standard deviation of the conditional probability forecast, which could arise from a high variance of the conditional variance, will increase the forecastability of the return sign. This suggests focusing on asset processes with high levels of kurtosis.

One can also show that:

$$Corr\left(I_{t+1},\ I_t\right) = Corr\left(I_{t+1},\ P_{t+1|t}\right) Corr\left(I_t,\ P_{t+1|t}\right)$$

Hence

$$Corr\left(I_{t+1},\ I_t\right) < Corr\left(I_{t+1},\ P_{t+1|t}\right)$$

The lower the correlation between today’s sign and today’s forecast of tomorrow’s sign, the lower the autocorrelation in the sign itself.
Conversely, notice that if the sign forecast were linear in the current realization then the correlation between today’s sign and today’s forecast of tomorrow’s sign would be one, and the autocorrelation would coincide with the correlation between the ex-ante predictor and ex-post realization.
Consequently it is the non-linearity in the dynamic process of the indicator sequence that lowers the autocorrelation relative to the cross-correlation between the ex-ante predictor and the ex-post realization. The bottom line is that sign predictability will not show up in sign autocorrelations, because of the non-linearity of the relationship between the forecast and actual sign sequences.

Runs Tests

A run is a sequence of consecutive zeros or ones. Hence the number of runs is the number of switches from 0 to 1, plus the number of switches from 1 to 0, plus 1. Hence

$$N_{runs} = 1 + \sum_{t=1}^{T} \left(1 - I_t\right) I_{t+1} + \sum_{t=1}^{T} \left(1 - I_{t+1}\right) I_t$$

Solving for $\Sigma I_t I_{t+1}$ and substituting into the formula for Corr(I_t,I_{t+1}) earlier yields the result

$$\widehat{Corr}\left(I_{t+1},\ I_t\right) = 1 - \frac{N_{runs} - 1}{2\,\Sigma I_t \left(1 - \frac{1}{T}\,\Sigma I_t\right)}$$

This makes clear that there is no information contained in the number of runs that is not also in the first-order autocorrelation of the sequence. So runs tests are no more likely to find evidence of sign predictability than autocorrelation tests.

Market Timing Tests

Hendriksson and Merton (1981) develop the “bull-bear” test statistic for market timing ability $p_1 + p_2 - 1$, where p_1 is the probability of correctly forecasting a positive return and p_2 is the probability of correctly forecasting a negative return.
Breen, Glosten and Jaganathan (1989) show that in the regression,

$$I\left(R_{t+1} > 0\right) = a + bI\left(P_{t+1|t} > 0\right) + e_{t+1}$$

we have that $b = p_1 + p_2 - 1$. Hence the absence of market timing ability in the sense of Hendriksson and Merton (1981) corresponds to a routine significance test of the null hypothesis $b = 0$.

The key point is that in these tests and others like them, for example the Pesaran and Timmermann (1992) sign test, $P_{t+1|t}$ enters through the indicator function $I(P_{t+1|t} > 0)$. This means that, while a value of 0.4999 is treated fundamentally differently from a value of 0.5001, the latter is treated no differently than a value of 0.9999. If $P_{t+1|t}$ never drops below 0.5 these tests will have no power. This is likely to happen for asset processes with constant, positive expected return, where the sign predictability enters via volatility dynamics rather than via variation in expected

(Continued on page 5)

HIGHER MOMENTS & SIGN PRECITION

(Continued from page 4)
returns.
The bottom line is that market timing tests lack power to detect sign predictability that arises from volatility dynamics rather than dynamics in expected returns.

"The bottom line is that market timing tests lack power to detect sign predictability that arises from volatility dynamics rather than dynamics in expected returns."

Higher Order Moments and Sign Prediction

$$\text{Define}: \phi = \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}}; \quad \text{domain}[\phi] = \{z, -\infty, \infty\}; \quad \text{and}$$

$$\Phi = \frac{1}{2} - \frac{1}{2}\,\text{Erf}\left[\frac{z}{\sqrt{2}}\right]$$

$$\text{where } z_{t+1|t} = \frac{R_{t+1|t} - \mu}{\sigma_{t+1|t}} \text{ are the normalized returns}$$

The CDF of the probability of positive return sis then:

$$1 - F \;/.\; z \to -\frac{\mu}{\sigma_{t+1|t}} =$$

$$\frac{1}{2} - \frac{1}{2}\,\text{Erf}\left[\frac{\mu}{\sqrt{2}\,\sigma_{1+t|t}}\right] +$$

$$\frac{1}{\sqrt{2\pi}}\left(e^{-\frac{\mu^2}{2\sigma^2_{1+t|t}}}\left(\frac{1}{6}\left(-1 + \frac{\mu^2}{\sigma^2_{1+t|t}}\right)\gamma_{3,1+t|t} + \frac{1}{24}\left(-\frac{\mu^3}{\sigma^3_{1+t|t}} + \frac{3\mu}{\sigma_{1+t|t}}\right)\gamma_{4,1+t|t}\right)\right)$$

The above result shows that, even in the absence of volatility dynamics, the probability of positive returns us time-varying for nonzero μ so long as either the third or fourth conditional moments is time-varying.
We can take this even further and show that even if μ is zero the probability of positive returns becomes

$$1 - F \;/.\; z \to 0 = \frac{1}{2} - \frac{\gamma_{3,1+t|t}}{6\sqrt{2\pi}}$$

which is time-varying as long the conditional skewness is present. Note that negative skewness implies a probability of positive returns greater than 1/2.

Forecasting S&P 500 Direction

"The period around the mid-1990's is characterized by probabilities of positive excess returns of around 0.65, followed by an extended downward trend to the 2002 low. Probabilities thereafter trend steadily upwards throughout 2003 and 2004 and remain relatively high into 2005.

It is also noteworthy that the extreme lows in sign probabilities precede the sustained market rallies commencing towards the end of 1987, 1990, 1998, and 2002."

Logit Regression Model

The analysis indicates the possibility of sign predictability being induced by volatility or higher moment dynamics. We now turn to the task of developing a model that will enable us potentially to exploit sign predictability. One candidate for such a model is a logit regression of the form

$$I_{t+n} = f\left(\frac{\mu}{\sigma_t}\right) + e_{t+n}$$

Where I_{t+30} is the sign indicator taking the value 1 if $R_{t+1,t+30} > 0$ and σ_t denotes a forecast of n-day excess return volatility. An obvious choice of f is the logistic density

$$f = \frac{e^{-x}}{(1 + e^{-x})^2}; \quad \text{domain}[f] = \{x, -\infty, \infty\};$$

which gives rise to the familiar logit regression.

We develop such a model to forecast 30-day returns signs for the S&P 500 Index using the VIX Index as our forecast of 30-day volatility and regressing I_{t+30} on $1/VIX_t$ and estimating the model by maximum likelihood.

Estimated Probabilities of Positive Excess Return

Estimates of the 30-day drift coefficient μ for the period January 1986 to December 1995 are shown in Figure 5.

Of particular note is the steady decline in estimated mean excess returns from 1987 through 1994 and the reversal of the trend from 1995 through 1999.

Estimates of the probability of positive excess returns are plotted in Figure 6. The range of estimates is strikingly wide, from a low of just under 0.54 in September 2002 to a high of over 0.7 in August 1987. The period around the mid-1990's is characterized by probabilities of positive excess returns of around 0.65, followed by an extended downward trend to the 2002 low. Probabilities thereafter trend steadily upwards throughout 2003 and 2004 and remain relatively high into 2005. It is also noteworthy that the extreme lows in sign probabilities precede the sustained market rallies commencing towards the end of 1987, 1990, 1998, and 2002.

Estimated Drift for 30-Day Excess Returns in the S&P 500 Index

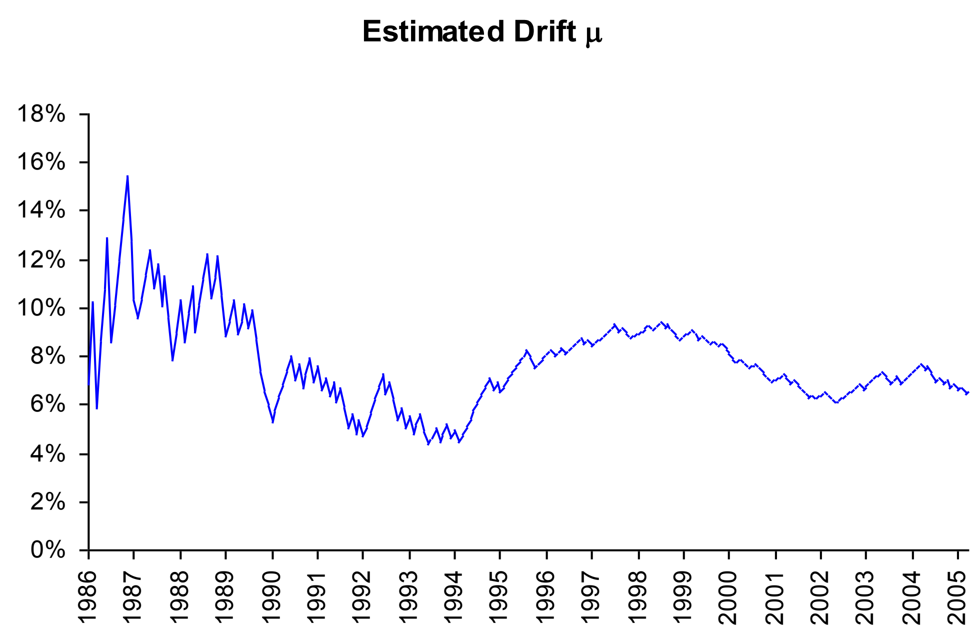


Figure 5

Responsiveness Estimates

Responsiveness

The responsiveness of the sign probability forecast to changes in the VIX is given by the marginal effect ξ_t and plotted in Figure 7.

As predicted by theory, the marginal effect is always negative and is largest in absolute terms when volatility is low, as it was in the mid 1990's and again in 2005.

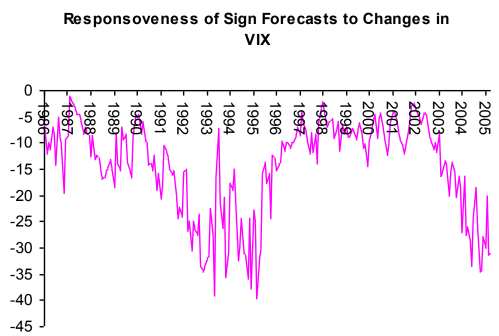


Figure 7: Time Series of Responsiveness of Sign Forecasts to Changes in VIX

A scatterplot of ξ_t against VIX, shown in Figure 8, aligns closely with the pattern expected from theory (as illustrated in Figure 2).

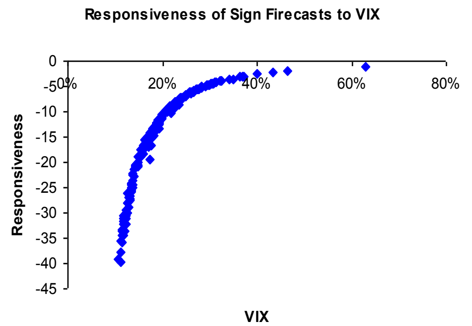


Figure 8: Scatterplot of Responsiveness of Sign Forecasts vs. VIX Index

Conditional Probability of Positive 30-Day Excess Returns in the S&P500 Index

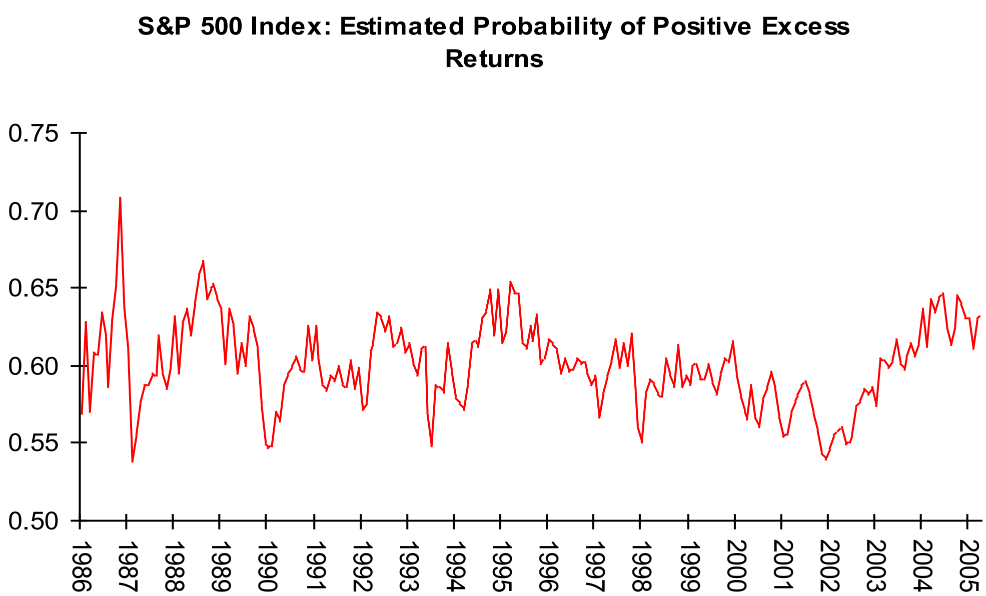


Figure 6

Software:

Case Study:

Logit Regression Model for Excess Returns in the S&P 500 Index

Excel Workbook:

SP500 Logit.xls

Data and analysis for Logit regression model.

Mathematica:

LogitModel.nb

Notebook containing mathematical derivations and formula

MatLab:

EstimateLogit.m

MatLab routines for estimating Logit regression, Uses James LeSage's econometrics package—see p10.

LOGIT MODEL TRADING STRATEGY

"The strategy performs exceptionally well in 1987, 1989 and 1995, when the ratio between expected returns and volatility remains close to optimum levels and the direction of the S&P 500 Index becomes highly predictable,

Of equal interest is the finding that the strategy largely avoids the market crash of 2000-2002 altogether. "

Trading Strategy

To illustrate some of the possibilities of this approach, we constructed a simple market timing strategy in which a position was taken in the S&P 500 index or in 90-Day T-Bills, depending on an ex-ante forecast of positive returns from the logit regression model (and using an expanding window to estimate the drift coefficient). We assume that the position is held for 30 days and rebalanced at the end of each period. In this test we make no allowance for market impact, or transaction costs.

Results

Annual returns for the strategy and for the benchmark S&P 500 Index are shown in Figure 9. The strategy performs exceptionally well in 1987, 1989 and 1995, when the ratio between expected returns and volatility remains close to optimum levels and the direction of the S&P 500 Index is highly predictable, Of equal interest is that the strategy largely avoids the market crash of 2000-2002 altogether, a period in which sign probabilities were exceptionally low.

In terms of overall performance, the model enters the market in 113 out of a total of 241 months (47%) and is profitable in 78 of them (69%). The average gain is 7.5% vs. an average loss of –4.11% (ratio 1.83). The compound annual return is 22.63%, with an annual volatility of 17.68%, alpha of 14.9% and Sharpe ratio of 1.10.

The under-performance of the strategy in 2003 is explained by the fact that direction-of-change probabilities were rising from a very low base in Q4 2002 and do not reach trigger levels until the end of the year. Even though the strategy out-performed the Index by a substantial margin of 6% , the performance in 2005 is of concern as market volatility was very low and probabilities overall were on a par with those seen in 1995. Further tests are required to determine whether the failure of the strategy to produce an exceptional performance on par with 1995 was the result of normal statistical variation or due to changes in the underlying structure of the process requiring model recalibration.

Future Research & Development

The obvious next step is to develop the approach described above to formulate trading strategies based on sign forecasting in a universe of several assets, possibly trading digital options. The approach also has potential for asset allocation, portfolio theory and risk management applications.

PRO-FORMA ANNUAL RETURNS

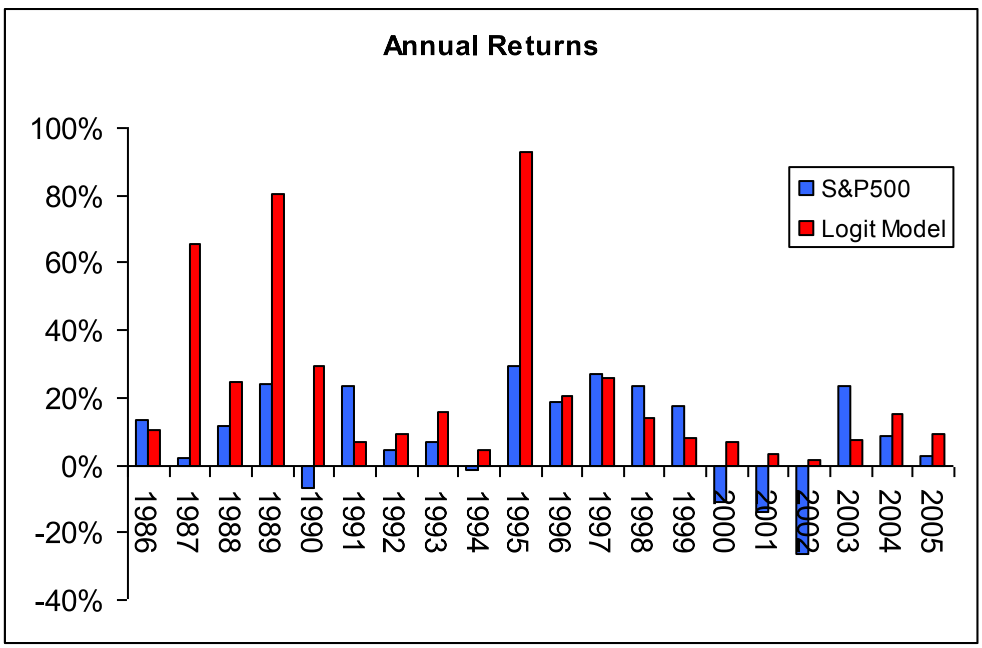


Figure 9

REFERENCES

Andersen, Torben G., Luca Benzoni, and Jesper Lund, 2000, Estimating jump-diffusions for equity returns, Manuscript, Kellogg Graduate School of Management.
Andersen, Torben G., Tim Bollerslev, and Francis X. Diebold, 2003, Parametric and nonparametric volatility measurement, in L.P. Hansen and Y. Ait-Sahalia (eds.), *Handbook of Financial Econometrics*. Amsterdam: North-Holland, forthcoming.
Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Heiko Ebens, 2001, The distribution of realized stock return volatility, *Journal of Financial Economics* 61, 43-76.
Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2001, The distribution of realized exchange rate volatility, *Journal of the American Statistical Association* 96, 42-55.
Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2003, Modeling and forecasting realized volatility, *Econometrica* 71, 579-626.
Bakshi, Gurdip, and Charles Cao (2003), Risk-neutral kurtosis, jumps and option pricing: evidence from 100 most actively traded firms on the CBOE, Manuscript, University of Maryland.
Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 1997, Empirical performance of alternative option pricing models, *Journal of Finance* 52, 2003-2049.
Balvers, Ronald J., Thomas F. Cosimano, and Bill McDonald, 1990, Predicting stock returns in an efficient market, *Journal of Finance* 45, 1109-1128.
Bates, David, 2000, Post-'87 crash fears in the S&P 500 futures option market, *Journal of Econometrics* 94, 181-238.
Bawa, Vijay S., 1978, Safety-first, stochastic dominance, and optimal portfolio choice, *Journal of Financial and Quantitative Analysis* 13, 255-271.
Bollerslev, Tim, Ray Y. Chou, and Kenneth F. Kroner, 1992, ARCH modeling in finance: A selective review of the theory and empirical evidence, *Journal of Econometrics* 52, 5-59.
Brandt, Michael W. and Qiang Kang, 2003, On the relationship between the conditional mean and volatility of stock returns: a latent VAR approach, *Journal of Financial Economics*, forthcoming.
Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989, Economic significance of predictable variations in stock index returns, *Journal of Finance* 44, 1177-1189.
Brock, William A., and Cars H. Hommes, 1997, A rational route to randomness, *Econometrica* 65, 1059- 1095.
Busse, Jeffrey A., 1999, Volatility timing in mutual funds: evidence from daily returns, *Review of Financial Studies* 12, 1009-1041.
Campbell, John, Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets*. Princeton: Princeton University Press.
Campbell, John, and Robert Shiller, 1988, Stock prices, earnings and expected dividends, *Journal of Finance* 46, 661-676.
Chernov, Mikhail, A. Ronald Gallant, Eric Ghysels, and George Tauchen, 2001, Alternative models for stock price dynamics, Manuscript, University of North Carolina.
Chernov, Mikhail, and Eric Ghysels, 2000, A Study towards a unified approach to the joint estimation of objective and risk neutral measures for the purpose of option valuation, *Journal of Financial Economics* 56, 407-458.
Cheung, Yin-Wong, Menzie D. Chinn, and Antonio G. Pascual, 2003, Empirical exchange rate models of the nineties: are any fit to survive?, NBER Working Paper 9393.
Christoffersen, Peter F., and Francis X. Diebold, 1996, Further results on forecasting and model selection under asymmetric loss, *Journal of Applied Econometrics* 11, 561-572.
Christoffersen, Peter F., and Francis X. Diebold, 1997, Optimal prediction under asymmetric loss, *Econometric Theory* 13, 808-817.
Cumby, Robert E., and David M. Modest, 1987, Testing for market timing ability: a framework for forecast evaluation, *Journal of Financial Economics* 19, 169-89.
Darolles, Serge, Christian Gourieroux, and Joanna Jasiak, 2001, Compound autoregressive models, Manuscript, York University.
Duffie, Darrell, Jun Pan, and Kenneth Singleton, 2000, Transform analysis and asset pricing for affine jump-diffusions, *Econometrica* 68, 1343-1376.
El Babsiri, Mohamed, and Jean-Michel Zakoian, 2001, Contemporaneous asymmetry in GARCH processes, *Journal of Econometrics* 101, 257-294.
Elliott, Graham, and Takatoshi Ito, 1999, Heterogeneous expectations and tests of efficiency in the Yen/Dollar forward foreign exchange market, *Journal of Monetary Economics* 43, 435-456.
Engle, Robert F., and Sharon Kozicki, 1993, Testing for common features, *Journal of Business andEconomic Statistics* 11, 369-380.
Eraker, Bjorn, Michael Johannes, and Nicholas Polson, 2000, The role of jumps in returns and volatility, *Journal of Finance*, forthcoming.
Estrella, Arturo, 1998, A new measure of fit for equations with dichotomous dependent variables, *Journal of Business and Economic Statistics* 16, 198-205.
Fama, Eugene F., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of* Fama, Eugene F., 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575-1617.
Fama, Eugene, and Kenneth French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 19, 3-29.
Fama, Eugene, and Kenneth French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.
Ferson, Wayne E., and Campbell R. Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527-566.
Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2001, The economic value of volatility timing, *Journal of Finance* 56, 329-352.
Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2003, The economic value of volatility timing using realized volatility, *Journal of Financial Economics* 67, 473-509.
Fontnouvelle, Patrick de, 2000, Information dynamics in financial markets, *Macroeconomic Dynamics* 4,139-169.
Foster, Douglass, Tom Smith, and Robert Whaley, 1997, Assessing goodness-of-fit of asset pricing models: the distribution of the maximal R2, *Journal of Finance* 52, 591-607.
Franses, Philip Hans, and Dick van Dijk, 2000, *Nonlinear Time Series Models in Empirical Finance*. Cambridge: Cambridge University Press.
French, Kenneth R., G. William Schwert and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3-29.
Gencay, Ramazan, 1998, Optimization of technical trading strategies and the profitability in security markets, *Economics Letters* 59, 249-254.
Ghysels, Eric, Andrew Harvey, and Eric Renault, 1996, Stochastic volatility, in G.S. Maddala and C.R. Rao (eds.), *Statistical Methods in Finance* (Handbook of Statistics, Volume 14). Amsterdam: North-Holland.
Glosten Lawrence R., Ravi Jaganathan, and David E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-1801.
Granger, Clive W.J., 1969, Prediction with a generalized cost of error function, *Operational Research Quarterly* 20, 199-207.
Gross, Leon, Joanna Keh, Sara Leventhal and Olivier Sarfati , 2003, Individual implied volatility predicts future stock movement, Research Report, Equity Derivative Sales, Citigroup.
Hagigi, Moshe, and Brian Kluger, 1987, Safety first: an alternative performance measure, *Journal of Portfolio Management* 13, 34-40.
Hansen, Bruce E., 1994, Autoregressive conditional density estimation, *International Economic Review* 35, 705-730.
Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263-1296.
Harvey, Campbell R., and Robert Whaley, 1992, Market volatility prediction and the efficiency of the S&P 100 index option market, *Journal of Financial Economics* 31, 43-73.
Henriksson, Roy D, and Robert C. Merton, 1981, On market timing and investment performance, II: statistical procedures for evaluating forecasting skills, *Journal of Business* 54, 513-33.
Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.
Jensen, Michael C., 1978, Some anomalous evidence regarding market efficiency, *Journal of Financial Economics* 6, 95-101.
Johannes, Michael, Nicholas Polson and Jon Stroud, 2002, Sequential optimal portfolio performance: market and volatility timing, Manuscript, Graduate School of Business, Columbia University.
Jones, Christopher, 1999, The dynamics of stochastic volatility, Manuscript, University of Rochester.
Kirby, Chris, 1997, Measuring the predictable variation in stock and bond returns, *Review of Financial Studies* 10, 579-630.
Kuan, Chung-Ming, and Tung Liu, 1995, Forecasting exchange rates using feed-forward and recurrent neural networks, *Journal of Applied Econometrics* 10, 347-64.
Larsen, Glen A. Jr, and Gregory D. Wozniak, 1995, Market timing can work in the real world, *Journal of Portfolio Management* 21, 74-81.
Leitch, Gordon, and J. Ernest Tanner, 1991, Economic forecast evaluation: profits versus the conventional error measures, *American Economic Review* 81, 580-590.
Lettau, Martin, and Sydney Ludvigson, 2003, Measuring and modeling variation in the risk-return tradeoff, in Yacine Ait-Shalia and Lars Peter Hansen (eds.), *Handbook of Financial Econometrics*, forthcoming.
Leung, Mark T., Hazem Daouk, and An-Sing Chen, 1999, Forecasting stock indices: a comparison of classification and level estimation models, working paper, Indiana University.
Levich, Richard M., 2001, *International Financial Markets*, Second Edition. New York: McGraw-Hill.
Lo, Andrew W., and A. Craig MacKinlay, 1999, *A Non-Random Walk Down Wall Street*. Princeton, NJ: Princeton University Press.
Mankiw, N. Gregory, David Romer, and Matthew D. Shapiro, 1991, Stock market forecastability and volatility: a statistical appraisal, *Review of Economic Studies* 58, 455-77.
Meddahi, Nour, 2001, An eigenfunction approach for volatility modeling, Manuscript, University of Montreal.
Meddahi, Nour, and Eric Renault, 2000, Temporal aggregation of volatility models, working paper, CIRANO.
Merton, Robert C., 1981, On market timing and investment performance, I: an equilibrium theory of value for market forecasts, *Journal of Business* 54, 363-406.
Nelson, Charles and Myung Kim, 1993, Predictable stock returns: the role of small sample bias, *Journal of Finance* 48, 641-661.
Pan, Jun, 2000, Integrated time-series analysis of spot and option prices, Manuscript, Sloan School of Management, MIT.
Patelis, Alex D., 1997, Stock return predictability and the role of monetary policy, *Journal of Finance* 52, 1951-1972.
Pesaran, Hashem, and Allan G. Timmermann, 1992, A simple non-parametric test of predictive performance, *Journal of business and economic statistics* 10, 461-465.
Pesaran, M. Hashem, and Allan G. Timmermann, 1995, Predictability of stock returns: robustness and economic significance, *Journal of Finance* 50, 1201-1228.
Pesaran, M. Hashem, and Allan G. Timmermann, 2001, How costly is it to ignore breaks when forecasting the direction of a time series?, Manuscript, Cambridge University and UCSD.
Rattray, Sandy and Venkatesh Balasubramanian, 2003, The new VIX as a market signal – it still works, Research Report, Equity Derivatives Strategy, Goldman Sachs.
Roy, A.D. 1952, Safety-first and the holding of assets, *Econometrica* 20, 431- 449.
Rydberg, Tina H. and Neil Shephard, 2003, Dynamics of trade-by-trade price movements: decomposition and models, *Journal of Financial Econometrics* 1, 2-25.
Schwert, G.William, 1989, Why does stock market volatility change over time?, *Journal of Finance* 44, 1115-1153.
Schwert, G.William, 1990a, Stock market volatility, *Financial Analysts Journal*, May-June, 23-34.
Schwert, G.William, 1990b, Stock volatility and the crash of '87, *Review of Financial Studies* 3, 77-102.
Schwert, G.William and P.J. Seguin, 1991, Heteroskedasticity in stock returns, *Journal of Finance* 45, 1129-1155.
Sentana, Enrique, and Sushil Wadhwani, 1991, Semi-parametric estimation and the predictability of stock market returns: some lessons from Japan, *Review of Economic Studies* 58, 547-563.
Stutzer, Michael, 2001, A portfolio performance index and its implications, Manuscript, University of Iowa.
Sweeney, Richard J., 1986, Beating the foreign exchange market, *Journal of Finance* 41, 163-182.
Wagner, Jerry, Steve Shellans, and Richard Paul, 1992, Market timing works where it matters most: in the real world, *Journal of Portfolio Management* 18, 86-90.
Whaley, Robert, 2000, The investor fear gauge, *Journal of Portfolio Management* 26, 12-27.
White, Halbert, 2000, A reality check for data snooping, *Econometrica* 68, 1097-1126.
Whitelaw, Robert F., 1997, Time-varying Sharpe ratios and market timing, Manuscript, NYU, Stern School of Business.
Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

End Notes

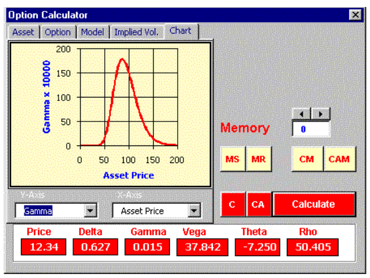
Analytics Tools

www.investmet-analytics.com/analytics

For this QuantNote:

- **MatLab programs**
- **Mathematica programs**
- **Excel/VB programs**

Other Analytics Tools



Clip-On Tools—Option Calculator V2.4

The Clip-On Toolkit provides state-of-the-art financial calculators in a convenient pop-up format for rapid-fire computations across a range of financial products.

Option Calculator Features

- Pricing of EU or American Options
- Equity, Currency or Futures
- OTC and Exotics
- Risk Sensitivity Analysis
- Risk Graphics
- Option Position Analysis
- Volatility Surface Modeling
- Multi-Function Memory
- Option Dataset Storage
- Functions Available in Excel

Time Series Modeling V4.16

This powerful and flexible time series modelling package (formerly known as TSMod, now TSM) estimates and forecasts ARIMA and ARFIMA models, several GARCH, FIGARCH, APARCH and EGARCH variants, bilinear models, Markov-switching and smooth transition models. Most model features can be freely combined. More details: http://www.timeseriesmodelling.com/

Volatility Arbitrage Program

The Investment Analytics Volatility Arbitrage Program uses proprietary econometric forecasting and multi-factor option pricing models to identify arbitrage opportunities in listed options series. Details: http://www.investment-analytics.com/volarbprogram.htm

Sponsors

Education

- **Lecture Notes**
  http://www.investment-analytics.com/lecture%20notes.htm

Finance Professors

- **Francis Diebold**
  http://ww.ssc.upenn.edu/~fdiebold/
- **James LeSage**
  http://www.econ.utoledo.edu/faculty/lesage/lesage.html
- **Hashem Pesaran**
  http://www.econ.cam.ac.uk/faculty/Pesaran/
- **Allan Timmermann**
  http://weber.ucsd.edu/~atimmerm/

Academic Research

- **IDEAS**
  http://ideas.uqam.ca/ideas/data/
  Claims to be the largest bibliographic database dedicated to economics on the Internet.
- **ResearchIndex**
  http://citeseer.nj.nec.com/cs
  Over 300,000 documents & 4 million citations.
- **SSRN**
  http://www.ssrn.com/
  Leading research delivered to your desktop.

CONTACT US

Phone: +1 (212) 786-1781
Fax: +1 (212) 208 2492

Editorial:
editor@investment-analytics.com

Advertising:
ads@investment-analytics.com

News/info/events:
info@investment-analytics.com

Web Site:
www.investment-analytics.com

Investment Analytics provides independent research focusing on applications of sophisticated mathematical and financial modeling techniques to problems of strategy development and repair, performance analysis and risk management for clients in the investment management industry in Europe and North America.

Our methodology represents a radical departure from traditional methods of research and is based instead on advanced techniques of quantitative finance that have proved highly successful in tackling complex problems in financial engineering and investment analysis. Investment Analytics has applied these powerful and robust techniques to the field of equity analysis, to bring fresh insights and a whole new approach to investment research

Register on our web site
www.investment-analytics.com