Does nonlinearity exist in financial TS?
Yes, especially in volatility & high-freq data

We focus on simple nonlinear models & neural networks

What is a linear time series?

\[ x_t = \mu + \sum_{i=0}^{\infty} \psi_i a_{t-i} \]

where \( \mu \) is a constant, \( \psi_i \) are real numbers with \( \psi_0 = 1 \), and \( \{a_t\} \) is an iid \((0, \sigma_a^2)\).

**General concept:** Let \( F_{t-1} \) denote the information available at time \( t-1 \).

Conditional mean:

\( \mu_t = E(x_t|F_{t-1}) \equiv g(F_{t-1}), \)

Conditional variance:

\( \sigma_t^2 = \text{Var}(x_t|F_{t-1}) \equiv h(F_{t-1}) \)

where \( g(.) \) and \( h(.) \) are well-defined functions with \( h(.) > 0 \).

For a linear series, \( g(.) \) is a linear function of \( F_{t-1} \) and \( h(.) = \sigma_a^2 \).

Statistics literature: focuses on \( g(.) \)

See the book by Tong (Oxford University Press, 1990)

Econometrics literature: focuses on \( h(.) \)
Some specific models

**TAR model**: a piecewise linear model in the space of a threshold variable.

Example: 2-regime AR(1) model

\[ x_t = \begin{cases} 
-1.5x_{t-1} + a_t & \text{if } x_{t-1} < 0, \\
0.5x_{t-1} + a_t & \text{if } x_{t-1} \geq 0, 
\end{cases} \]

where \( a_t \)'s are iid \( N(0, 1) \).

Here the delay is 1 time period, \( x_{t-1} \) is the **threshold** variable, and the threshold is 0. The threshold divides the range (or space) of \( x_{t-1} \) into two regimes with Regime 1 denoting \( x_{t-1} < 0 \).

What is so special about this model? See the time plot.

Special features of the model: (a) asymmetry in rising and declining patterns, (more data points are positive than negative) (b) the mean of \( x_t \) is not zero even though there is no constant term in the model, (c) the lag-1 coefficient may be greater than 1 in absolute value.

**Financial applications**:


\[ r_t = \alpha + \beta r_{m,t} + \epsilon_t. \]

A simple nonlinear model:

\[ r_t = \begin{cases} 
\alpha_1 + \beta_1 r_{m,t} + \epsilon_t, & \text{if } r_{m,t} \leq 0 \\
\alpha_2 + \beta_2 r_{m,t} + \epsilon_t, & \text{if } r_{m,t} > 0.
\end{cases} \]
> da=read.table("m-gmsp6708.txt",header=T)
> head(da)
    Date   GM   SP
1 19670331 0.053541 0.039410
....
6 19670831 -0.004720 -0.011715
> gm=log(da$GM+1)
> sp=log(da$SP+1)
> m1=lm(gm~sp)  # Market model
> summary(m1)

Call: lm(formula = gm ~ sp)

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)       -0.004861   0.003434  -1.415 0.158
sp                  1.072508   0.077177  13.897 <2e-16 ***
---

Residual standard error: 0.07652 on 500 degrees of freedom
Multiple R-squared:  0.2786,    Adjusted R-squared:  0.2772

Figure 1: A simulated two-regime TAR process
\begin{verbatim}
> length(gm)
[1] 502
> idx=c(1:502)[sp <= 0] % Locate all non-positive market returns
> nsp=rep(0,502) % Create the variable of non-positive market returns
> nsp[idx]=sp[idx]
> c1=rep(0,502) % Create a variable for intercept of non-positive market returns.
> c1[idx]=1
> xx=cbind(gm,sp,c1,nsp) % Show the resulting variables
> head(xx)
   gm     sp    c1     nsp
[1,] 0.052 0.039 0.000 0.000
[2,] 0.126 0.041 0.000 0.000
[3,] -0.083 -0.054 1.000 -0.054
[4,] -0.024 0.017 0.000 0.000
[5,] 0.098 0.044 0.000 0.000
[6,] -0.005 -0.012 1.000 -0.012
> m2=lm(gm~c1+sp) % with different intercepts
> summary(m2)
Call: lm(formula = gm ~ c1 + sp)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.015    0.006   -2.52   0.012 *  
c1           0.022    0.011    2.09   0.040 *  
sp           1.258    0.118  10.70  <2e-16 ***
---
Residual standard error: 0.076 on 499 degrees of freedom  
Multiple R-squared: 0.285, Adjusted R-squared: 0.282

> m3=lm(gm~sp+nsp)
> summary(m3)
Call: lm(formula = gm ~ sp + nsp)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.002    0.005    0.44   0.650
sp           0.848    0.147    5.75  1.5e-08 ***
\end{verbatim}
\textbf{nsp} 0.421989  0.236424 1.785  0.0749 .

---

Residual standard error: 0.07635 on 499 degrees of freedom
Multiple R-squared: 0.2832,  Adjusted R-squared: 0.2803

\texttt{> m4=lm(gm~sp+c1+nsp)}
\texttt{> summary(m4)}
\texttt{Call: lm(formula = gm ~ sp + c1 + nsp)}

\textbf{Coefficients:}

|                | Estimate | Std. Error | t value | Pr(>|t|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.007778 | 0.007369   | -1.055  | 0.2917   |
| sp             | 1.041129  | 0.176838   | 5.887   | 7.21e-09 *** |
| c1             | 0.020713  | 0.010550   | 1.963   | 0.0502 . |
| nsp            | 0.387630  | 0.236399   | 1.640   | 0.1017   |

---

Residual standard error: 0.07613 on 498 degrees of freedom
Multiple R-squared: 0.2887,  Adjusted R-squared: 0.2844

\textbf{(B) Modeling asymmetry in volatility (recall EGARCH model)}

\textbf{Example:} Daily log returns of IBM stock from July 3, 1962 to December 31, 2003 for 10,446 observations. See Figure 4.3 of the text (p. 162).

\textbf{AR(2)-GARCH(1,1) model:}

\[ r_t = 0.062 - 0.024 r_{t-2} + a_t, \quad a_t = \sigma_t \epsilon_t \]
\[ \sigma_t^2 = 0.037 + 0.077 a_{t-1}^2 + 0.913 \sigma_{t-1}^2 \]

Std residuals: \( Q(10) = 5.19(0.88) \) and \( Q(20) = 24.38(0.23) \)
Sq. std. res.: \( Q(10) = 11.67(0.31) \) and \( Q(20) = 18.25(0.57) \).

\textbf{AR(2)-TAR-GARCH(1,1) model}

\[ r_t = 0.033 - 0.023 r_{t-2} + a_t, \quad a_t = \sigma_t \epsilon_t \]
\[ \sigma_t^2 = 0.098 a_{t-1}^2 + 0.954 \sigma_{t-1}^2 + (0.060 - 0.52 a_{t-1}^2 - 0.069 \sigma_{t-1}^2) I(a_{t-1} > 0). \]

**Further simplification:**

\[ r_t = 0.068 - 0.027 r_{t-2} + a_t, \quad a_t = \sigma_t \epsilon_t \]

\[ \sigma_t^2 = (1.0 - 0.926) a_{t-1}^2 + 0.926 \sigma_{t-1}^2 + (0.045 - 0.38 a_{t-1}^2 + 0.021 \sigma_{t-1}^2) I(a_{t-1} > 0). \]

Rewrite the TAR-GARCH(1,1) as

\[ \sigma_t^2 = \begin{cases} 
0.074 a_{t-1}^2 + 0.926 \sigma_{t-1}^2 & \text{if } a_{t-1} \leq 0 \\
0.045 + 0.036 a_{t-1}^2 + 0.947 \sigma_{t-1}^2 & \text{if } a_{t-1} > 0, 
\end{cases} \]

Discussion: The asymmetry in volatility is clearly seen. When \( a_{t-1} < 0 \), the volatility follows an IGARCH model without any drift. However, the volatility follows a GARCH(1,1) model when \( a_{t-1} \) is positive. But the persistent coefficient is close to unity for \( a_{t-1} > 0 \).

**A different formulation:** Recall GJR (or TGARCH) model.

A TGARCH(\(m, s\)) model assumes the form

\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2, \]

where \( N_{t-i} \) is an indicator for negative \( a_{t-i} \), that is,

\[ N_{t-i} = \begin{cases} 
1 & \text{if } a_{t-i} < 0, \\
0 & \text{if } a_{t-i} \geq 0, 
\end{cases} \]

and \( \alpha_i, \gamma_i \) and \( \beta_j \) are non-negative parameters satisfying conditions similar to those of GARCH models.
Note that the impact of $a_{t-i}$ on $\sigma_t^2$ is
\[
\begin{cases}
\alpha_i a_{t-i}^2 & \text{if } a_{t-1} \geq 0 \\
(\alpha_i + \gamma_i) a_{t-i}^2 & \text{if } a_{t-1} < 0.
\end{cases}
\]

**Example.** Consider the monthly log returns of IBM stock from 1926 to 2003. The fitted TGARCH(1,1) model with "ged" innovations is
\[
\begin{align*}
    r_t &= 0.0121 + a_t, \quad a_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim \text{ged}(1.51), \\
    \sigma_t^2 &= 3.45 \times 10^{-4} + (0.0658 + 0.0843 N_{t-1}) a_{t-1}^2 + 0.8182 \sigma_{t-1}^2.
\end{align*}
\]
The model seems adequate.

**Markov switching model**
Two-state MS model:
\[
x_t = \begin{cases}
c_1 + \sum_{i=1}^p \phi_{1,i} x_{t-i} + a_{1t} & \text{if } s_t = 1, \\
c_2 + \sum_{i=1}^p \phi_{2,i} x_{t-i} + a_{2t} & \text{if } s_t = 2,
\end{cases}
\]
where $s_t$ assumes values in $\{1,2\}$ and is a first-order Markov chain with trans. prob.
\[
P(s_t = 2|s_{t-1} = 1) = w_1, \quad P(s_t = 1|s_{t-1} = 2) = w_2,
\]
where $0 \leq w_1 \leq 1$ is the probability of switching out State 1 from time $t-1$ to time $t$. A large $w_1$ means that it is easy to switch out State 1, i.e. cannot stay in State 1 for long. The inverse, $1/w_1$, is the expected duration (number of time periods) to stay in State 1. Similar idea applies to $w_2$. 

Example: Growth rate of US quarterly real GNP 47-91. See Figure 4.4 of the textbook (p.188).

<table>
<thead>
<tr>
<th>Par</th>
<th>$c_i$</th>
<th>$\phi_1$</th>
<th>$\phi_2$</th>
<th>$\phi_3$</th>
<th>$\phi_4$</th>
<th>$\sigma_i$</th>
<th>$w_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Est</td>
<td>0.909</td>
<td>0.265</td>
<td>0.029</td>
<td>−0.126</td>
<td>−0.110</td>
<td>0.816</td>
<td>0.118</td>
</tr>
<tr>
<td>S.E</td>
<td>0.202</td>
<td>0.113</td>
<td>0.126</td>
<td>0.103</td>
<td>0.109</td>
<td>0.125</td>
<td>0.053</td>
</tr>
</tbody>
</table>

State 2

<table>
<thead>
<tr>
<th>Par</th>
<th>$c_i$</th>
<th>$\phi_1$</th>
<th>$\phi_2$</th>
<th>$\phi_3$</th>
<th>$\phi_4$</th>
<th>$\sigma_i$</th>
<th>$w_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Est</td>
<td>−0.420</td>
<td>0.216</td>
<td>0.628</td>
<td>−0.073</td>
<td>−0.097</td>
<td>1.017</td>
<td>0.286</td>
</tr>
<tr>
<td>S.E</td>
<td>0.324</td>
<td>0.347</td>
<td>0.377</td>
<td>0.364</td>
<td>0.404</td>
<td>0.293</td>
<td>0.064</td>
</tr>
</tbody>
</table>

Discussion

- Regime 2, which has a negative expectation, denotes “recession” periods. The S.E. of the estimates are large due to the small number of data in the regime.

- The expected durations for Regime 1 and 2 are 8.5 and 3.5 quarters, respectively. \((1/w_i)\)

Neural networks

- a semi-parametric approach to data analysis
• Structure of a network
  – Output layer
  – Input layer
  – Hidden layer
  – Nodes

• Activation function:
  – Logistic function:
    \[ \ell(z) = \frac{\exp(z)}{1 + \exp(z)} \]
  – Heaviside (or threshold) function:
    \[ H(z) = \begin{cases} 
      1 & \text{if } z > 0 \\
      0 & \text{if } z \leq 0 
    \end{cases} \]

• Use \( \ell(z) \) for the hidden layer

Feed-forward neural network:
Hidden node:
\[ x_j = f_j(\alpha_j + \sum_{i \rightarrow j} w_{ij} x_i) \]
where \( f_j(.) \) is an activation function which is typically taken to be the logistic function
\[ f_j(z) = \frac{\exp(z)}{1 + \exp(z)}, \]
\( \alpha_j \) is called the bias, the summation \( i \rightarrow j \) means summing over all input nodes feeding to \( j \), and \( w_{ij} \) are the weights.

Output node:

\[
y = f_o \left( \alpha_o + \sum_{j \rightarrow o} w_{jo} x_j \right),
\]

where the activation function \( f_o(.) \) is either linear or a Heaviside function. By a Heaviside function, we mean \( f_o(z) = 1 \) if \( z > 0 \) and \( f_o(z) = 0 \), otherwise.

General form:

\[
y = f_o \left[ \alpha_o + \sum_{j \rightarrow o} w_{jo} f_j \left( \alpha_j + \sum_{i \rightarrow j} w_{ij} x_i \right) \right].
\]

With direct connections from the input layer to the output layer:

\[
y = f_o \left[ \alpha_o + \sum_{i \rightarrow o} w_{io} x_i + \sum_{j \rightarrow o} w_{jo} f_j \left( \alpha_j + \sum_{i \rightarrow j} w_{ij} x_i \right) \right],
\]

Training and forecasting

Divide the data into training and forecasting subsamples.

**Training**: build a few network systems

**Forecasting**: based on the accuracy of out-of-sample forecasts to select the “best” network.

**Example**: Monthly log returns of IBM stock 26-99.

See text for details.

**Some R commands**:

You must load the library “nnet” into S-Plus before running the command `nnet`. 
x=read.table(‘m-ibmln.txt’)  
y=x[4:864]     % select the output: r(t)  
# obtain the input variables: r(t-1), r(t-2), and r(t-3)  
ibm.x_cbind(x[3:863],x[2:862],x[1:861])  
# build a 3-2-1 network with skip layer connections  
# and linear output.  
ibm.nn_nnet(ibm.x,y,size=2,linout=T,skip=T,maxit=10000,  
decay=1e-2,reltol=1e-7,abstol=1e-7,range=1.0)  
# print the summary results of the network  
summary(ibm.nn)  
# compute & print the residual sum of squares.  
sse=sum((y-predict(ibm.nn,ibm.x))^2)  
print(sse)  
#eigen(nnet.Hess(ibm.nn,ibm.x,y),T)$values  
# setup the input variables in the forecasting subsample  
ibm.p=cbind(x[864:887],x[863:886],x[862:885])  
# compute the forecasts  
yh=predict(ibm.nn,ibm.p)  
# The observed returns in the forecasting subsample  
yo=x[865:888]  
# compute & print the sum of squares of forecast errors  
ssfe=sum((yo-yh)^2)  
print(ssfe)  

**Remark**: One-step ahead Out-of-sample-forecasts using `nnet` command. A R script, `backnnet.R`, is developed to carry out the evaluation of 1-step ahead out-of-sample forecasts. For illustration,  
> source(‘backnnet.R’)  
> m3=backnnet(x,y,nsize,orig,nl,nsk,miter)
Some references

Related to Credit Risk


Analysis of High-Frequency Financial Data & Market Microstructure

**Market microstructure:** Why is it important?

1. Important in market design & operation, e.g. to compare different markets (NYSE vs NASDAQ)
2. To study price discovery, liquidity, volatility, etc.
3. To understand costs of trading
4. Important in learning the consequences of institutional arrangements on observed processes, e.g.
   - Nonsynchronous trading
   - Bid-ask bounce
   - Impact of changes in tick size, after-hour trading, etc.
   - Impact of daily price limits (many foreign markets)

**Nonsynchronous trading:**

Key implication: may induce serial correlations even when the underlying returns are iid.

Setup: log returns \( \{r_t\} \) are iid \((\mu, \sigma^2)\)

For each time index \( t \), \( P(\text{no trade}) = \pi \).

Cannot observe \( r_t \) if there is no trade.

What is the observed log return series \( r_t^o \)?
It turns out \( r_t^0 \) is given in Eq. (5.1),

\[
\begin{align*}
    r_t^0 &= \begin{cases} 
    0 & \text{with prob. } \pi \\
    r_t & \text{with prob. } (1 - \pi)^2 \\
    r_t + r_{t-1} & \text{with prob. } (1 - \pi)^2 \pi \\
    \vdots \\
    \sum_{i=0}^{k} r_{t-i} & \text{with prob. } (1 - \pi)^2 \pi^k \\
    \vdots 
    \end{cases}
\end{align*}
\]

One can use this relation to show that

\[
\begin{align*}
    \text{Var}(r_t^0) &= \sigma^2 + \frac{2\pi \mu^2}{1 - \pi} \\
    \text{Cov}(r_t^0, r_{t-j}^0) &= -\mu^2 \pi^j, \quad j \geq 1.
\end{align*}
\]

**Bid-ask bounce**

Bid and ask quotes introduce **negative** lag-1 serial correlation.

Setup: simplest case of Roll(1984)

True price \( P_t^* = \frac{P_a + P_b}{2} \) is unchanged over time, i.e. \( P_t^* = P_{t-1}^* \)

\( S = P_a - P_b \) is the bid-ask spread

\[
P_t = P_t^* + \begin{cases} 
    S/2 & \text{with prob. } 0.5 \\
    -S/2 & \text{with prob. } 0.5
    \end{cases}
\]

Then, \( P_t = P_t^* + \frac{S}{2} I_t \) and

\[
\Delta P_t \equiv P_t - P_{t-1} = (I_t - I_{t-1}) \frac{S}{2}
\]

where \( I_t \) and \( I_{t-1} \) are independent binary variables with \( P(I_i = 1) = 0.5 \) and \( P(I_i = -1) = 0.5 \).
Note: \( E(I_t) = 0 \) and \( \text{Var}(I_t) = 1 \) for all \( t \).

One can show that

\[
\begin{align*}
\text{Var}(\Delta P_t) &= S^2/2 \\
\text{Cov}(\Delta P_t, \Delta P_{t-1}) &= -S^2/4 \\
\text{Cov}(\Delta P_t, \Delta P_{t-j}) &= 0, \quad j > 1.
\end{align*}
\]

The result continues to hold if \( P^*_t \) follows a random walk model.
That is, \( P^*_t = P^*_{t-1} + e_t \) with \( e_t \sim iid(0, \sigma^2_2) \).

**High-Frequency Financial Data**

Observations taken with time intervals 24 hours or less

Some example:

1. Transaction (or tick-by-tick) data
2. 5-minute returns in FX
3. 1-minute returns on index futures and cash market

Some Basic Features of the Data:

1. Irregular time intervals
2. Leptokurtic or Heavy tails
3. Discrete values, e.g. price in multiples of tick size
4. Large sample size
5. Multi-dimensional variables, e.g. price, volume, quotes, etc.
6. Diurnal Pattern

**An illustration**

IBM stock transaction data from 11/01/1990 to 1/31/1991

- Source: Trades, Orders Reports and Quotes (TORQ)
- Trading days: 63
- Sample size: 60,328
- Intraday trades: 60,265.
- Data available: bid, ask, transaction prices, volume, time, etc.
- Zero durations: 6531 (about 11%).
- Kurtosis of adj-duration: 44.23(.02)

**Frequencies of price change**

<table>
<thead>
<tr>
<th>Number(tick)</th>
<th>$\leq -3$</th>
<th>$-2$</th>
<th>$-1$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>$\geq 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>0.66</td>
<td>1.33</td>
<td>14.53</td>
<td>67.06</td>
<td>14.53</td>
<td>1.27</td>
<td>0.63</td>
</tr>
</tbody>
</table>

**Number of trades in 5-minute intervals**

See Figures 5.1 and 5.2 on page 214 of the text.

Another example: Transaction data of IBM stock in December 1999, from TAQ.

Two important changes

- Number of trades increased to sixfold (134,120 trades)
– trades with zero time-duration became 23%
– 42 trades in a single second in December 3, 1999.

• Tick size reduces to $1/16; the percentage of trades without price change decreased from 67% to 46%.

**Econometric models**

1. Time Duration and Duration Models
2. Nonlinearity in Time Durations
3. A Model for Price Change and Duration
4. Hierarchical Models
5. Models for bid and ask quotes

Include statistical tools and methods useful in analyzing HF financial data

**Data quality** (need some cleaning)

• Trading hours (FX-24, US-market: 6.5 hours, but ...)
• Time stamp vs transaction time
• Missing values
• Order types (market or limit orders)

**Important statistical issues:**
1. Stationarity
2. Nonlinearity
3. Structural breaks

**Price Change**: Discrete values

- Ordered probit model: Hauseman, Lo, & MacKinlay (1992)

Look at a simple ADS decomposition:

- Price $P_t = P_0 + \sum_i N(t) C_i$
- Number of transactions in [0,t]: $N(t)$
- $C_i = A_i D_i S_i$
  - Action:
    $$A_i = \begin{cases} 1 & \text{if } C_i \neq 0 \\ 0 & \text{otherwise} \end{cases}$$
  - Direction, given $A_i = 1$:
    $$D_i = \begin{cases} 1 & \text{if } C_i > 0 \\ -1 & \text{if } C_i < 0 \end{cases}$$
  - Size, given $A_i = 1$ and $D_i$: multiple of tick size
- Can be estimated by logistic regression
Model specification:

- **Action** $A_i$: Governed by a logistic regression
  \[
P(A_i = 1|F_{i-1}) = \logit(F_{i-1})
  \]

- **Direction given** $A_i = 1$:
  \[
P(D_i = 1|F_{i-1}, A_i = 1) = \logit(A_i, F_{i-1})
  \]

- **Size given** $A_i = 1$ and $D_i$:
  \[
P(S_i = s|A_i = 1, D_i = 1, F_{i-1}) \sim 1 + g(\lambda_{u,i})
  \]
  \[
P(S_i = s|A_i = 1, D_i = -1, F_{i-1}) \sim 1 + g(\lambda_{d,i})
  \]
  where $g(.)$ denotes a Geometric distribution and $\lambda_{j,i}$ is governed by a logistic equation:
  \[
  \ln\left(\frac{\lambda_{j,i}}{1 - \lambda_{j,i}}\right) = \text{linear function of } F_{i-1}, A_i = 1, D_i.
  \]

**Likelihood function:**

\[
P(C_i = s|F_{i-1}) = P(S_i = s|A_i = 1, D_i, F_{i-1})P(D_i|A_i = 1, F_{i-1})P(A_i = 1|F_{i-1}).
\]

**A simple ADS model:** IBM data 59,775 observations.

- **Predictors:** \{\(A_{i-1}, D_{i-1}, S_{i-1}, V_{i-1}, x_{i-1}, BA_i\}\}
  1. $V_{i-1}$: volume of the previous trade (divided by 1000)
  2. $x_{i-1}$: previous duration
3. \( BA_i \): the prevailing bid-ask spread

- Model:
  1. Action: \( P(A_i|F_{i-1}) = p_i, \logit(p_i) = \beta_0 + \beta_1 A_{i-1} \)
  2. Direction: \( P(D_i = 1|A_i = 1, F_{i-1}) = \gamma_i, \logit(\gamma_i) = \delta_0 + \delta_1 D_{i-1} \)
  3. Size: \( \logit(\lambda_{j,i}) = \theta_{j,0} + \theta_{j,1} S_{i-1} \) with \( j = d \) or \( u \).

- Results:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \delta_0 )</th>
<th>( \delta_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>-1.057</td>
<td>0.962</td>
<td>-0.067</td>
<td>-2.307</td>
</tr>
<tr>
<td>Std.Err.</td>
<td>0.104</td>
<td>0.044</td>
<td>0.023</td>
<td>0.056</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( \theta_{u,0} )</th>
<th>( \theta_{u,1} )</th>
<th>( \theta_{d,0} )</th>
<th>( \theta_{d,1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>2.235</td>
<td>-0.670</td>
<td>2.085</td>
<td>-0.509</td>
</tr>
<tr>
<td>Std.Err.</td>
<td>0.029</td>
<td>0.050</td>
<td>0.187</td>
<td>0.139</td>
</tr>
</tbody>
</table>

**Implication**

1. Prob of price change:

\[
P(A_i = 1|A_{i-1} = 0) = 0.258
\]

\[
P(A_i = 1|A_{i-1} = 1) = 0.476.
\]

2. Interpretation: **Odds ratio**

Because \( A_{i-1} \) is also a binary variable, we have a 2 \( \times \) 2 table:
Odds Ratio: Row one divided by Row 2, then Column 1 divided by Column 2.

\[ OR = e^{\beta_1}, \quad \text{or} \quad \beta_1 = \ln(OR). \]

3. Direction of price change:

\[
P(D_i = 1 | F_{i-1}, A_i) = \begin{cases} 
0.483 & \text{if } D_{i-1} = 0, \text{ i.e. } A_{i-1} = 0 \\
0.085 & \text{if } D_{i-1} = 1, \ A_i = 1 \\
0.904 & \text{if } D_{i-1} = -1, \ A_i = 1 
\end{cases}
\]

Bid-ask bounce

4. Weak evidence of price change cluster: price increases

\[
S_i | (D_i = 1) \sim 1 + g(\lambda_{u,i}), \quad \lambda_{u,i} = 2.235 - 0.670S_{i-1}. 
\]

R command: glm stands for generalized linear model.

```r
> da=read.table("ibm91-ads.txt",header=T)
> da1=read.table("ibm91-adsx.txt",header=T)
> head(da)
  Ai  Di  Si
1  1  0  0  0
2  2  0  0  0
3  3  0  0  0
4  4  0  0  0
```
> head(da1)

<table>
<thead>
<tr>
<th></th>
<th>Vim1</th>
<th>Durm1</th>
<th>BAi</th>
<th>Aim1</th>
<th>Dim1</th>
<th>Sim1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>0.4</td>
<td>0.125</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0.1</td>
<td>0.370</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1.0</td>
<td>0.125</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0.1</td>
<td>0.125</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>0.1</td>
<td>0.625</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>62</td>
<td>1.0</td>
<td>0.625</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

> Ai=da$Ai
> Di=da$Di
> Aim1=da1$Aim1
> Dim1=da1$Dim1
> m1=glm(Ai~Aim1,family=binomial) % fit a linear logistic regression
> summary(m1)

Call:
glm(formula = Ai ~ Aim1, family = binomial)

Coefficients:
  Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.05667 0.01142 -92.55 <2e-16 *** % See Table 5.6 of the text
Aim1       0.96164 0.01827  52.62 <2e-16 ***
---

> di=Di[Ai==1]
> dim1=Dim1[Ai==1]
> di=(di+abs(di))/2 % Transform di into a binary variable
> m2=glm(di~dim1,family=binomial)
> summary(m2)

Call:
glm(formula = di ~ dim1, family = binomial)

Coefficients:
  Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.06663 0.01728  -3.855  0.000116 *** % See Table 5.6 of the text
dim1        -2.30693 0.03595  -64.171 < 2e-16 ***
---

Null deviance: 27335 on 19717 degrees of freedom
Duration and Duration Models

Focus on intraday time duration between transactions

Autoregressive conditional duration (ACD) model:

- Engle and Russell (1998)
- Intraday durations between trades, in seconds.
- Use ideas of GARCH models

Define

1. \( t_i \): time of the \( i \)-th trade, starting at midnight, measured in seconds.
2. \( X_i = t_i - t_{i-1} \)
3. \( f(t) \): Diurnal pattern of daily trading.
4. \( x_i = X_i / f(t_i) \): adjusted time duration of \( i \)-th trade
5. \( F_i \): information set available at \( t_i \) (inclusive)
6. \( \psi_i \): Expected duration, \( E(x_i|F_{i-1}) \).

ACD\((r,s)\) model:

\[
\frac{x_i}{\psi_i} \sim \epsilon_i, \quad \epsilon_i \sim i.i.d. \quad g(\theta), \quad E(\epsilon_i) = 1
\]

\[
\psi_i = \omega_0 + \sum_{j=1}^{r} \gamma_j x_{i-j} + \sum_{j=1}^{s} \omega_j \psi_{i-j}.
\]
The distribution of $\epsilon_i$ is either Standard Exponential or Standardized Weibull. Refer to as an EACD or WACD model, respectively.

Let $\eta_i = x_i - \psi_i$.

- $\{\eta_i\}$ is a martingale difference sequence.
- ACD($r$, $s$) model becomes

$$x_i = \omega_0 + \sum_{j=1}^{\max(r,s)} (\gamma_j + \omega_j)x_{i-j} - \sum_{j=1}^{s} \omega_j \eta_{i-j} + \eta_j.$$ 

Some properties of ACD model are easily available.

**Remark:** Duration models can be estimated via programs similar to GARCH models.

Focus on the first 5 days of November, 1990.

- Dates: November 1, 2, 5, 6, 7 of 1990
- Sample size: 3534 data points

A simple model: WACD(1,1)

$$x_i = \psi_i\epsilon_i, \quad \psi_i = 0.291 + 0.077x_{i-1} + 0.836\psi_{i-1}$$

where $\{\epsilon_i\}$ iid Weibull with $\hat{\alpha} = 0.878(0.011)$.

**Implication:**
- $E(x_i) = 3.34$ (vs 3.29, sample)
• Not strongly persistent: $\hat{\gamma}_1 + \hat{\omega}_1 \approx 0.91$

• Decaying intensity function.

Model diagnostics:

• ACF of $\hat{\epsilon}_i = \frac{x_i}{\hat{\psi}_i}$: $Q(12) = 5.7$ and $Q(24) = 19.9$

• ACF of $\hat{\epsilon}_i^2$: $Q(12) = 6.5$ and $Q(24) = 15.1$