Volatility Analysis

of

Healthcare

Stocks

January 2002

Summary

The volatility processes of the group of healthcare stocks studied in this analysis are well conditioned and highly correlated. All show a high degree of persistency, having fractional integration parameters well in excess of that of a purely random (White Noise) process. These long memory effects can be modeled to produce volatility direction forecast accuracy at levels averaging 70% or higher. There is evidence that subgroups exist which are fractionally cointegrated of order (d,0), with 0.2 < d < 0.3, indicating the potential for statistical arbitrage of volatility baskets. Once such basket comprises ABT, BMY, JNJ and PFE, which together account for over 71% of the variation in the volatility of the Major Drug Manufacturers Index.

Our conclusion is that dispersion trading of this group may well produce abnormal returns, although further testing would be required to confirm this and to determine the optimal investment mechanisms. In addition, there may be further strategies that could be developed on the basis of the insights from this research, such as covered call writing and other yield enhancement strategies. It is possible also that the research would provide useful insights applicable in the area of merger arbitrage.

Data Analysis

We analyzed monthly data over the period from Jan 1985 to Nov 2001 for the following stocks: ABT, AHP, AMGN, BAX, BMY, CI, JNJ, LLY, MDT, PFE, PHA, SGP. In addition the analysis included industry indices for Medical Instruments and Major Drug Manufacturers.

Volatility was computed using our proprietary range-based volatility metric, which has the benefit of superior estimation efficiency and distributional properties. Sample volatility time series are illustrated below.

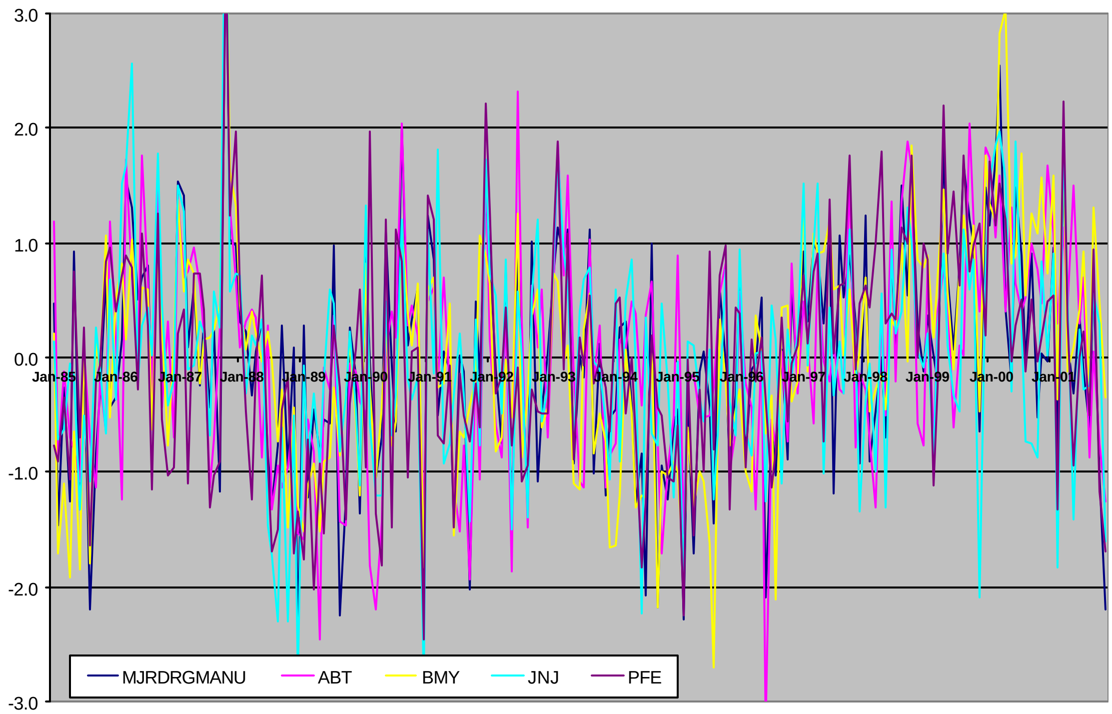

Fig 1. Volatility time series for selected healthcare stocks

All of the volatility series are well conditioned having stable distributions that are typically Gaussian. Kolmagorov-Smirnov, Lilliefors and the more powerful Shapiro-Wilk test all fail to reject the null hypothesis of Normally distributed volatility, by a substantial margin in most cases. This has important, positive implications for modeling of the volatility processes. Figure two illustrates a typical volatility distribution.

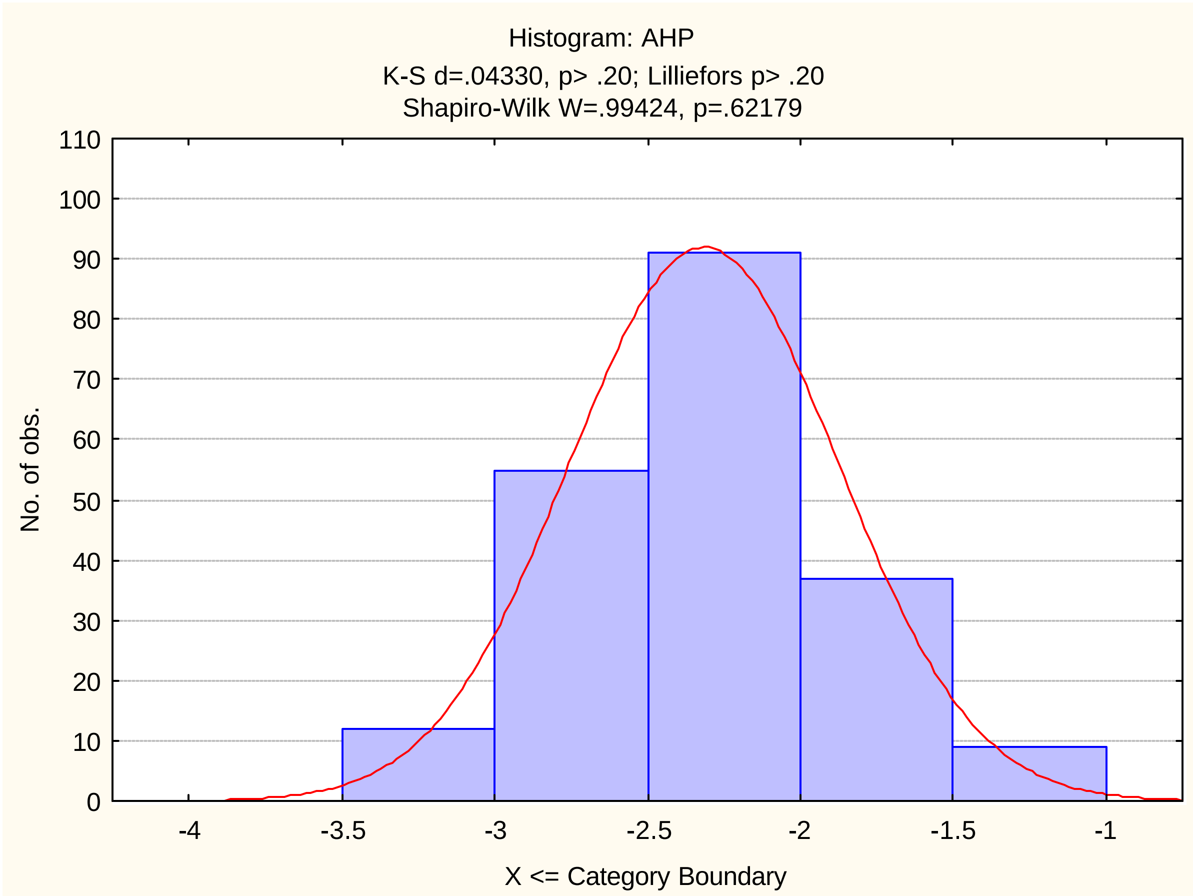

Fig 2. Volatility distribution for AHP

Volatility Factorization

Our metric of volatility can be related to the usual standard deviation measure using a simple volatility factorization model. This breaks down standard deviation into two components: a range-based metric (which we refer to as Vol) and its standard deviation (which we refer to as the volatility of volatility, or Vvol). The advantage of this approach is that it enables us to better model the long memory effects in the volatility process and hence produce more accurate forecasts. Most of the variation in returns standard deviation can be explained by these two factors, as the following regression summary shows. Conversely, measurement of Vol and Vvol enable accurate estimates of standard deviation to be obtained, as figure 3 illustrates.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	94%
R Square	89%
Adjusted R Square	87%
Standard Error	2.49%
Observations	18

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.072432	0.036216	58.23357	8.5E-08
Residual	15	0.009329	0.000622		
Total	17	0.081761			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.5951	7.1%	8.419117	0.00%	0.4444	0.7457
Vol	0.2456	2.3%	10.76429	0.00%	0.1970	0.2943
Vvol	0.5175	17.4%	2.977961	0.94%	0.1471	0.8878

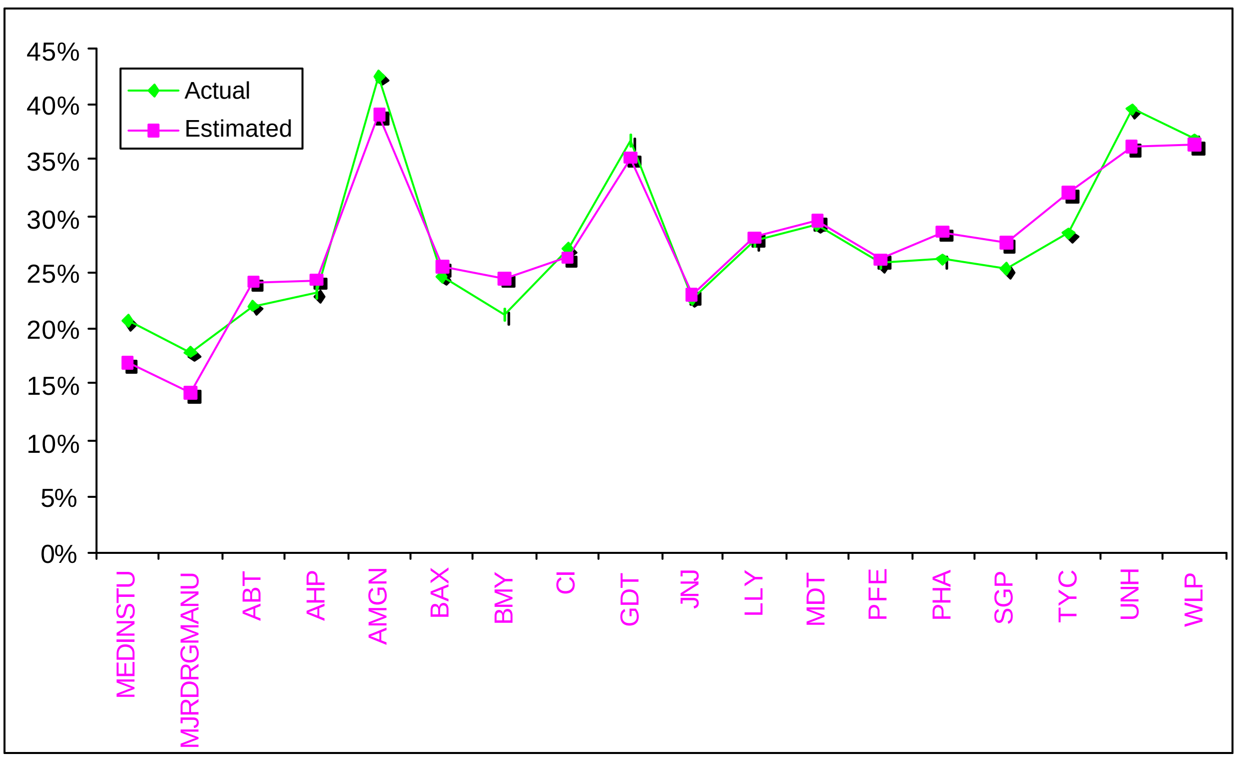

Fig 3. Volatility factorization & estimation

Long Memory

We next examine the long memory properties of the volatility processes. Long memory persistence is an important characteristic of financial processes in general, and volatility processes in particular. The basic idea is that shocks to the process continue to effect it over long periods of time and events that occur many months in the past continue to have a significant impact on the process today. Autocorrelations follow a slow-decaying hypergeometric pattern of the form:

$$r(t) \sim L(t)t^{2d-1} \quad as\ t \to \infty, 0 < d < \frac{1}{2}$$

Models that are capable of capturing such effects can, in principle, produce more accurate forecasts of future volatility.

An examination of the pattern of autocorrelations in the drug stock volatility processes reveals clear evidence of this pattern of slow decay as figure 4 illustrates.

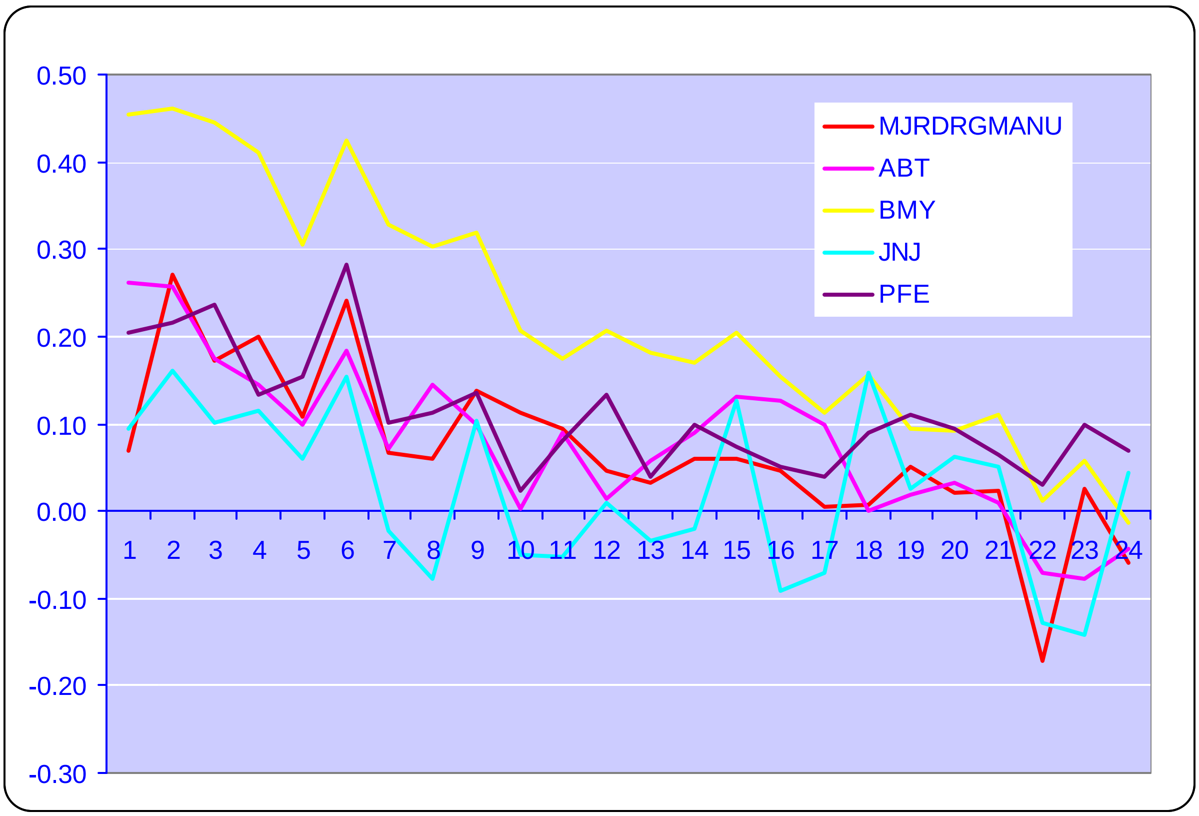

Fig 4. Volatility autocorrelations

The long memory persistence in a process may be measured by the Hurst exponent, H, which relates the rescaled range (R/S, a measure of dispersion, or distance traveled) to time in an equation of the form:

$$R/S = cT^H$$

A White Noise process will have a Hurst exponent of 0.5. A persistent, Black Noise process will have Hurst exponent H> 0.5. Such a process exhibits trending behavior, which becomes increasingly marked for larger values of H.

Estimated Hurst exponents for the healthcare stocks are shown in figure 5 below. All are significantly in excess of 0.5, and demonstrate clear evidence of long memory persistence.

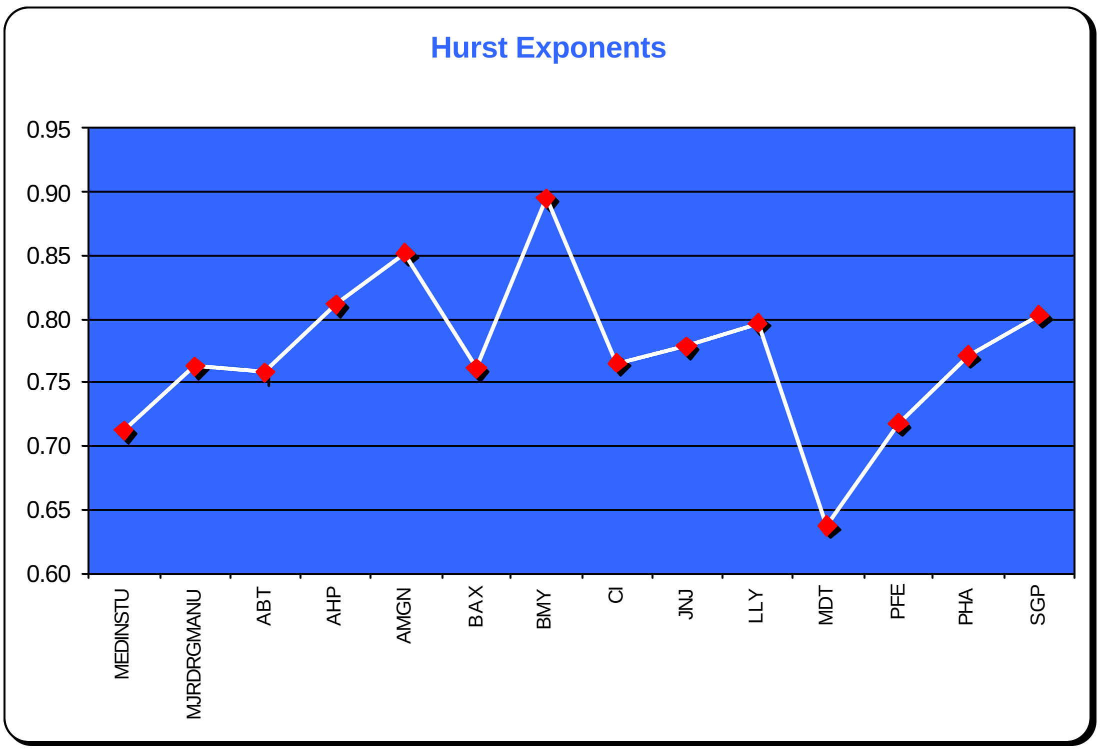

Fig 5. Estimated Hurst exponents for Healthcare stocks

Volatility Modeling and Forecasting

Long memory processes are fractionally integrated and may be modeled using *Auto-Regressive Fractionally Integrated Moving Average* (ARFIMA) models of the form:

$$f(L)(1-L)^d y_t = q(L)e_t$$

$$(1-L)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j-d)L^j}{\Gamma(-d)\Gamma(j+1)}$$

Where:

d is a fractional differencing parameter d = H-0.5

ϕ and θ are polynomials order p and q

ARFIMA-GARCH (FIGARCH) models extend this concept to permit time varying volatility processes of the form:

$$E_{t-1}e_t^2 = s_t^2 = a_0 + \sum_{i=1}^{q} a_i e_{t-i}^2 + \sum_{i=1}^{p} b_i s_{t-i}^2$$

Using models of this form we are able to capture both the long memory and the "error shock" effects which are detectable in volatility processes. Our models enable the direction of volatility to be forecast with a high degree of accuracy: as figure 6 illustrates, forecast direction accuracy tends to average 70% or higher for most of the stocks in the group.

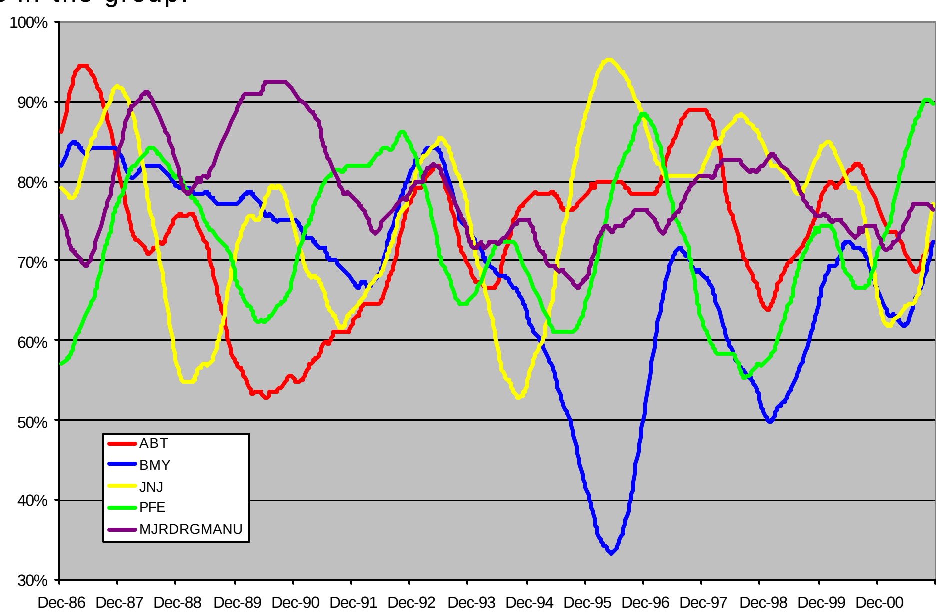

Fig 6. 12M moving average volatility direction prediction accuracy

Volatility Correlation & Cointegration

As table 1 below indicates, all of the volatility processes are correlated at the 1% significance level.

	MEDINSTU	MJRDRG MANU	ABT	AHP	AMGN	BAX	BMY	CI	JNJ	LLY	MDT	PFE	PHA	SGP
MEDINSTU	1.00	0.60	0.46	0.43	0.35	0.62	0.55	0.25	0.49	0.37	0.39	0.50	0.46	0.49
MJRDRGMANU	0.60	1.00	0.68	0.65	0.40	0.45	0.74	0.36	0.70	0.59	0.49	0.70	0.52	0.68
ABT	0.46	0.68	1.00	0.57	0.39	0.41	0.59	0.40	0.58	0.49	0.48	0.55	0.47	0.62
AHP	0.43	0.65	0.57	1.00	0.37	0.41	0.68	0.47	0.46	0.56	0.48	0.58	0.59	0.65
AMGN	0.35	0.40	0.39	0.37	1.00	0.26	0.39	0.31	0.39	0.25	0.30	0.35	0.30	0.30
BAX	0.62	0.45	0.41	0.41	0.26	1.00	0.48	0.29	0.45	0.36	0.31	0.32	0.39	0.41
BMY	0.55	0.74	0.59	0.68	0.39	0.48	1.00	0.42	0.60	0.56	0.47	0.61	0.66	0.68
CI	0.25	0.36	0.40	0.47	0.31	0.29	0.42	1.00	0.32	0.37	0.40	0.32	0.46	0.39
JNJ	0.49	0.70	0.58	0.46	0.39	0.45	0.60	0.32	1.00	0.52	0.45	0.60	0.41	0.49
LLY	0.37	0.59	0.49	0.56	0.25	0.36	0.56	0.37	0.52	1.00	0.42	0.54	0.43	0.55
MDT	0.39	0.49	0.48	0.48	0.30	0.31	0.47	0.40	0.45	0.42	1.00	0.46	0.39	0.47
PFE	0.50	0.70	0.55	0.58	0.35	0.32	0.61	0.32	0.60	0.54	0.46	1.00	0.44	0.61
PHA	0.46	0.52	0.47	0.59	0.30	0.39	0.66	0.46	0.41	0.43	0.39	0.44	1.00	0.56
SGP	0.49	0.68	0.62	0.65	0.30	0.41	0.68	0.39	0.49	0.55	0.47	0.61	0.56	1.00

Table 1. Volatility correlations

In fact the relationship between the processes is rather more profound than a simple correlation coefficient is able to describe. Our findings indicate that several of the processes are cointegrated, meaning that divergences between volatility processes are less persistent than the volatility processes themselves. The implication is that there may be opportunities for statistical arbitrage between cointegrated volatility markets which entail relatively low degrees of risk. Typically such opportunities may be exploited by buying and selling options in a basket of cointegrated stocks.

One such basket comprises the major drug manufacturers ABT, BMY, JNJ and PFE. As the regression below indicates, these four stocks account for over 71% of the variance in the MAJDRGMANU Index.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	85.1%
R Square	72.4%
Adjusted R Square	71.9%
Standard Error	53.1%
Observations	203

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.002	0.037	-0.060	95.183%	-0.076	0.071
ABT	0.225	0.050	4.469	0.001%	0.125	0.324
BMY	0.319	0.053	6.012	0.000%	0.214	0.424
JNJ	0.242	0.052	4.649	0.001%	0.139	0.344
PFE	0.237	0.051	4.599	0.001%	0.135	0.338

Conclusion

The volatility processes of the healthcare stocks considered in this study are fractionally integrated processes with well defined long memory properties that can be modeled using standard ARFIMA-GARCH models to produce consistently accurate volatility forecasts. Furthermore, there is evidence that certain of the processes are (fractionally) cointegrated, indicating the possibility of statistical arbitrage using basket trading techniques.