The Actuarial Profession
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# The use of Econometric Time Series Modelling Techniques in ERM

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Richard Shaw (Horgen Capital & Risk Ltd)

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# Topics

- Introduction
- Spurious Relationship
- Stochastic Trends
- ARIMA Modelling
- Case Studies
- Conclusions
- Q&A

# Introduction
## Motivation

- Empirical analyses of many financial and business time series data sets reveals autoregressive nature of dependency structures over time e.g.
  - Annual RPI, Annual NAE, Annual FTSE All Share Return etc (see later)
  - Underwriting cycle in non-life insurance

- Fitting distributions to many years, months or days worth of data effectively loses any potentially valuable information that might be in such patterns over time

- ICA – Conditional Stress Tests
  - Equities – After a large stock market fall ~ 30 - 50%. Is an ICA Equity Stress Test of a further 40% price fall realistic ?
  - Credit Spreads – 2008 saw a large widening in credit spreads. Should an existing ICA Credit Spread Stress Test credit spread movement be reduced ?

# Introduction
## Objectives

- Two different methodologies:
  - Multivariate Methods – These methods seek relationships between the target and explanatory variable using linear or multiple regression techniques
  - Univariate Methods – These methods use only the time series of the target variable and exploit the non-independence of successive observations

- This presentation investigates the use of Univariate Methods only

- The following topics are outside the scope of this presentation:
  - Multivariate modelling or partial Univariate / Multivariate models
  - ARCH / GARCH modelling
  - Back-testing

# Spurious Relationship
## Two independent random variables X and Y

- Consider two independent random variables $X_t$ and $Y_t$

  $X_t = X_{t-1} + \varepsilon_t$

  $Y_t = Y_{t-1} + \delta_t$

  $\varepsilon_t$ and $\delta_t$ are N(0,1) distributed

  $X_0 = Y_0 = 5$

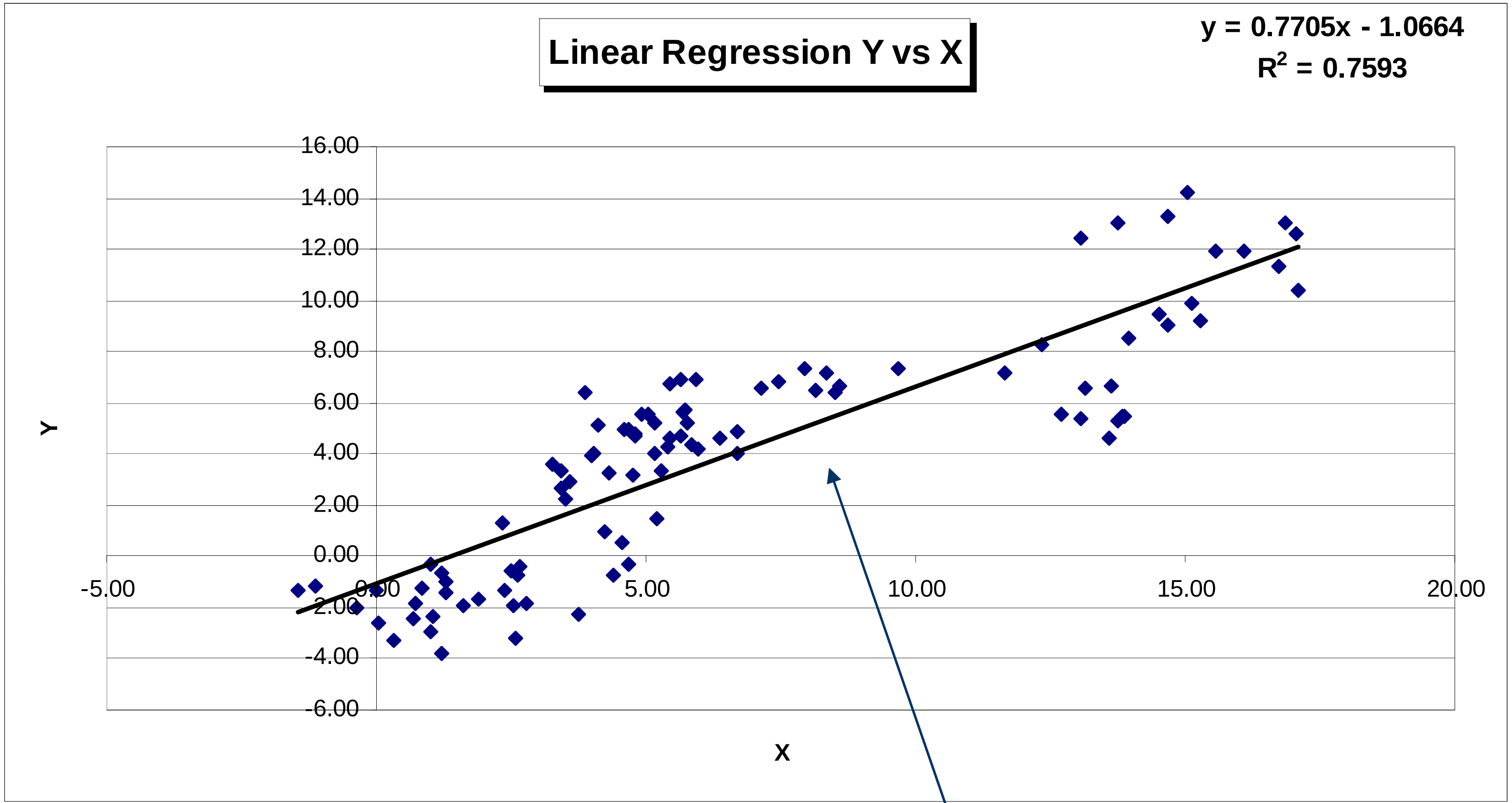
- Generate a random sample of 100 values for $X_t$ and $Y_t$ for t = 1 to 100

- Using this output the linear correlation and $R^2$ have been calculated

- X and Y are not related and yet it is common, in repeated runs, to observe very high correlations far in excess of those expected from sampling error in the N(0,1) values

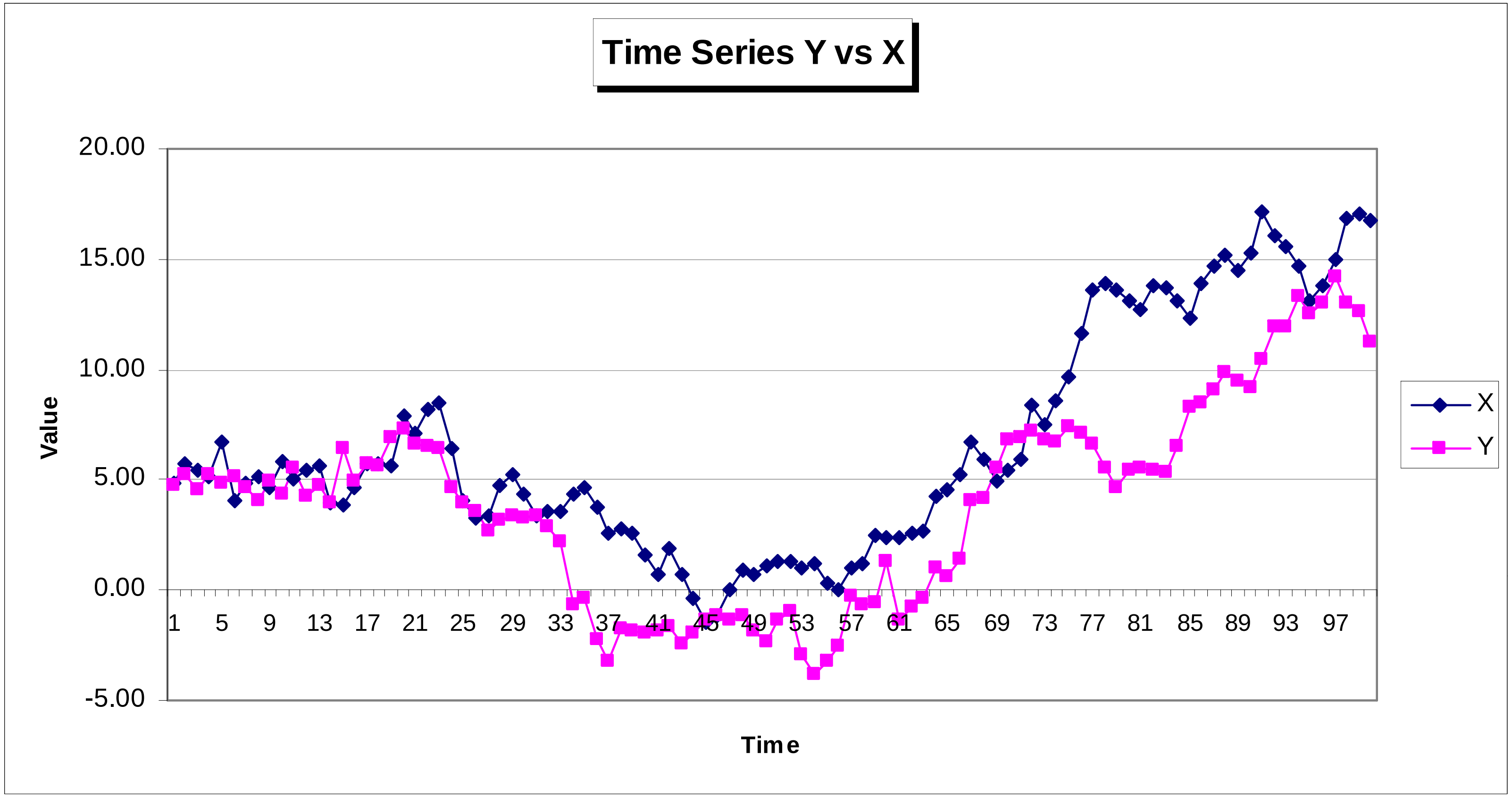
# Spurious Relationship

## Scatter Diagram – Linear Regression

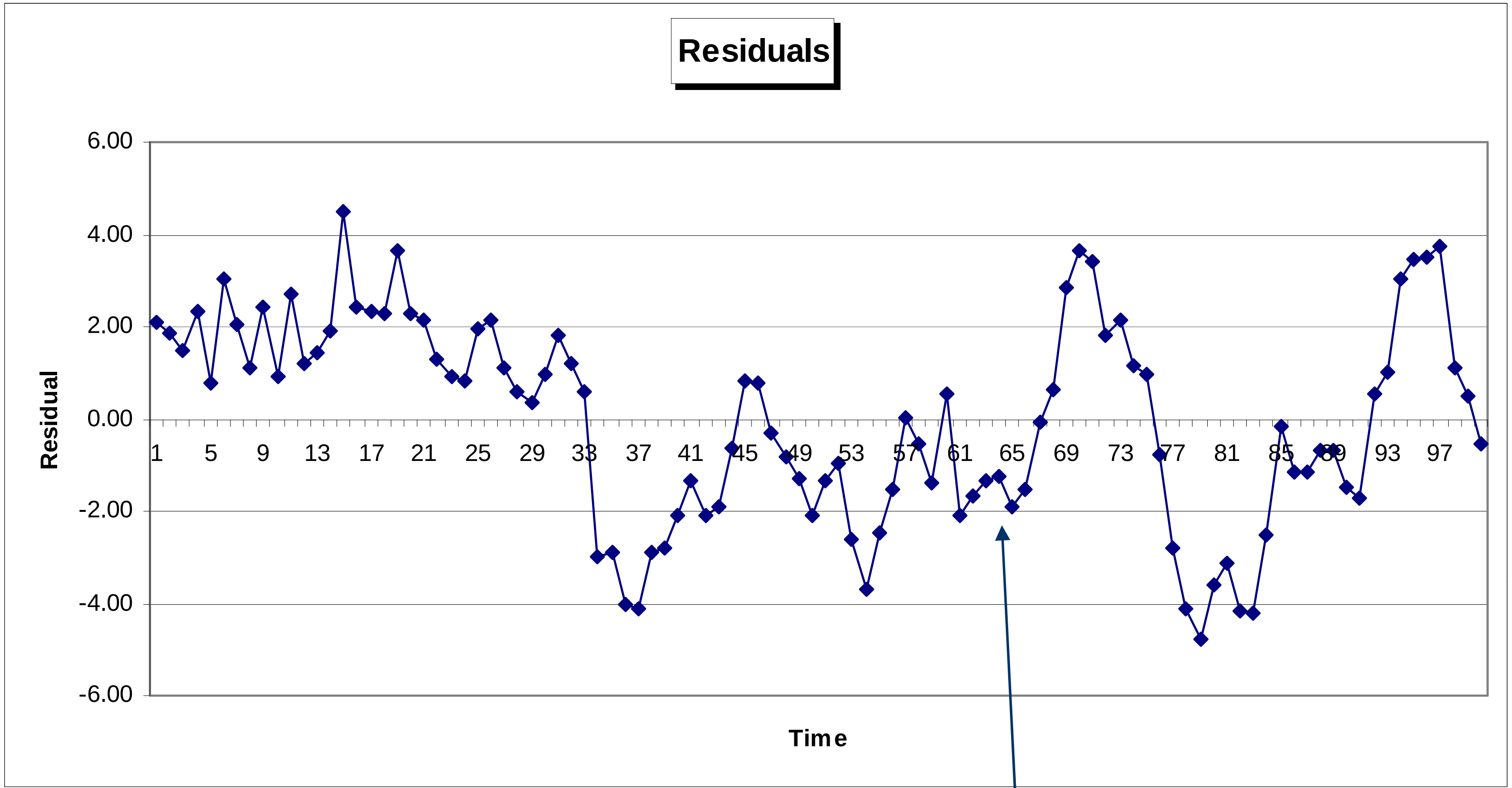



**Linear Correlation = 87.1% ; DW = 0.283**

# Spurious Relationship
## Time Series Diagram



# Spurious Relationship
## Residuals Diagram




**Significant autocorrelation in residuals**

# Spurious Relationship
## Residual Assumptions

- Actual$_t$ – Fitted$_t$ = Residual $\varepsilon_t$

- Quality of parameter estimates and validity of significance tests rely upon the residuals $\varepsilon_t \sim N(0,\sigma)$

- Residuals must be
  - Normally distributed
  - Independent (no autocorrelation)
  - Same variance (no heteroscedasticity)

- Intuitively residuals should be simple randomness that remain after the deterministic part of the variation in a target variable has been modelled
  - Any systematic component in the error terms should really be in the model
  - If each residual is related to it's predecessor they are described as **autocorrelated**

# Spurious Relationship
## Trending Variables

- The stochastic trends in $X_t$ and $Y_t$ are unrelated so linear regression cannot explain the variation of one with the other.
  - The residuals contain both stochastic trends – hence autocorrelation

- Establishing existence of trend is important for univariate modelling. Trend must first of all be removed. There are two types of trend:
  - Deterministic: e.g. $y_t = a + bt$
  - Stochastic: e.g. random walk $y_t = y_{t-1} + \varepsilon_t$

- Most trending series in economics and business are not deterministic but are stochastic i.e. they exhibit random walk type behaviour
  - The identification of stochastic trend is a test for stationarity
  - A stochastic trend is removed by differencing e.g. cconverting an RPI value at month t to an annual RPI return at month t is in effect differencing the variable.

# Stochastic Trends
## Autocorrelation

- Let the variable y at time t = $y_t$ and lagged variable y at time t-k = $y_{t-k}$
  - 1st order autocorrelation $r_1 = corr(y_t, y_{t-1})$
  - 2nd order autocorrelation $r_2 = corr(y_t, y_{t-2})$
  - **kth order autocorrelation $r_k = corr(y_t, y_{t-k})$**

- The Autocorrelation Function (“ACF”) measures the correlation between 2 variables $y_t$ and $y_{t-k}$.

- The Partial Autocorrelation Function (“PACF”) measures the additional effect of $y_{t-k}$ on $y_t$, once effects of $y_{t-1}, y_{t-2}, y_{t-(k-1)}$ have been accounted for

- Autocorrelation Plot (Correlogram)
  - This s very useful for analysing time series data and determining the most appropriate time series model
  - The correlogram displays 95% bounds at each lag that enable quick tests of whether each value is significantly different from zero.

# Stochastic Trends
## Uses for Autocorrelation

- $y_t$ Random
  - All autocorrelations are small
- $y_t$ Stationary
  - Autocorrelations rapidly decrease as lag increases
- $y_t$ Trending
  - Many large autocorrelations
- Checking residuals are simple randomness.
  - It can be impossible to eliminate all autocorrelations from residuals
- ARIMA Modelling (see later)

# Stochastic Trends
## Some Useful Time Series

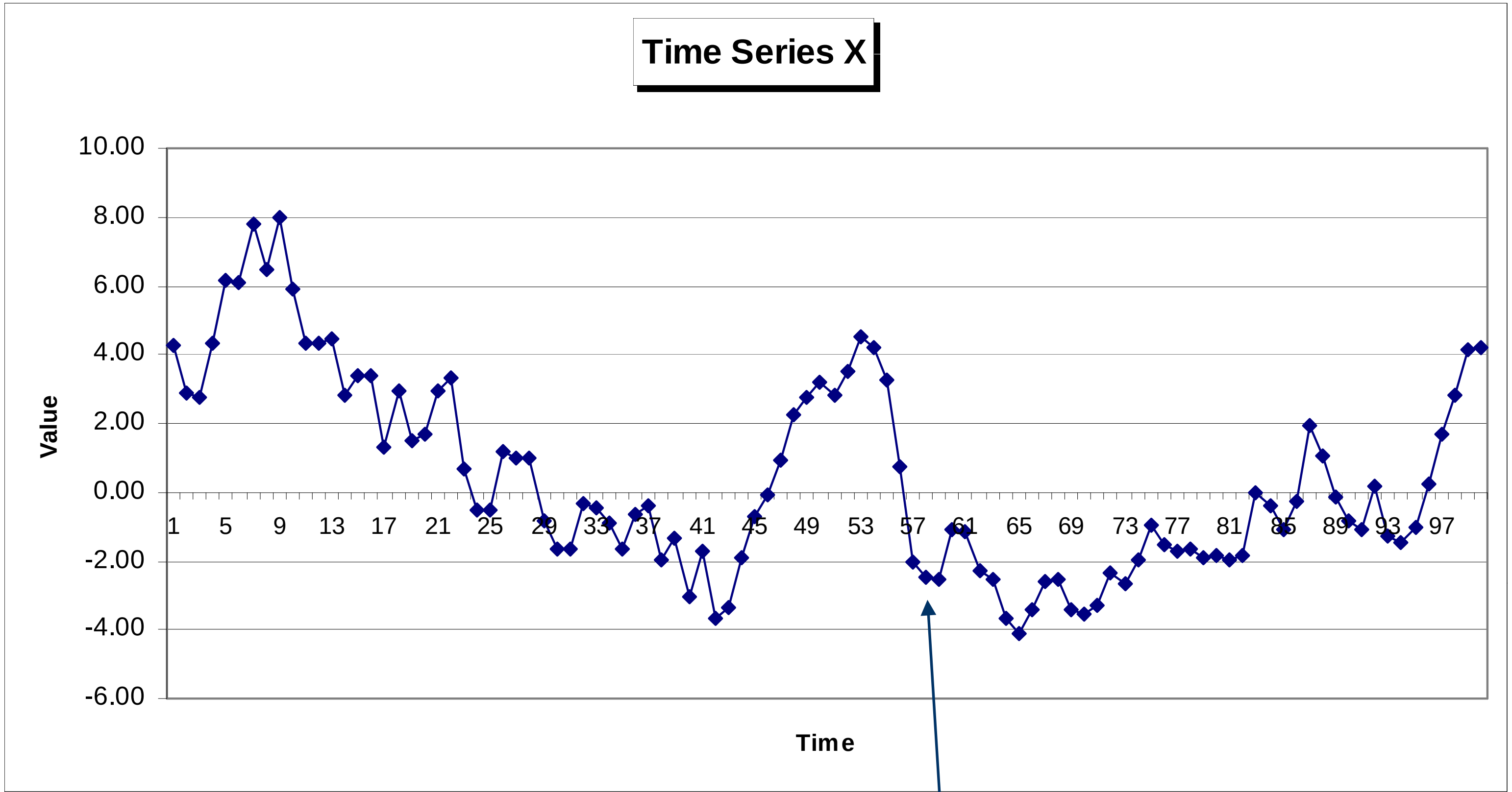
- $y_t = \varepsilon_t$ Purely random process ('white noise')
  - $\varepsilon_t$ has the same mean and variance and no auotcorrelation

- $y_t$ follows an autoregressive process if it depends linearly on past observations of $y_t$
  - $y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} \ldots + a_p y_{t-p} + \varepsilon_t$
  - $\varepsilon_t$ is white noise as above
  - Simplest case is autoregression of order one $y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$

- Let $y_t = \phi y_{t-1} + \varepsilon_t$
  - If Mod($\phi$) > 1 then $y_t$ is said to be non-stationary – these are easy to spot
  - If Mod($\phi$) < 1 then $y_t$ is said to be stationary (mean reverting) – the forecast function converges to the mean
  - If Mod($\phi$) = 1 then $y_t$ is non-stationary – it meanders stochastically and is known as a random walk

# Stochastic Trends

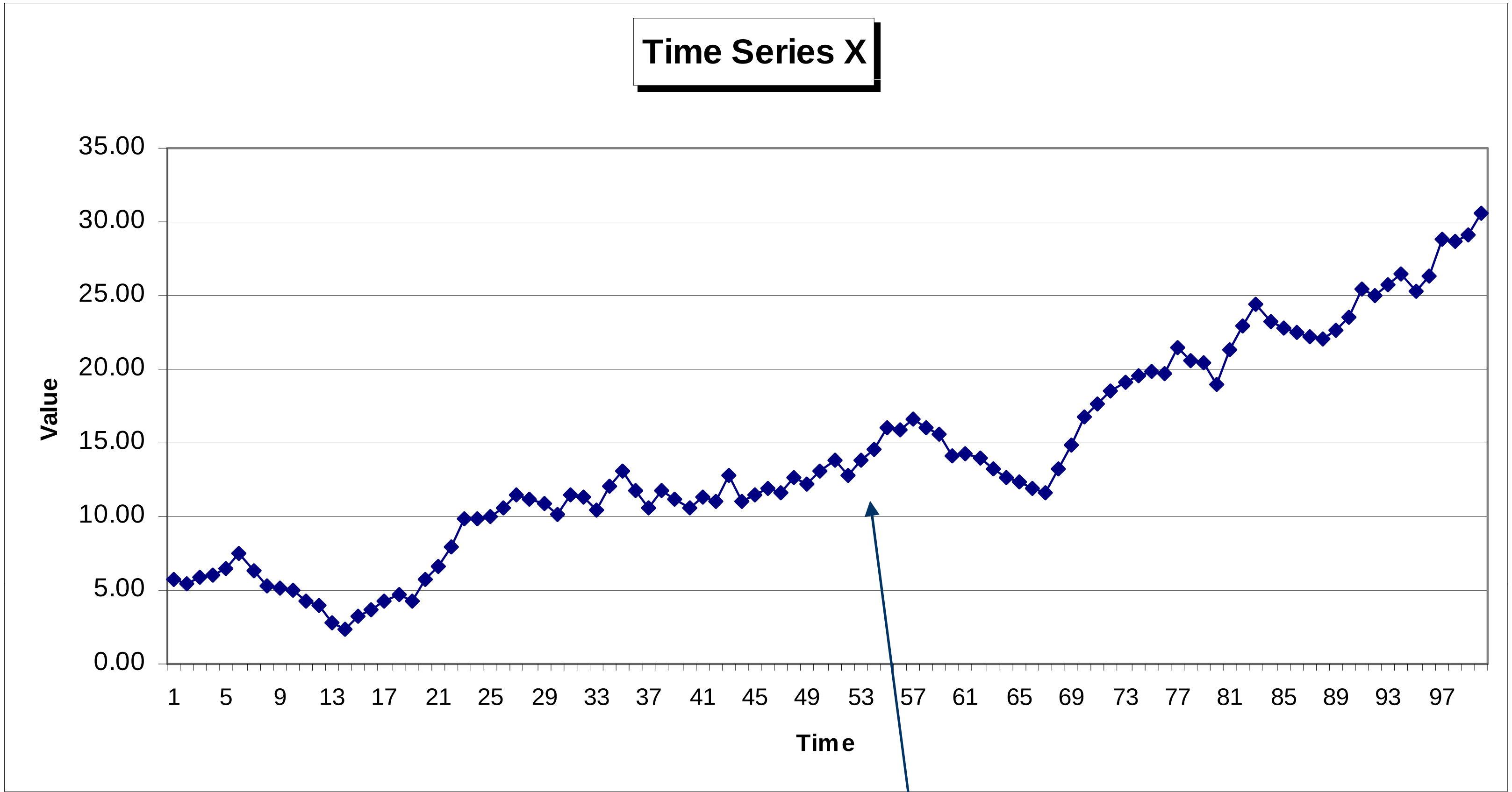
## Some Useful Time Series – $y_t = 0.9y_{t-1} + \varepsilon_t$




**Example of a mean reverting trend**

# Stochastic Trends

## Some Useful Time Series – $y_t = 1.03y_{t-1} + \varepsilon_t$




**Example of a non-stationary trend**

# ARIMA Modelling
## Stationarity

- Time Series Modelling requires knowledge of the mean, variance and autocorrelations
- A series $y_t$ is said to be stationary if it has constant mean, constant variance and constant autocorrelations at each lag
- If a series is stationary, modelling can proceed by estimating the mean, variance and auotcorrelations from significantly long time averages of the series
- A stationary series is not necessarily completely random as it can have autocorrelation
- The most fundamental property is stationarity in the mean

# ARIMA Modelling
## ARIMA (p,d,q)

- Box-Jenkins is a univariate forecasting approach
  - It involves the careful examination of time series in order to identify the underlying data-generating process
  - The choice of best model can be systematically made using this approach

- It is useful to restrict the search for models to the class of **A**utoRegressive **I**ntegrated **M**oving **A**verage **M**odels – ARIMA(p,d,q)

- An ARMA(p,q) model for variable $y_t$ is a combination of an autoregressive process of order p, AR(p) and a moving average process of order q, MA(q) where:

AR(p), ARMA(p,0) process $y_t = a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} \ldots + a_p y_{t-p} + \varepsilon_t$

MA(q), ARMA(0,q) process $y_t = b_1 e_{t-1} + b_2 e_{t-2} + b_3 e_{t-3} \ldots + b_q e_{t-q} + \varepsilon_t$

# ARIMA Modelling
## ARIMA (p,d,q)

- An ARIMA(p,d,q) process:

  $y_t = a_1y_{t-1} + a_2y_{t-2} + a_3y_{t-3} \ldots + a_py_{t-p} + b_1e_{t-1} + b_2e_{t-2} + b_3e_{t-3} \ldots + b_qe_{t-q} + \varepsilon_t$

  - If a variable must be differenced d times in order to achieve stationarity it is said to be integrated or order d.
  - d =1 would mean that the variable now being modelled = $\Delta y_t = y_t - y_{t-l}$

- An AR model of sufficiently high order can usually be found to model any business series
  - If a large number of parameters are required for a good fit, forecasts can be poor. This motivates working with a broader class of models
  - Since the amount of data is limited it is preferable to fit a model involving as few a parameters as possible
  - This is known as the "**Principle of Parsimony**".

- Experience suggests that an ARMA(p,q) model may achieve as good a fit as an AR(p') model but with fewer parameters i.e. p+q < p'

# ARIMA Modelling
## Box-Jenkins Methodology

- Differencing a time series to achieve Stationarity

- Identification of a model to be tentatively used
  - Inspection of the Autocorrelation function (“ACF”) and
  - Partial autocorrelation function (”PACF”) at different lags

- Estimating the parameters of the model
  - Maximum Likelihood, Least Squares etc.
  - This amounts to the minimisation of a complicated non-linear function of parameters that involves iterative numerical procedures

- Diagnostic Evaluation – Is the model adequate
  - t-statistics (and p-values); Durbin-Watson (“DW”)
  - Residuals; Ljung-Box Q-statistic; AIC, SIC, Adj. $R^2$ etc.

# ARIMA Modelling
## Comparing the fit of different models

- Adjusted $R^2$ ("Adj. $R^2$")
  **Adj. $R^2 = 1/(n-k-1)\ \Sigma_{i=1}\, e_i^2\ /\ 1/(n-1)\ \Sigma_{i=1}\ (y_i - E(y))^2$**

- Akaike Information Criterion ("AIC")
  **$AIC = 1 + \ln(2\pi) + \ln(SSR/n) + 2k\ /\ n$**

- Schwartz Bayesian Criterion ("SBC")
  **$SBC = 1 + \ln(2\pi) + \ln(SSR/n) + k\ \ln(n)\ /\ n$**

  Sum of Squared Residuals ("SSR")
  **$SSR = \Sigma_{i=1}\, e_i^2$**

  n = number of observations; k = number of explanatory variables

# ARIMA Modelling
## Durbin-Watson ("DW") Statistic

- The DW Statistic evaluates autocorrelation for residuals placed in the same order as the data observations

- **DW =** $\mathbf{\Sigma_{i=2}(e_i - e_{i-1})^2 / \Sigma_{i=1}e_i^2}$

- **DW ~ 2(1-r)** where r = autocorrelation
  - DW = 2 – no autocorrelation
  - DW > 2 – negative autocorrelation
  - DW < 2 – positive autocorrelation

- The DW statistic is used instead of r because strict tests exist to examine whether DW is significantly different from 2

# ARIMA Modelling
## Autocorrelation diagnostic evaluation

- Residuals should be white noise
- The ACF of residuals should be investigated
- Can test for autocorrelation in residuals for several lags together
- Under null hypothesis of no autocorrelation in the first m lags, the Ljung-Box Q-statistic has a chi-squared distribution with d.f. = (m-p-q)

$$\mathbf{Q(m) = n(n+2)\ \Sigma_{i=1}\ r_i^2 / (n-i) \sim \chi^2_{m-p-q}}$$

where $r_i = \text{corr}(e_t, e_{t-i})$

# Case Studies
## RPI Case Study – Data

- Data
  - Monthly data has been used
  - RPI_Index(t) – RPI at the end of each month for the period Jan 1970 to Dec 2008 as provided by the Office of National Statistics (“ONS”).
  - Constructed an historical time series of a month rolling value of RPI(t) at month t, where:

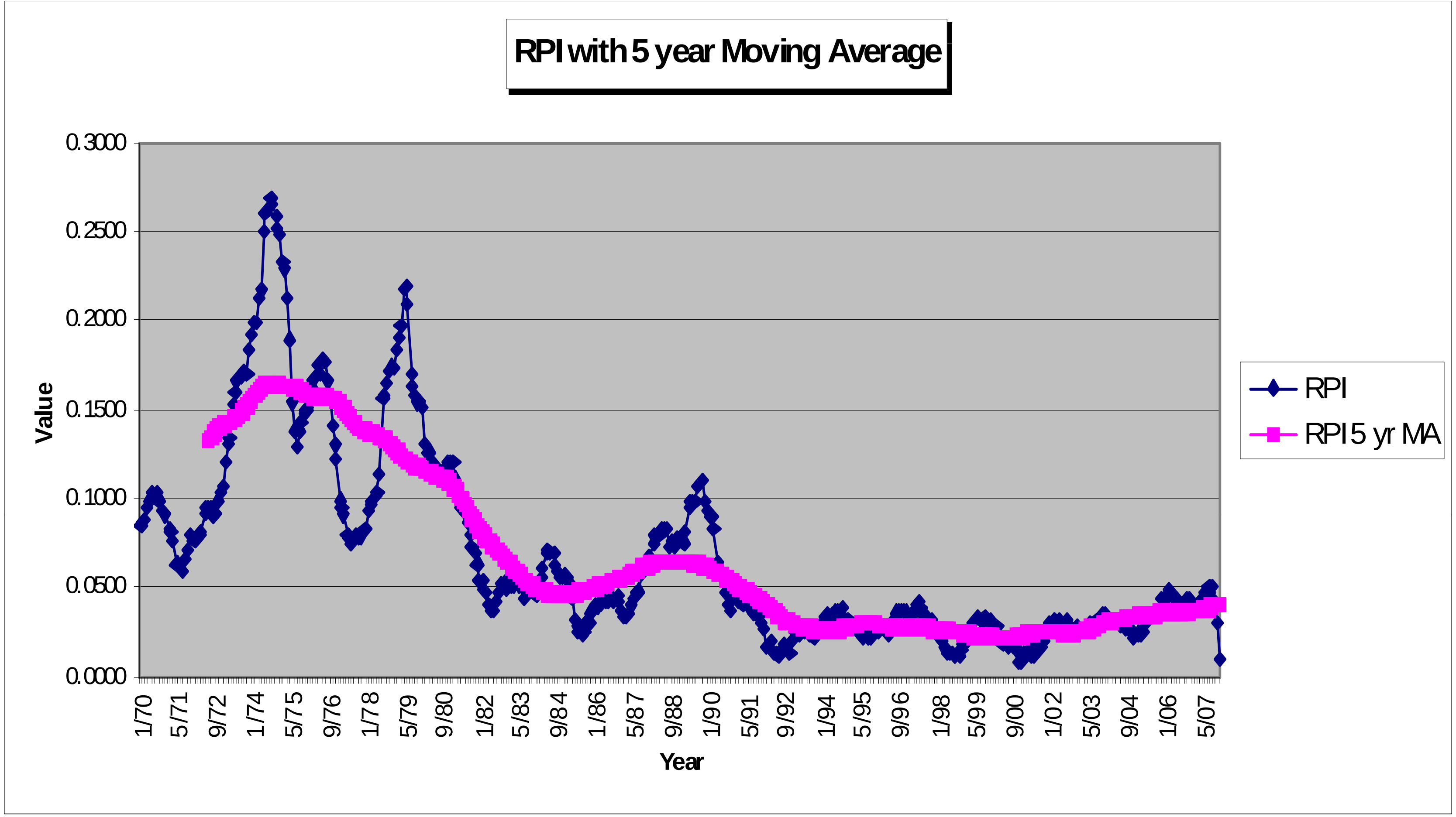
    **RPI(t) = Annual RPI Change = RPI_Index(t) / RPI_Index(t-12) - 1**

- ARIMA(2,[12]) Model Fit
  - Monthly data Jan 1987 to Dec 2008
  - Box-Jenkins Diagnostic Evaluation tests OK
  - Large residuals in 2008
  - Simulation of 5,000 path-dependent scenarios of length 120 months

**RPI(t) = 0.02187 + Y(t)**
**Y(t) = 1.37756 Y(t-1) - 0.38514 Y(t-2) - 0.7521 e(t-12) + e(t)**
**e(t) ~ N(0.00000,0.00296)**

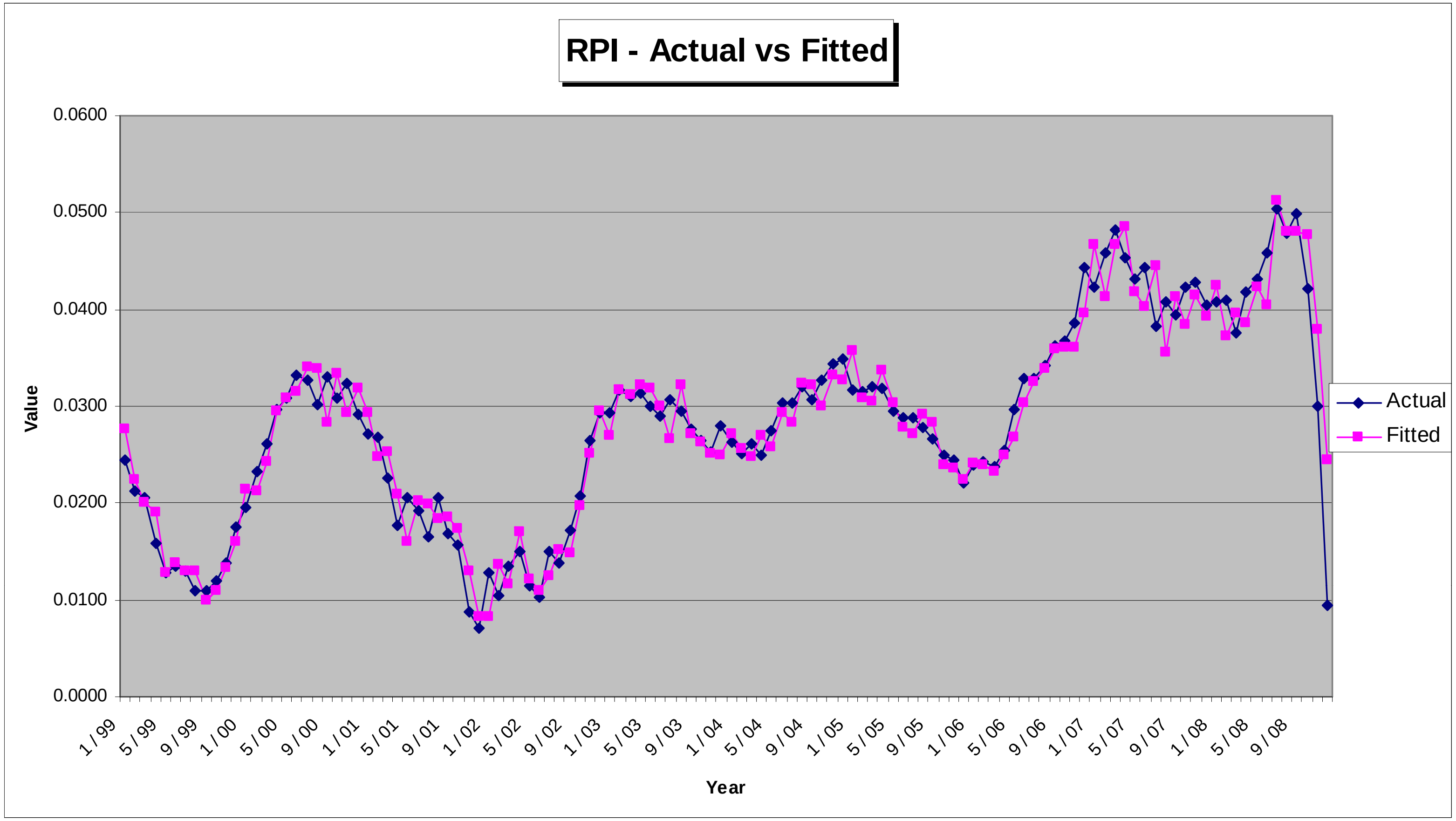
# Case Studies

## RPI Case Study – Annual RPI Data (1/70 to 12/08)



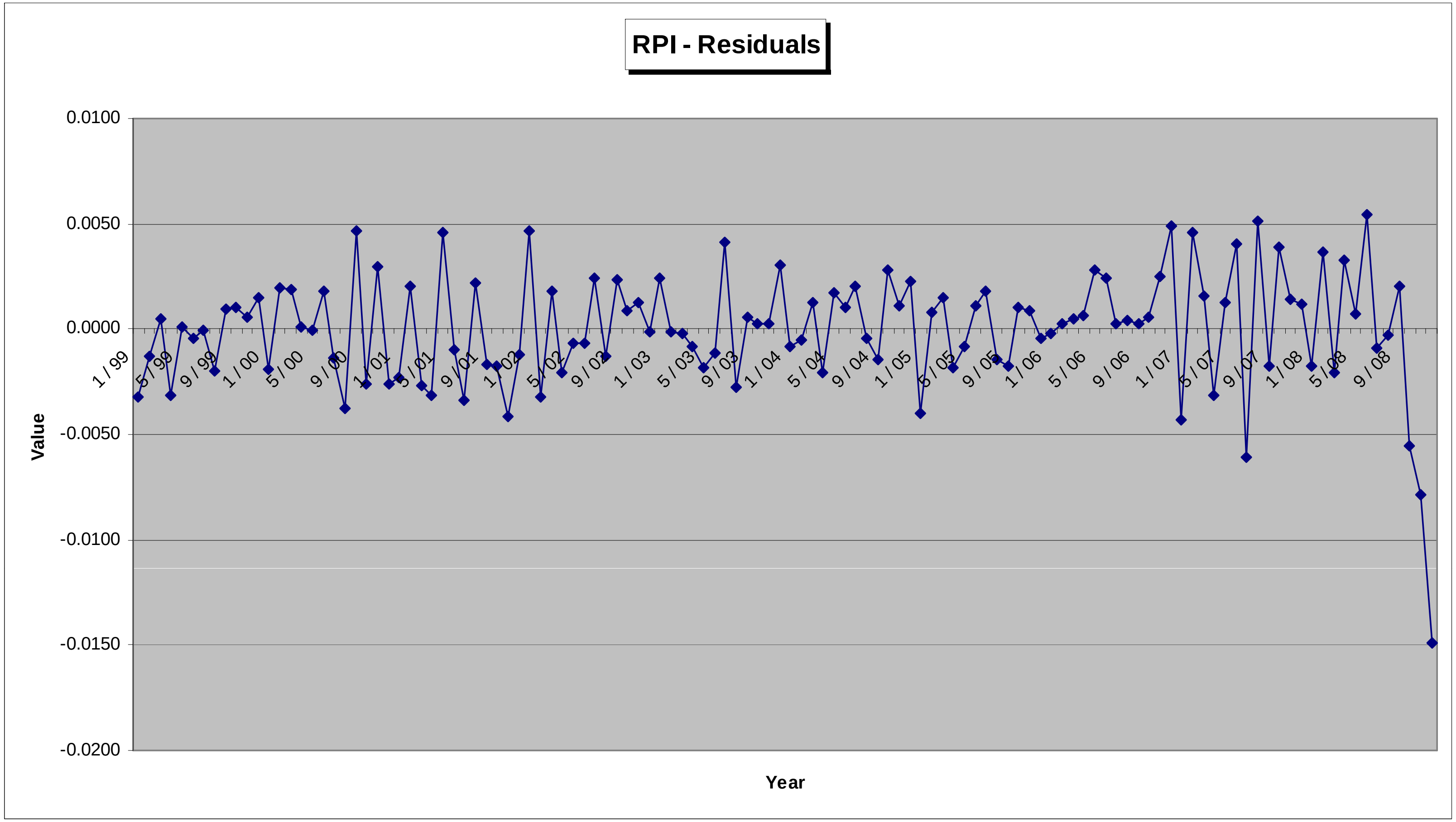
# Case Studies

## RPI Case Study – Actual vs Fitted (Last 10 years shown)



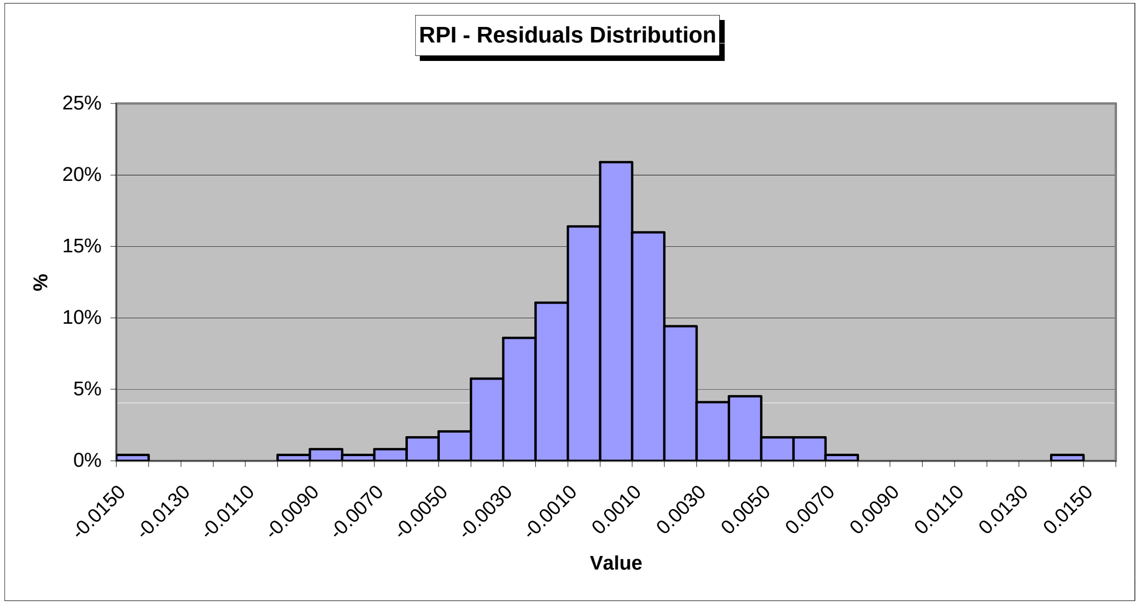
# Case Studies

## RPI Case Study – Residuals (Last 10 years shown)



# Case Studies

## RPI Case Study – Residuals Distribution (All years)




| Residuals | |
|---|---|
| Sample No. | 262 |
| Mean | 0.000094 |
| Minimum | -0.014877 |
| Maximum | 0.014730 |
| Std Dev | 0.002958 |
| Skewness | -0.285210 |
| Kurtosis | 7.529413 |

# Case Studies

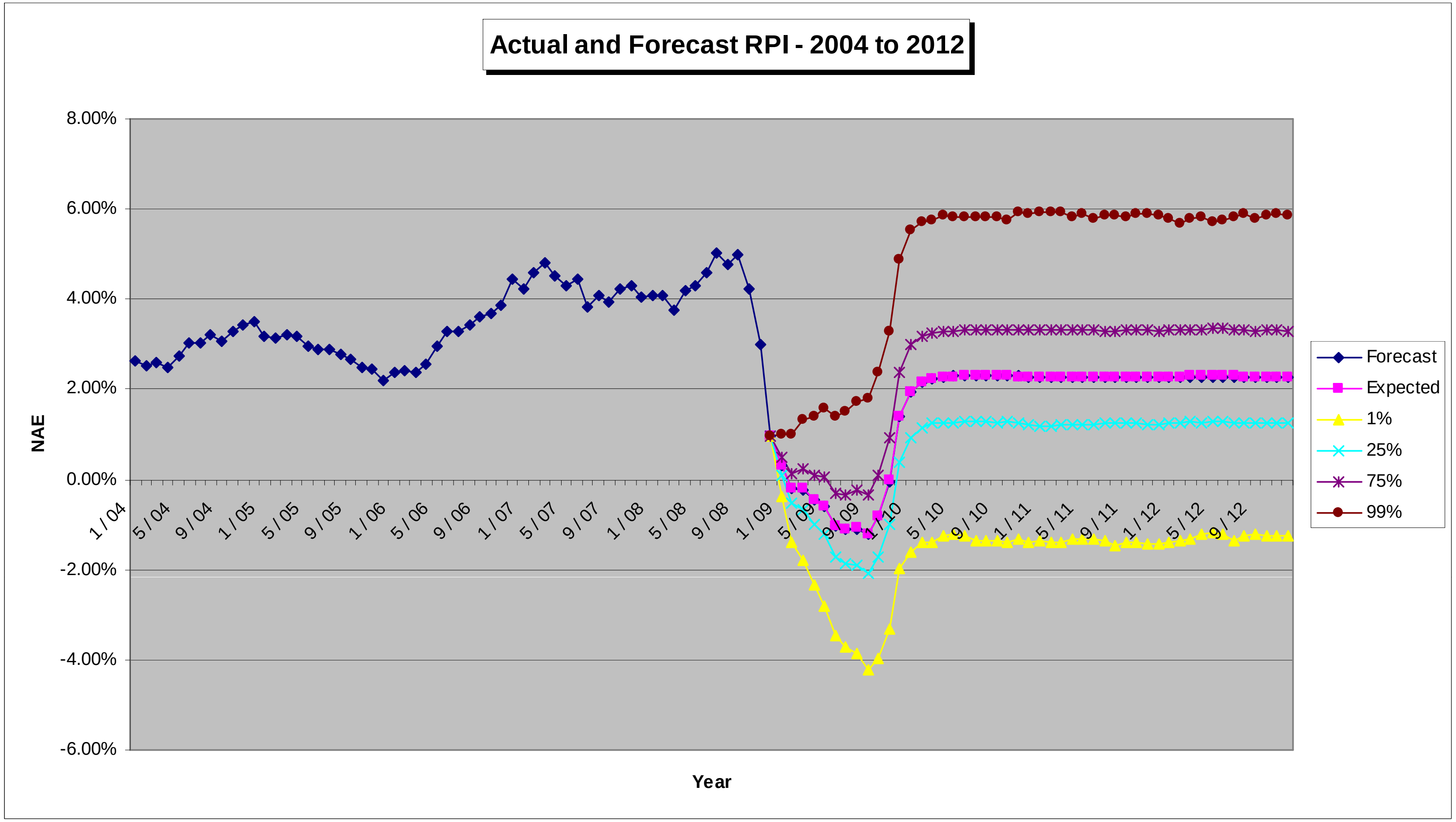
## RPI Case Study – Model Fit and Future Projections

| **RPI** | | | |
|---|---|---|---|
| **Start** | 1987 | | |
| **End** | 2008 | | |
| | | | |
| **Variable** | **Coefficient** | **t-statistic** | **Probability** |
| C | 0.02187 | 2.112 | 3.56% |
| Y(t-1) | 1.37756 | 22.084 | 0.00% |
| Y(t-2) | -0.38514 | -6.204 | 0.00% |
| e (t-12) | -0.75210 | 0.041 | 0.00% |
| | | | |
| **Adj $R^2$** | 97.9% | | |
| **Durbin Watson** | 2.0022 | | |
| **SSR** | 0.0023 | | |
| **AIC** | -8.7805 | | |
| **SC** | -8.7261 | | |

| | **12 / 09** | **12 / 10** | **12 / 11** | **12 / 12** | **12 / 13** | **12 / 14** | **12 / 15** | **12 / 16** | **12 / 17** | **12 / 18** |
|---|---|---|---|---|---|---|---|---|---|---|
| Forecast | 1.39% | 2.29% | 2.27% | 2.26% | 2.25% | 2.24% | 2.23% | 2.23% | 2.22% | 2.22% |
| Expected | 1.40% | 2.28% | 2.27% | 2.28% | 2.23% | 2.27% | 2.24% | 2.25% | 2.25% | 2.22% |
| Standard Deviation | 1.50% | 1.57% | 1.55% | 1.53% | 1.54% | 1.56% | 1.55% | 1.55% | 1.55% | 1.54% |
| Minimum | -3.79% | -3.94% | -2.82% | -2.81% | -3.72% | -3.20% | -3.62% | -3.48% | -3.45% | -5.17% |
| Maximum | 6.57% | 7.62% | 7.65% | 7.70% | 7.62% | 7.38% | 7.84% | 8.08% | 8.49% | 7.99% |
| | | | | | | | | | | |
| **Percentile** | | | | | | | | | | |
| 0.5% | -2.50% | -1.78% | -1.87% | -1.58% | -1.68% | -1.70% | -1.64% | -1.86% | -1.70% | -1.78% |
| 1.0% | -1.99% | -1.41% | -1.42% | -1.26% | -1.28% | -1.30% | -1.36% | -1.32% | -1.35% | -1.42% |
| 5.0% | -1.04% | -0.29% | -0.36% | -0.24% | -0.30% | -0.28% | -0.36% | -0.31% | -0.29% | -0.34% |
| 25.0% | 0.39% | 1.23% | 1.23% | 1.26% | 1.19% | 1.17% | 1.21% | 1.22% | 1.22% | 1.20% |
| 50.0% | 1.36% | 2.31% | 2.31% | 2.25% | 2.23% | 2.31% | 2.24% | 2.26% | 2.24% | 2.22% |
| 75.0% | 2.39% | 3.32% | 3.30% | 3.29% | 3.25% | 3.34% | 3.28% | 3.30% | 3.29% | 3.23% |
| 95.0% | 3.87% | 4.89% | 4.76% | 4.80% | 4.79% | 4.82% | 4.82% | 4.82% | 4.84% | 4.76% |
| 99.0% | 4.88% | 5.91% | 5.86% | 5.85% | 5.77% | 5.94% | 5.87% | 5.80% | 5.92% | 5.72% |
| 99.5% | 5.25% | 6.34% | 6.22% | 6.30% | 6.06% | 6.28% | 6.22% | 6.18% | 6.37% | 5.95% |

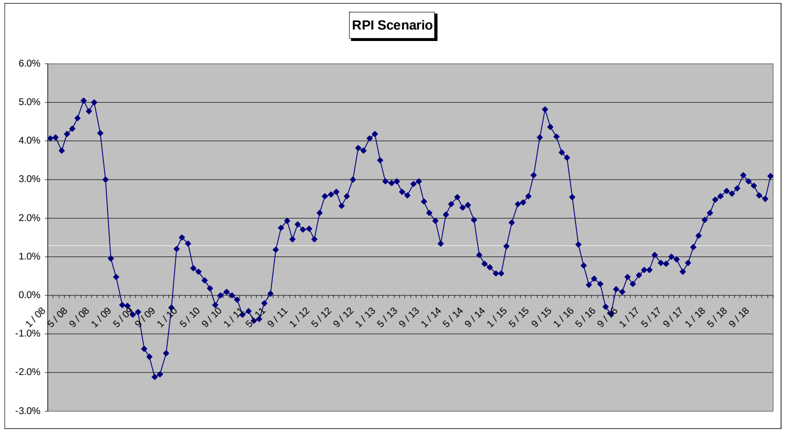
# Case Studies

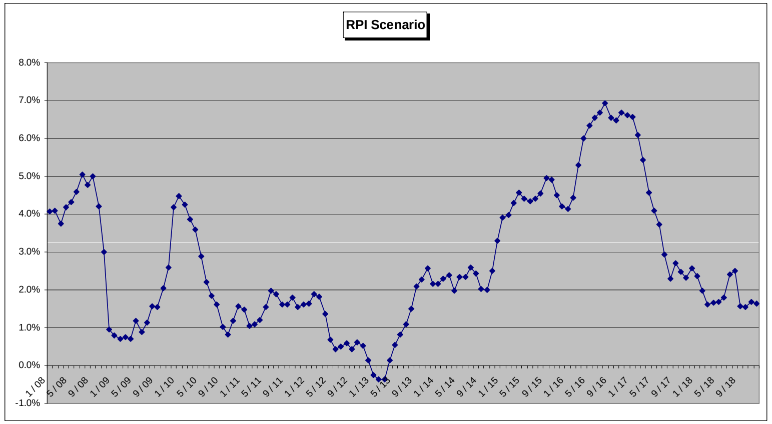
## RPI Case Study – Future Projections

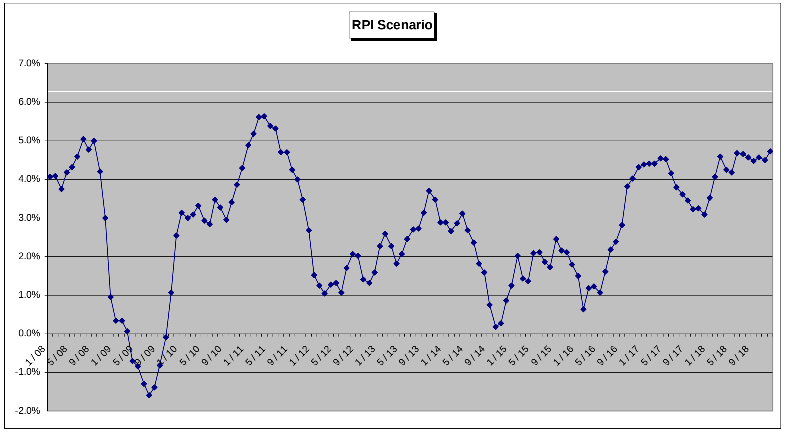


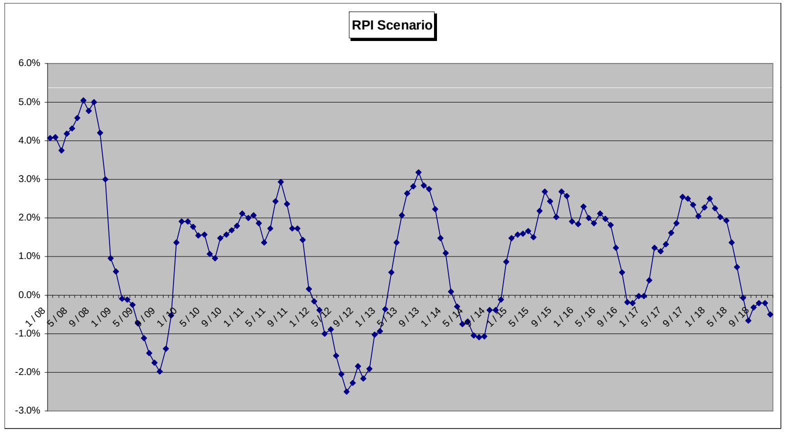
# Case Studies

## RPI Case Study – Four Random Scenarios (Press F9)



# Case Studies

## FTSE All Share Case Study – Data

- Data
  - Monthly data has been used
  - FTSEASTR(t) – FTSE All Share Total Return Index at the end of each month for the period Jan 1987 to Dec 2008 as provided by Bloomberg
  - Constructed an historical time series of a month rolling value of FTSEAS(t) at month t, where:

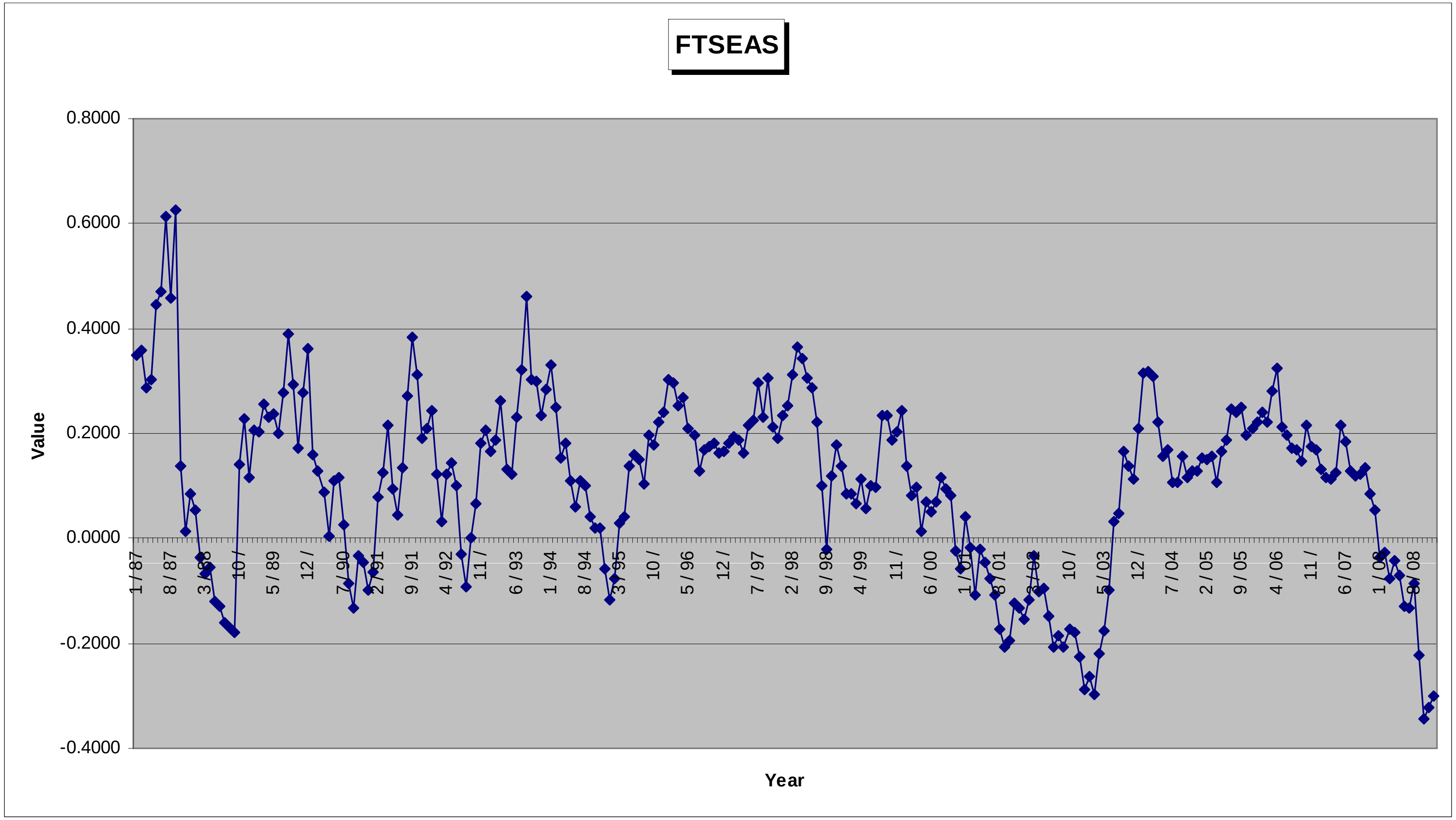
    **FTSEAS(t) = FTSEAS Annual Return = FTSEASTR(t) / FTSEASTR(t-12) - 1**

- ARIMA(1,[12]) Model Fit
  - Monthly data Jan 1987 to Dec 2008
  - Box-Jenkins Diagnostic Evaluation tests OK
  - Relatively largish residuals but still random
  - Simulation of 5,000 path-dependent scenarios of length 120 months

**FTSEAS(t) = 0.07479 + Y(t)**
**Y(t) = 0.97975 Y(t-1) - 0.93485 e(t-12) + e(t)**
**e(t) ~ N(0.00000,0.05191)**

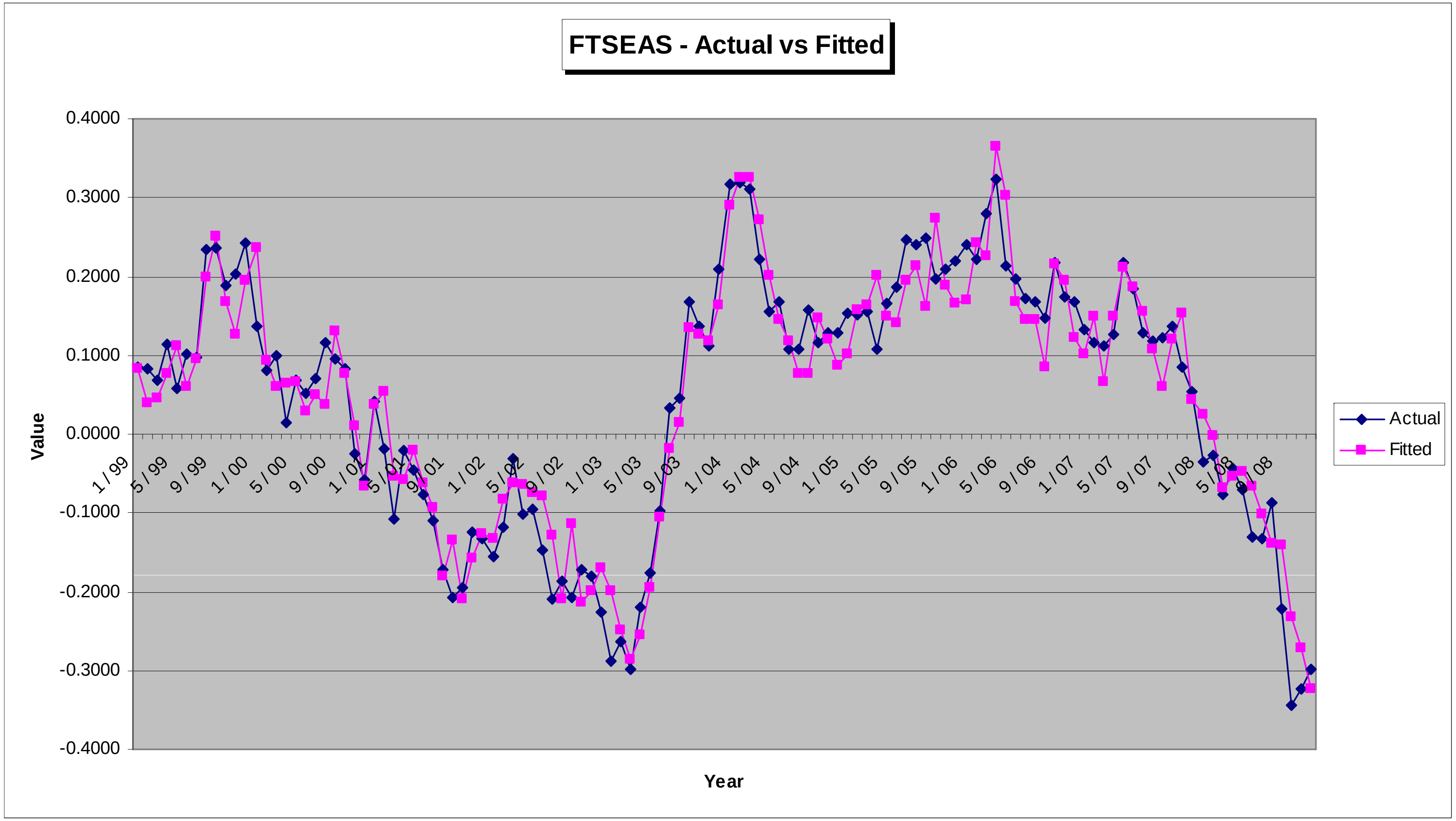
# Case Studies

## FTSE All Share Case Study – Annual FTSEAS Data (1/87 to 12/08)



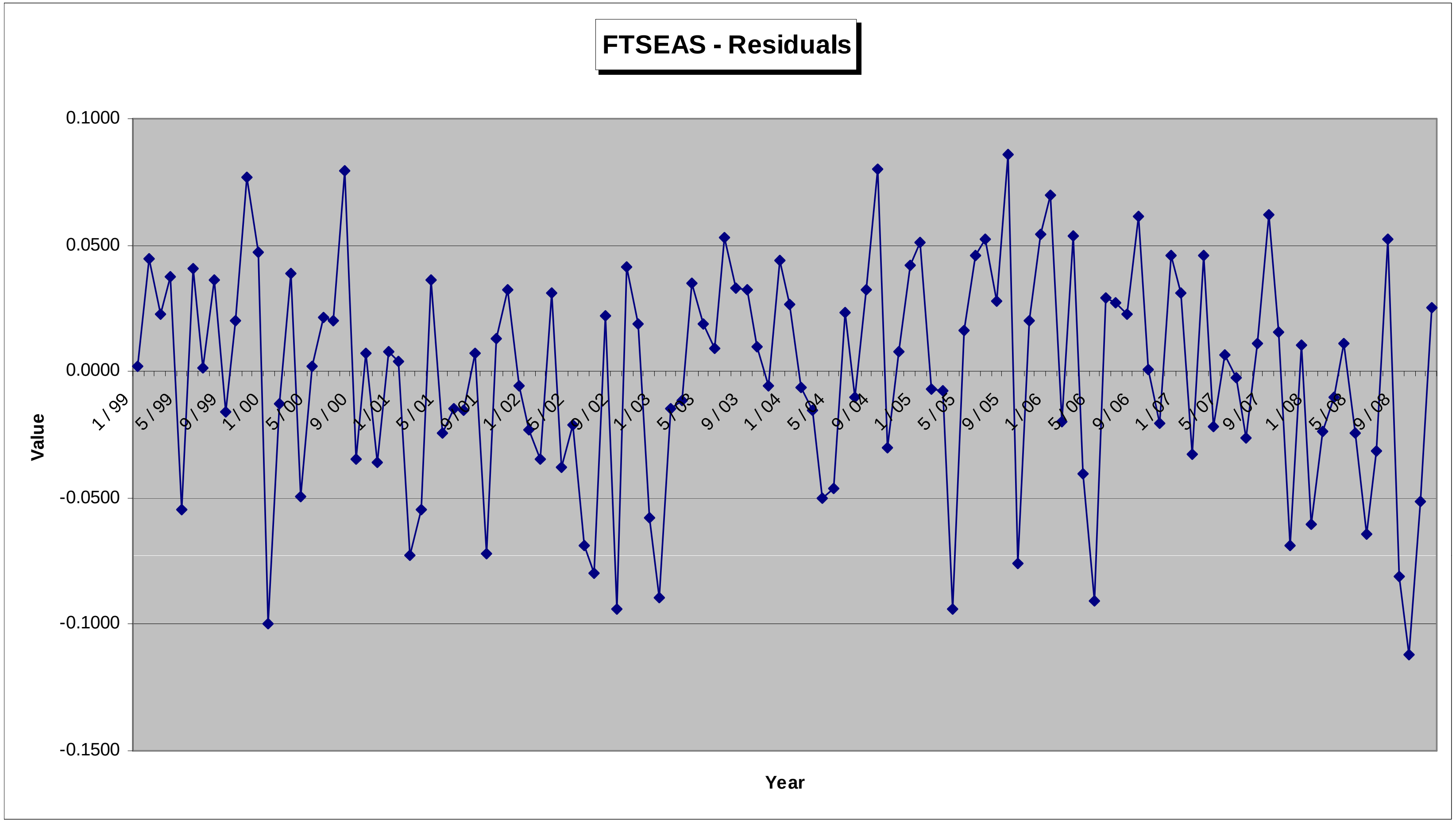
# Case Studies

## FTSE All Share Case Study – Actual vs Fitted (Last 10 years shown)



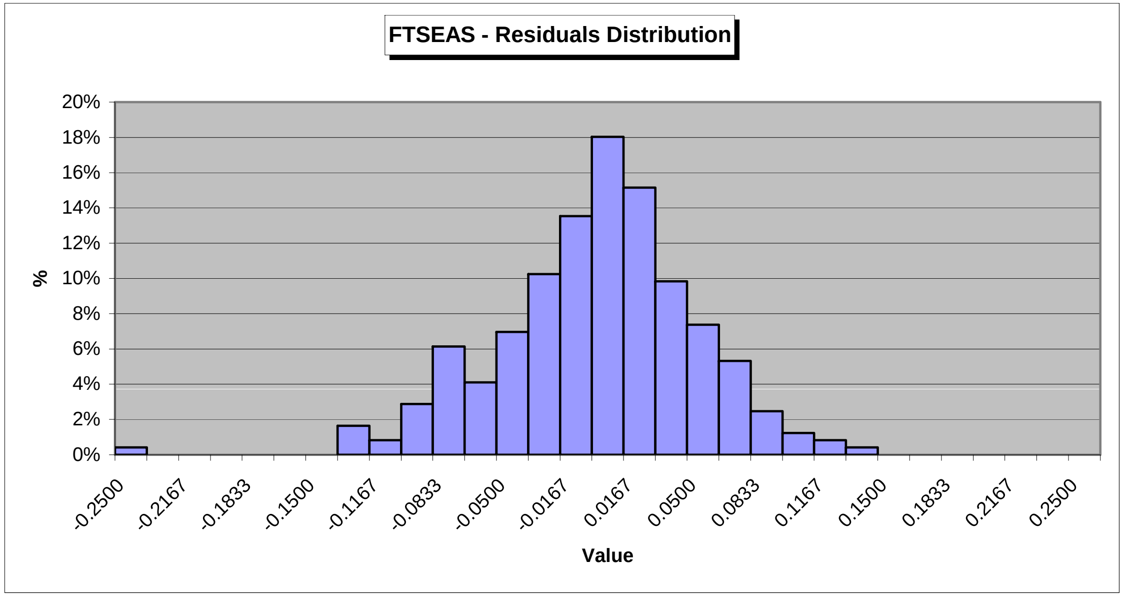
# Case Studies

## FTSE All Share Case Study – Residuals (Last 10 years shown)



# Case Studies

## FTSE All Share Case Study – Residuals Distribution (All years)




| Residuals | |
|---|---|
| Sample No. | 263 |
| Mean | 0.002808 |
| Minimum | -0.246123 |
| Maximum | 0.137776 |
| Std Dev | 0.051908 |
| Skewness | -0.562577 |
| Kurtosis | 4.535745 |

# Case Studies

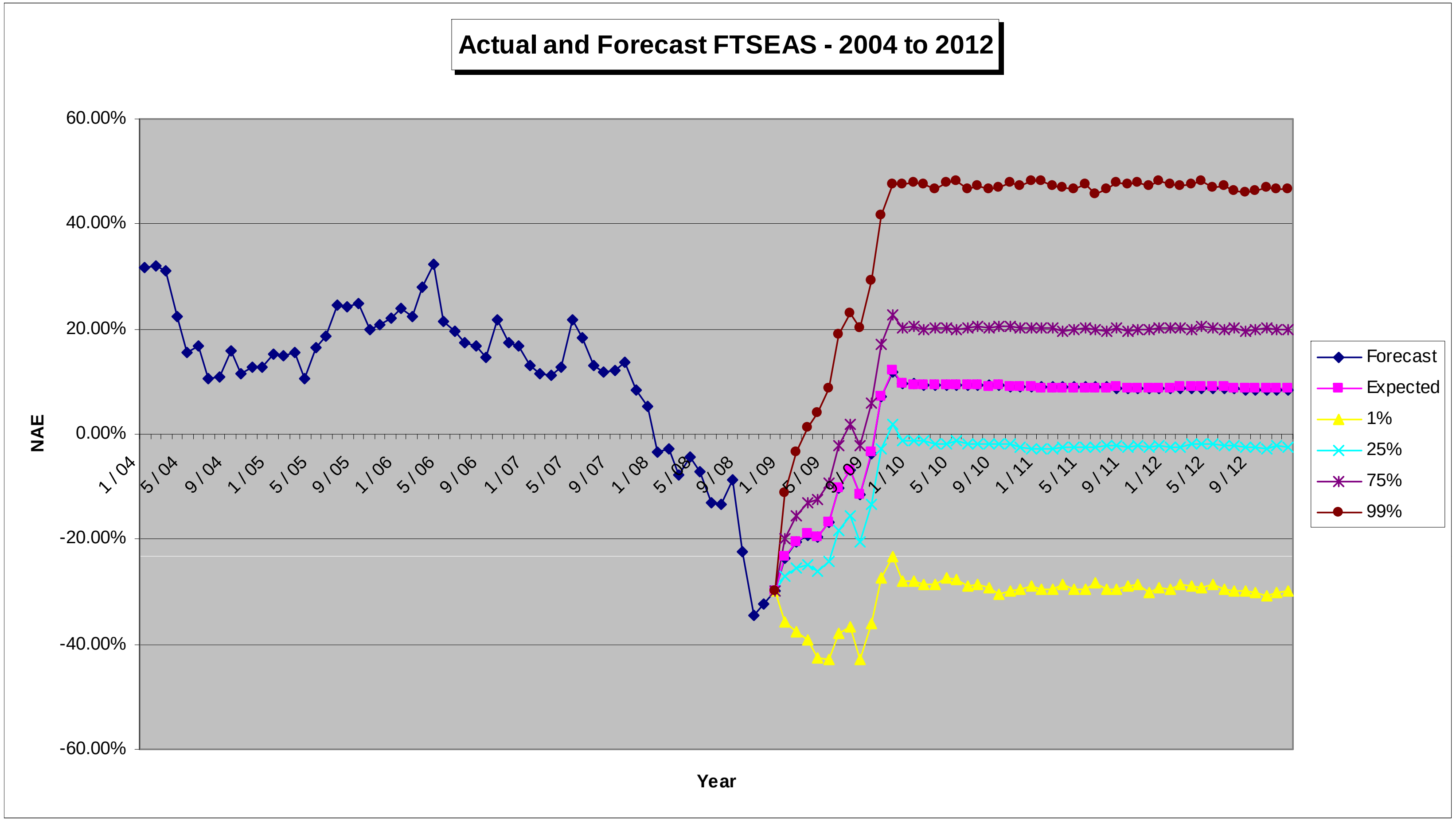
## FTSE All Share Case Study – Model Fit and Future Projections

| FTSEAS | | | |
|---|---|---|---|
| **Start** | 1987 | | |
| **End** | 2008 | | |
| | | | |
| **Variable** | **Coefficient** | **t-statistic** | **Probability** |
| C | 0.07479 | 2.057 | 4.07% |
| Y(t-1) | 0.97975 | 64.273 | 0.00% |
| e (t-12) | -0.93485 | -78.133 | 0.00% |
| | | | |
| **Adj $R^2$** | 90.1% | | |
| **Durbin Watson** | 1.8982 | | |
| **SSR** | 0.7080 | | |
| **AIC** | -3.0567 | | |
| **SC** | -3.0160 | | |

| | **12 / 09** | **12 / 10** | **12 / 11** | **12 / 12** | **12 / 13** | **12 / 14** | **12 / 15** | **12 / 16** | **12 / 17** | **12 / 18** |
|---|---|---|---|---|---|---|---|---|---|---|
| Forecast | 9.53% | 9.08% | 8.73% | 8.46% | 8.25% | 8.08% | 7.95% | 7.85% | 7.77% | 7.70% |
| Expected | 9.60% | 8.97% | 8.74% | 8.69% | 7.93% | 8.47% | 7.92% | 8.11% | 7.90% | 7.47% |
| Standard Deviation | 16.15% | 16.95% | 16.63% | 16.65% | 16.59% | 16.78% | 16.64% | 16.71% | 16.49% | 16.71% |
| Minimum | -46.81% | -58.43% | -48.94% | -50.47% | -65.04% | -52.33% | -55.41% | -58.17% | -61.01% | -73.11% |
| Maximum | 64.70% | 71.63% | 70.16% | 64.54% | 63.85% | 74.63% | 70.24% | 79.36% | 84.84% | 68.42% |
| | | | | | | | | | | |
| **Percentile** | | | | | | | | | | |
| 0.5% | -32.46% | -34.16% | -33.22% | -34.09% | -34.18% | -32.63% | -32.75% | -34.93% | -34.49% | -34.11% |
| 1.0% | -27.88% | -28.91% | -29.30% | -29.93% | -30.46% | -29.02% | -29.77% | -30.07% | -30.88% | -31.18% |
| 5.0% | -16.64% | -18.50% | -18.70% | -19.43% | -19.62% | -18.98% | -19.39% | -18.98% | -19.44% | -19.94% |
| 25.0% | -1.24% | -2.82% | -2.29% | -2.36% | -3.15% | -3.38% | -3.46% | -3.00% | -3.18% | -3.88% |
| 50.0% | 9.28% | 8.83% | 9.09% | 9.02% | 7.93% | 8.44% | 7.86% | 8.19% | 7.89% | 7.32% |
| 75.0% | 20.35% | 20.27% | 20.12% | 19.87% | 19.14% | 19.97% | 19.16% | 18.97% | 18.74% | 18.97% |
| 95.0% | 36.12% | 37.15% | 35.83% | 36.30% | 35.22% | 36.00% | 35.28% | 36.22% | 35.42% | 34.91% |
| 99.0% | 47.53% | 48.27% | 48.18% | 46.62% | 45.53% | 48.05% | 47.32% | 47.12% | 45.73% | 45.82% |
| 99.5% | 51.84% | 52.94% | 52.45% | 50.54% | 49.29% | 52.37% | 51.51% | 49.60% | 50.70% | 48.94% |

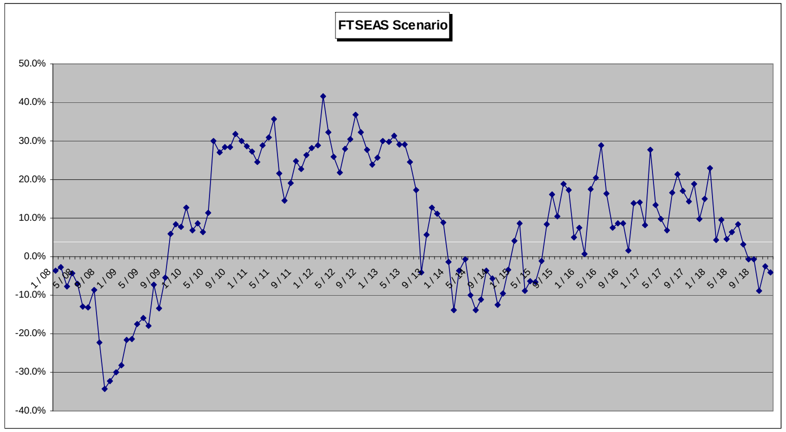
# Case Studies

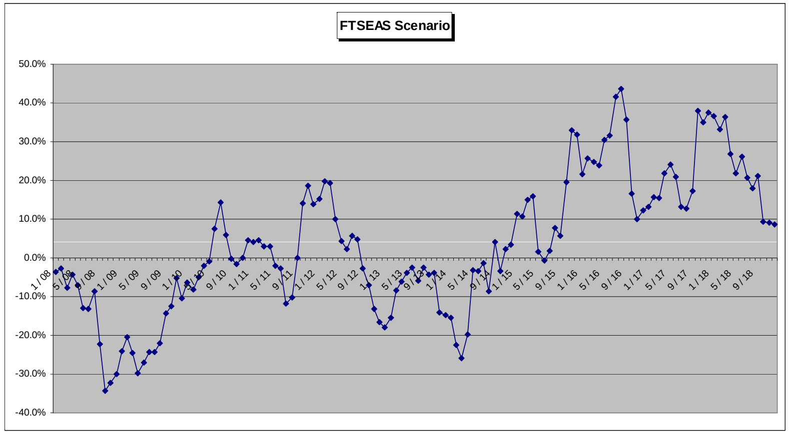
## FTSE All Share Case Study – Future Projections

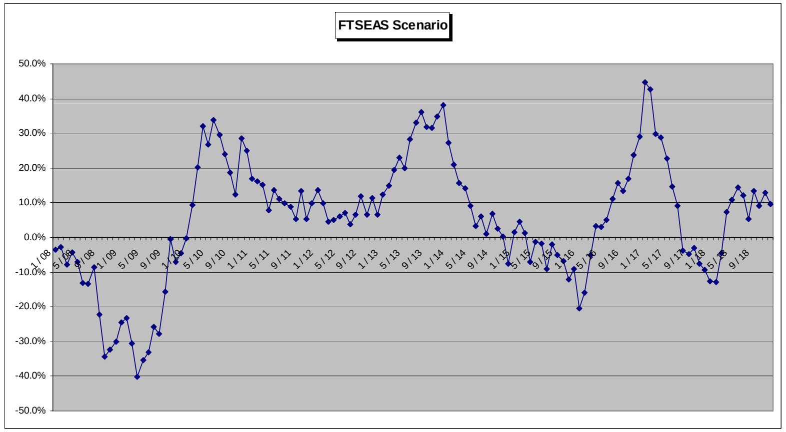


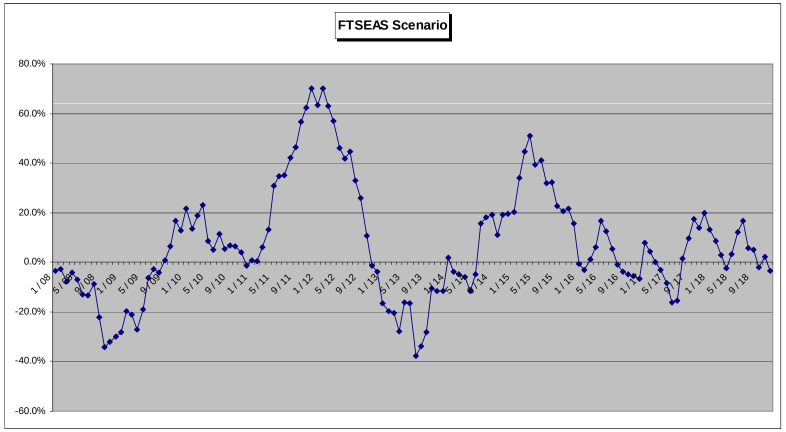
# Case Studies

## FTSE All Share Case Study – Four Random Scenarios (Press F9)



# Case Studies

## Underwriting ("UW") Cycle Case Study – Risk Drivers *

- Target variable $y_t$
  - The concern here is price. If a company cannot compete at the prevailing price then it will lose money or business, yet price is multidimensional
  - Most analyses focus on some form of profitability measure such as the loss ratio or combined ratio with possible adjustments for the time value of money

- There are many potential explanatory variables:
  - Prior period values of profitability and its components
  - Other internal financial variables such as reserves, investment income, catastrophe losses, total capital and reinsurance
  - Regulatory / ratings variables – especially upgrades and downgrades
  - Reinsurance section financials
  - Economic variables such as inflation, unemployment and GNP
  - Financial market variables such as interest rates and stock market returns

* Enterprise Risk Analysis for Property & Liability Insurance Companies"; (2007); Guy Carpenter

# Case Studies
## UW Cycle Case Study – Data

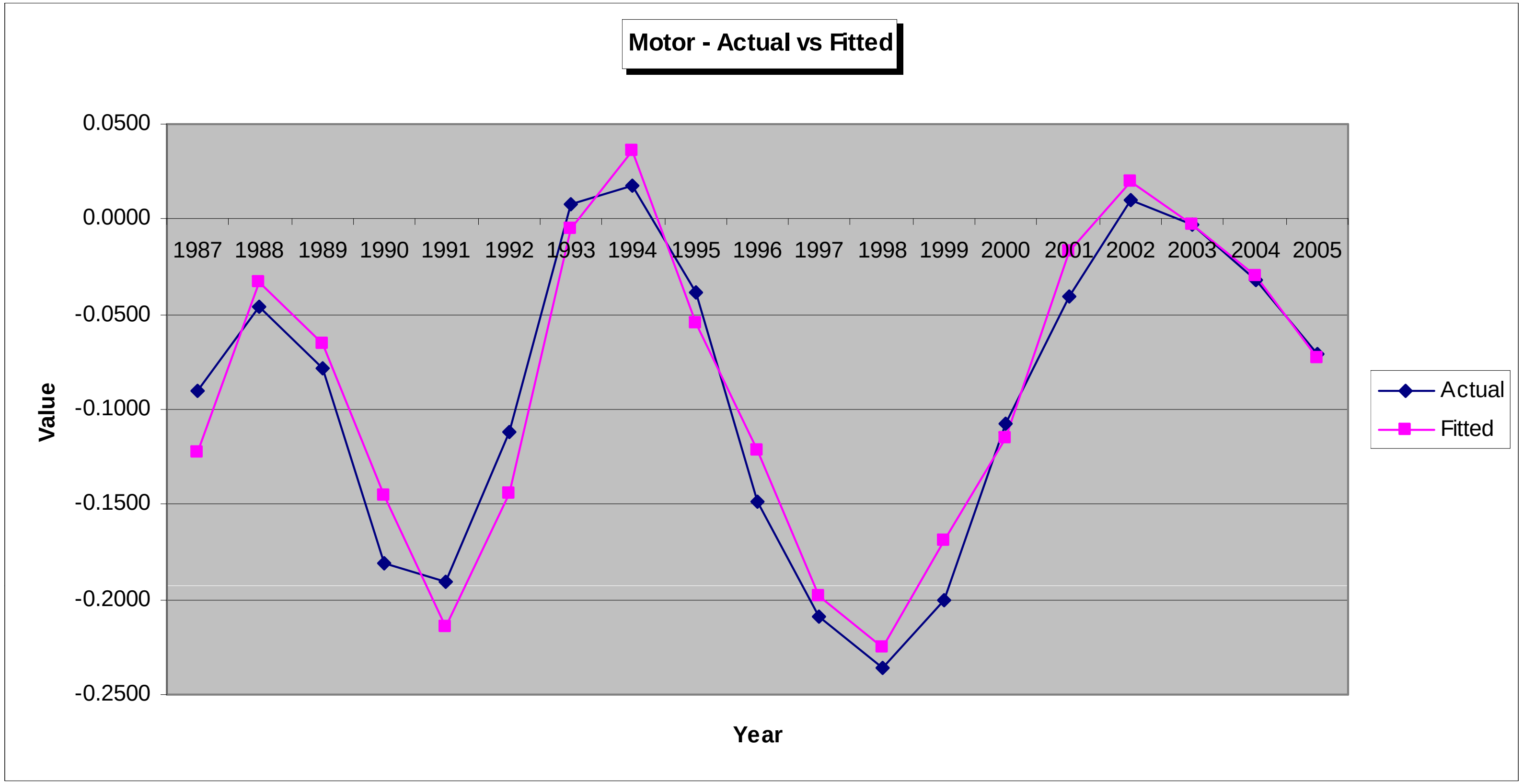
- Data
  - Annual data has been used
  - Annual Underwriting Profit as % of Net Written Premium for the FSA Motor insurance class grouping at an overall UK industry level.
  - *[ Data by FSA insurance class grouping was provided to me. I have not been able to verify independently the data. The analysis therefore is more for illustration purposes only ]*

- ARIMA(2,[3]) Model Fit
  - Annual data 1987 to Dec 2005
  - Box-Jenkins Diagnostic Evaluation tests OK
  - Not a large volume of data
  - Residuals OK but do not appear as random, more a data volume issue

**Motor(t) = - 0.09598 + Y(t)**
**Y(t) = 1.37739 Y(t-1) - 0.81563 Y(t-2) - 0.98131 e(t-3) + e(t)**
**e(t) ~ N(-0.00370,0.02046)**

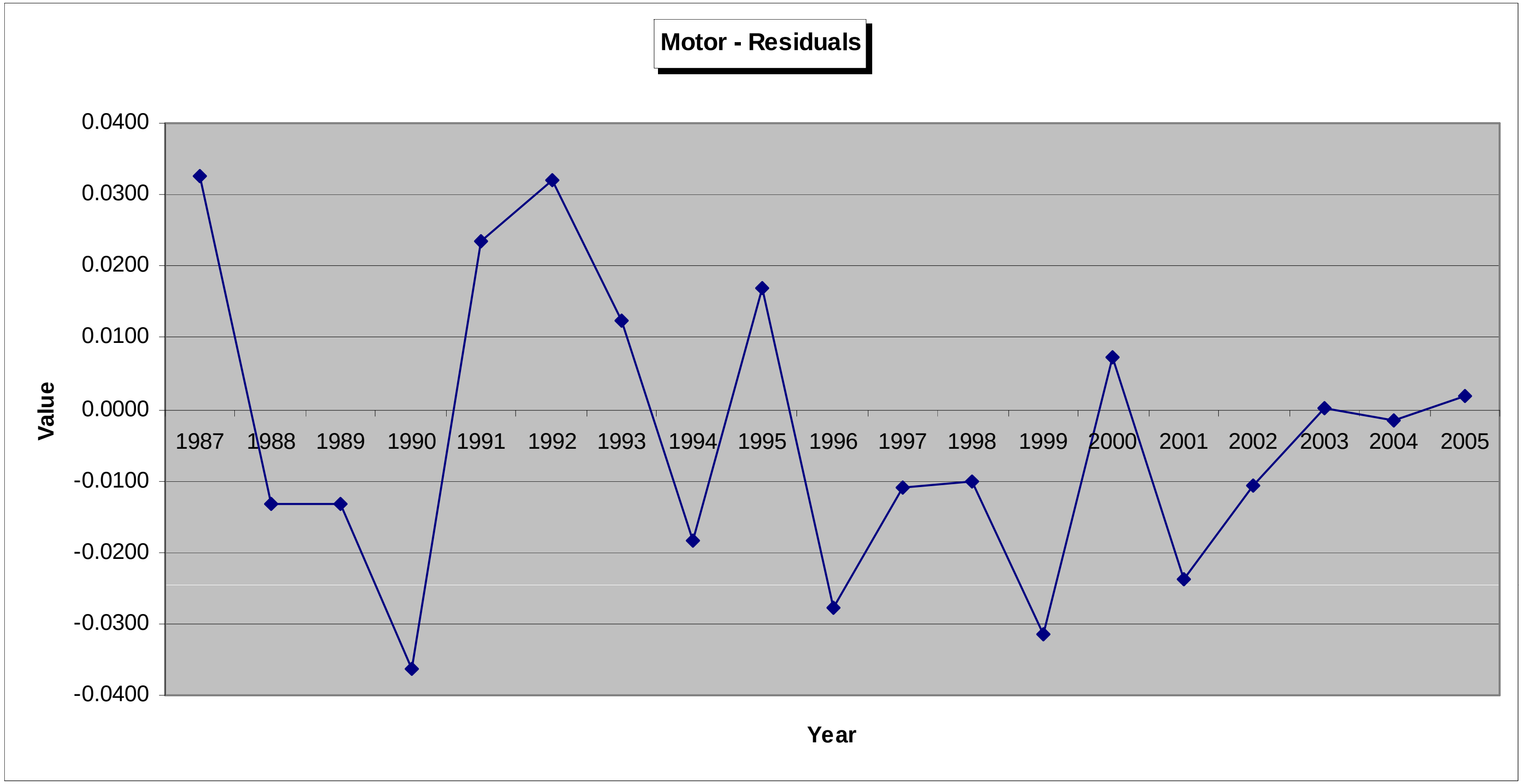
# Case Studies

## UW Cycle Case Study – Actual vs Fitted (All years)



# Case Studies

## UW Cycle Case Study – Residuals (All years)



# Case Studies

## UW Cycle Case Study – Model Fit

| **Motor** | | | |
|---|---|---|---|
| **Start** | 1987 | | |
| **End** | 2005 | | |
| | | | |
| **Variable** | **Coefficient** | **t-statistic** | **Probability** |
| C | -0.09598 | -20.794 | 0.00% |
| Y(t-1) | 1.37739 | 9.340 | 0.00% |
| Y(t-2) | -0.81563 | -5.325 | 0.01% |
| e(t-3) | -0.98131 | -10.934 | 0.00% |
| | | | |
| **Adj $R^2$** | 92.2% | | |
| **Durbin Watson** | 1.8374 | | |
| **SSR** | 0.0228 | | |
| **AIC** | -4.5397 | | |
| **SC** | -4.3409 | | |

# Conclusions
## Conclusions

- Time Series modelling techniques can provide an informative insight
  - It is helpful if target variables are functions of explanatory variables or prior values of itself that have economic or business rationale
  - Avoid over-parameterised models – in-sample vs out-of-sample testing
- A visual inspection of the data is key to any analysis
- Models fits need to be supported by rigorous statistical diagnostics:
  - It is far too easy to determine optimal models and parameters that fail basic statistical tests such as those for t-statistics and autocorrelation in residuals
  - If the Model fails these tests one needs to try a different model
- Test sensitivity of the model parameters and forecasts to different start and end periods

# Q&A
## Q&A

- Questions ?