Booth Honor Code:  
*I pledge my honor that I have not violated the Honor Code during this examination.*

Signature: ____________________________ Name: ____________________________ ID: ____________________________

Notes:

- This is a 3-hour, open-book, and open-note exam.
- Write your answer in the blank space provided for each question.
- There are 16 pages, including some R output.
- For simplicity, **ALL** tests use the 5% significance level, and all **risk-measure** calculations use 1% tail probability. Furthermore, unless specified, all VaR and expected shortfall are for the next trading day for market risk and the next year for credit risk.
- Round your answer to 3 significant digits.
- You may bring a PC or calculator to the exam. **No internet is allowed during the exam!**

Problem A: (40 points) Answer briefly the following questions.

1. Consider a stationary two-dimensional time series $X_t$. Let $\Gamma_1 = \text{Cov}(X_t, X_{t-1})$ be the lag-1 auto-covariance matrix of $X_t$. More specifically, we have

   $$ X_t = \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix}, \quad \Gamma_1 = \begin{bmatrix} \Gamma_{11}(1) & \Gamma_{12}(1) \\ \Gamma_{21}(1) & \Gamma_{22}(1) \end{bmatrix}. $$

   Write down the meanings of $\Gamma_{11}(1)$ and $\Gamma_{12}(1)$.

2. Suppose that $X_t$ follows a 2-dimensional stationary vector AR(1) model,

   $$ \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} 1.0 \\ 2.0 \end{bmatrix} + \begin{bmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{bmatrix} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}, $$

   where $a_t$ is a sequence of independent and identically distributed Gaussian random vectors. What are the meanings of the coefficients $-0.6$ and $0.3$, respectively.
3. Consider the log prices \( p_{1t} \) and \( p_{2t} \) of two assets. Assume that both log price series have a unit root. Describe two approaches that can be used to verify the existence of a linear combination \( w_t = p_{1t} + \gamma p_{2t} \), which has no unit root.

4. Suppose the price \( P_t \) of a stock follows the stochastic diffusion equation (SDE) \( dP_t = 0.04P_t dt + 0.25P_t dw_t \), where \( w_t \) denotes the standard Brownian motion. What are the drift and diffusion terms of the squared process \( P_t^2 \)?

5. Describe two alternative approaches to compute the daily price volatilities of a stock using the intra-day transaction data.

6. Consider the quarterly earnings of a company. Assume that the moving average component of the earnings follows the model \( x_t = (1 - 0.4B - 0.5B^4 + 0.2B^5)a_t \), where \( a_t \) is a univariate white noise series and \( B \) denotes the back-shift operator. Let \( \rho_\ell \) be the lag-\( \ell \) autocorrelation of \( x_t \), where \( \ell > 0 \). How many non-zero autocorrelations \( x_t \) has? Write down the lags of those non-zero autocorrelations.

7. Given one advantage and one dis-advantage of using value at risk (VaR) as a risk measure for a financial position.

8. Let \( F(x) \) be the cumulative distribution function of a loss variable. Assume that \( F(x) \) satisfies

\[
F(x) = \begin{cases} 
0.8725 & \text{for } x = 85 \\
0.9025 & \text{for } x = 90 \\
0.95 & \text{for } x = 96 \\
0.99 & \text{for } x = 100.
\end{cases}
\]

Next, define a new loss variable \( Y \) by

\[
Y = \begin{cases} 
X & \text{if } X \leq 96 \\
0 & \text{otherwise.}
\end{cases}
\]

What is the VaR of the loss \( X \) if the upper tail probability is 5%? What is the VaR of \( Y \) if the upper tail probability is 5%?
9. Consider a 2-2-1 feed-forward neural network. Let \( x_i \) denote the input nodes \((i = 1, 2)\), \( h_j \) denote the hidden nodes \((j = 1, 2)\) and \( o \) be the output node. Write down the logistic function for the hidden node \( h_2 \). Also, if the skip layer is used and the output is a continuous variable, write down the function for network.

10. Consider the monthly log returns of the S&P 500 index. Suppose we are interested in predicting the direction of the movement of the index, i.e., up or down. Describe two methods discussed in the lecture that can be used for such an analysis.

11. Describe two advantages of using the peaks over threshold (POT) method of extreme value theory over the traditional block maximum method.

12. Give two characteristics of the intraday transaction data of U.S. stocks.

13. The GARCH-M models are harder to estimate for stock returns, compared with the conventional GARCH volatility models. Give two reasons that justify the use of GARCH-M models.

14. (For Questions 14 to 16) Suppose that the quarterly log earnings \( x_t \) of company A follows the model

\[
(1 - B)(1 - B^4)x_t = (1 - 0.57B)(1 - 0.18B^4)a_t
\]

\[
a_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim N(0, 1)
\]

\[
\sigma_t^2 = 8.09 \times 10^{-5} + 0.244a_{t-1}^2 + 0.711\sigma_{t-1}^2.
\]

Suppose that the last 5 log earnings, residuals, and volatilities are

<table>
<thead>
<tr>
<th>time</th>
<th>96</th>
<th>97</th>
<th>98</th>
<th>99</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_t )</td>
<td>1.05</td>
<td>1.30</td>
<td>0.91</td>
<td>1.12</td>
<td>1.18</td>
</tr>
<tr>
<td>( a_t )</td>
<td>0.0221</td>
<td>-0.0318</td>
<td>0.0010</td>
<td>-0.0108</td>
<td>0.0113</td>
</tr>
<tr>
<td>( \sigma_t )</td>
<td>0.03608</td>
<td>0.03416</td>
<td>0.03323</td>
<td>0.02951</td>
<td>0.02669</td>
</tr>
</tbody>
</table>
Consider the forecast origin $T = 100$. Calculate the 1-step and 2-step ahead predictions of the log earnings?

15. Again, consider the forecast origin $T = 100$. Compute the 1-step and 2-step ahead volatility forecasts (not the variances).

16. Compute the unconditional standard error of $a_t$. Also, let $w_t = (1 - B)(1 - B^4)x_t$. What is the mean equation for $w_t$ conditional on information available at time $t - 1$?

17. Describe two applications of VaR (value at risk) in making financial decision.

18. Consider the AR(2) model $x_t = 1.1x_{t-1} - 0.5x_{t-2} + a_t, \ a_t \sim N(0, 1)$. Does it exhibit business-cycle pattern? If yes, what is the average length of the business cycles?

19. Describe two ways that a GARCH model can generate a heavy-tailed distribution.

20. Describe two scenarios under which we observe an asset return series that follow a moving-average model.
Problem B. (26 points) Consider the daily adjusted close prices of the stocks of IBM and Caterpillar (CAT), starting from January 4, 2005 for 1866 observations. We compute the daily log returns from the price series, resulting in 1865 returns. The tick symbols are IBM and CAT, respectively. Consider a short position of $2 million on IBM stock and $1 million on CAT stock. Use the attached output to answer the following questions.

1. (3 points) If RiskMetrics is used, calculate the VaR for the portfolio.

2. (3 points) If Gaussian GARCH(1,1) models are used for both log return series, what is the VaR for the portfolio?

3. (2 points) Focus on the Gaussian GARCH(1,1) model for the IBM stock return. What is the expected shortfall for the stock?

4. (4 points) If a GARCH(1,1) model with standardized Student-$t$ innovations is employed for the IBM log returns, what are the VaR and expected shortfall?

5. (4 points) If the traditional method of block maximum is used to study the extreme-value behavior of IBM log returns, what are the parameter estimates? Are the estimates statistically significant? Why?
6. (2 points) What are the 1-day and 10-day VaRs for the IBM position based on the traditional block-maximum method?

7. (4 points) Finally, consider the peaks over threshold (POT) approach. The threshold of 1% is used for both IBM and CAT log returns. Write down the parameter estimates for both stocks? Are these estimates significantly different from zero? Why?

8. (4 points) What are the VaR and expected shortfall for each of the two stock positions based on the POT method?
Problem C. (18 points). Consider the intraday trading of the Caterpillar (CAT) stock from December 04 to December 08, 2010. There were 155,072 trades in the data. Among them, there were 27,859 price increases and 27,510 price decreases. Let $A_i$ and $D_i$ be the action and direction of the price change for the $i$th trade. That is, $A_i = 1$ if and only if the $i$th trade results in a non-zero price change, and $D_i = 1$ if $C_i > 0$, $D_i = -1$ if $C_i < 0$, and $D_i = 0$, otherwise, where $C_i$ denotes the price change of the $i$th trade. The data for the last four trades are given below:

<table>
<thead>
<tr>
<th>ith trade</th>
<th>155069</th>
<th>155070</th>
<th>155071</th>
<th>155072</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_i$</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$D_i$</td>
<td>1</td>
<td>0</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>$A_{i-1}$</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$D_{i-1}$</td>
<td>-1</td>
<td>1</td>
<td>0</td>
<td>-1</td>
</tr>
</tbody>
</table>

Logistic regressions are used to model $A_i$ and $D_i$. The output is attached. Answer the following questions:

1. (3 points) Write down the fitted model $m_1$ for $A_i$. Are the estimates significantly different from zero? Why?

2. (2 points) Based on the refined model, called $m_2$, and the data, obtain the probability that the next trade has a non-zero price change at the origin $i = 155072$. That is, calculate $P(A_{155073} = 1|F_{155072})$, where $F_i$ denotes information available at the $i$-th trade (inclusive).

3. (3 points) Write down the fitted model for $D_i$ conditional on $A_i = 1$ when both $D_{i-1}$ and $A_{i-1}$ are used. [That is, $m_3$.] Are the estimates significantly different from zero? Why?

4. (2 points) Write down the refined model for $D_i$. That is, the model $m_4$. 

7
5. (6 points) Based on the refined model, calculate $P(D_i = 1|A_i = 1, D_{i-1} = 1)$, $P(D_i = 1|A_i = 1, D_{i-1} = 0)$ and $P(D_i = 1|A_i = 1, D_{i-1} = -1)$.

6. (2 points) Interpret the implications of the probabilities calculated in the prior question #5.
**Problem D.** (16 points). This problem applies CreditMetrics to compute VaR of a loan for the next year. Consider a five-year fixed-rate loan of $100 million made to a borrower rated A at 5% annual interest rate. Based on the historical data, we have the following one-year transition probability for A-rated borrower

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>Defaulty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>0.28</td>
<td>3.32</td>
<td>88.4</td>
<td>5.52</td>
<td>1.65</td>
<td>0.52</td>
<td>0.12</td>
<td>0.15</td>
</tr>
</tbody>
</table>

One-year forward zero-coupon curves plus credit spreads by credit rating category:

<table>
<thead>
<tr>
<th>Category</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>3.60</td>
<td>4.17</td>
<td>4.73</td>
<td>5.12</td>
</tr>
<tr>
<td>AA</td>
<td>3.65</td>
<td>4.22</td>
<td>4.78</td>
<td>5.17</td>
</tr>
<tr>
<td>A</td>
<td>3.72</td>
<td>4.32</td>
<td>4.93</td>
<td>5.32</td>
</tr>
<tr>
<td>BBB</td>
<td>4.10</td>
<td>4.67</td>
<td>5.25</td>
<td>5.63</td>
</tr>
<tr>
<td>BB</td>
<td>5.55</td>
<td>6.02</td>
<td>6.78</td>
<td>7.27</td>
</tr>
<tr>
<td>B</td>
<td>6.05</td>
<td>7.02</td>
<td>8.03</td>
<td>8.52</td>
</tr>
<tr>
<td>CCC</td>
<td>15.05</td>
<td>15.02</td>
<td>14.03</td>
<td>13.52</td>
</tr>
</tbody>
</table>

Value of the loan at the end of Year 1, under different rating changes (including first-year coupon):

<table>
<thead>
<tr>
<th>Rating</th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>Defaulty</th>
</tr>
</thead>
<tbody>
<tr>
<td>value</td>
<td>104.78</td>
<td>XXXX</td>
<td>XXXX</td>
<td>103.00</td>
<td>97.59</td>
<td>93.76</td>
<td>XXXX</td>
<td>51.13</td>
</tr>
</tbody>
</table>

1. (3 points) Calculate the value of the loan at the end of Year 1 if the borrower is upgraded to AA, remains at A, or down-graded to CCC. That is, fill in the missing parts of the value of the loan at the end of Year 1.

2. (3 points) What is the mean value of the loan at the end of Year 1?

3. (3 points) What is the standard error of the value of the loan at the end of Year 1?
4. (4 points) Based on CreditMetrics, the loss on the loan is assumed to be normally distributed with mean zero and variance given by that of the value of the loan. What is the 5% VaR of the loan for Year 1? What is the corresponding expected shortfall?

5. (3 points) If the actual distribution is used, what is the 2.44% VaR of the loan for Year 1?
### Problem B ######

```r
> getSymbols("IBM", from="2005-01-04", to="2012-XXXX")
[1] "IBM"
> head(IBM)

<table>
<thead>
<tr>
<th>IBM.Open</th>
<th>IBM.High</th>
<th>IBM.Low</th>
<th>IBM.Close</th>
<th>IBM.Volume</th>
<th>IBM.Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>97.74</td>
<td>98.42</td>
<td>96.52</td>
<td>96.70</td>
<td>5711000</td>
<td>85.97</td>
</tr>
</tbody>
</table>

....

<table>
<thead>
<tr>
<th>IBM.Open</th>
<th>IBM.High</th>
<th>IBM.Low</th>
<th>IBM.Close</th>
<th>IBM.Volume</th>
<th>IBM.Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>95.68</td>
<td>95.79</td>
<td>94.71</td>
<td>95.00</td>
<td>4746400</td>
<td>84.46</td>
</tr>
</tbody>
</table>

> getSymbols("CAT", from="2005-01-04", to="2012-XXXX")
[1] "CAT"
> ibm=diff(log(as.numeric(IBM$IBM.Adjusted)))
> cat=diff(log(as.numeric(CAT$CAT.Adjusted)))

> cor(ibm,cat)
[1] 0.5439475
>
> m1=Igarch(ibm)
Estimates: 0.9415312

Coefficient(s):

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|---------|
| beta 0.9415312 | 0.0122166 | 77.0696 | < 2.22e-16 *** |

---

> length(ibm)
[1] 1865
> v1=m1$volatility
> v1[1865]
[1] 0.008542807
> ibm[1865]
[1] -0.008414473

### You may use the R script "RMeasure.R" to compute VaR and ES.

> m6=Igarch(cat)
Estimates: 0.9607564

Coefficient(s):

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|---------|
| beta 0.96075638 | 0.00488572 | 196.646 | < 2.22e-16 *** |

---

> v6=m6$volatility
> v6[1865]
[1] 0.01909394
> cat[1865]
[1] -0.02879839

> m2=garchFit(~garch(1,1),data=ibm,trace=F)

```
> summary(m2)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(1,1), data = ibm, trace =F)

Mean and Variance Equation:
  data ~ garch(1, 1) [data = ibm]

Conditional Distribution: norm

Error Analysis:

|       | Estimate  | Std. Error | t value | Pr(>|t|) |
|-------|-----------|------------|---------|----------|
| mu    | 7.876e-04 | 2.578e-04  | 3.055   | 0.00225 ** |
| omega | 7.506e-06 | 1.645e-06  | 4.562   | 5.07e-06 *** |
| alpha1| 1.144e-01 | 1.897e-02  | 6.029   | 1.65e-09 *** |
| beta1 | 8.483e-01 | 2.306e-02  | 36.780  | < 2e-16 *** |

Standardised Residuals Tests:

<table>
<thead>
<tr>
<th>Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box Test R</td>
<td>25.24911 0.1920663</td>
</tr>
<tr>
<td>Ljung-Box Test R^2</td>
<td>13.57915 0.8511772</td>
</tr>
</tbody>
</table>

> predict(m2,5)

<table>
<thead>
<tr>
<th>meanForecast</th>
<th>meanError</th>
<th>standardDeviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0007876217</td>
<td>0.01018001</td>
<td>0.01018001</td>
</tr>
</tbody>
</table>

> m2a=garchFit(~garch(1,1),data=cat,trace=F)
> summary(m2a)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(1, 1), data = cat, trace = F)

Mean and Variance Equation:
  data ~ garch(1, 1) [data = cat]

Conditional Distribution: norm

Error Analysis:

|       | Estimate  | Std. Error | t value | Pr(>|t|) |
|-------|-----------|------------|---------|----------|
| mu    | 9.605e-04 | 4.378e-04  | 2.194   | 0.028235 * |
| omega | 9.797e-06 | 2.833e-06  | 3.458   | 0.000545 *** |
| alpha1| 6.176e-02 | 1.099e-02  | 5.622   | 1.89e-08 *** |
| beta1 | 9.184e-01 | 1.474e-02  | 62.315  | < 2e-16 *** |

Standardised Residuals Tests:

<table>
<thead>
<tr>
<th>Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box Test R</td>
<td>20.10922 0.4511164</td>
</tr>
</tbody>
</table>
Ljung-Box Test  R^2  Q(20)  5.421842  0.999483

> predict(m2a,1)
  meanForecast meanError standardDeviation
1  0.0009604689  0.02153353  0.02153353

> m3=garchFit(~garch(1,1),data=ibm,trace=F,cond.dist="std")
> summary(m3)

Title: GARCH Modelling
Call:garchFit(formula="garch(1,1), data=ibm,cond.dist="std",trace=F)

Mean and Variance Equation: data ~ garch(1, 1)[data = ibm]

Conditional Distribution: std

Error Analysis:
              Estimate Std. Error t value Pr(>|t|)
mu  6.377e-04  2.392e-04  2.666  0.00768 **
omega 3.606e-06  1.329e-06  2.714  0.00665 **
alpha1 8.452e-02  1.852e-02  4.564  5.01e-06 ***
beta1 8.992e-01  2.168e-02 41.483  < 2e-16 ***
shape  5.368e+00  6.553e-01  8.191  2.22e-16 ***
---

Standardised Residuals Tests:

Ljung-Box Test  R  Q(20)  25.52523  0.1820706
Ljung-Box Test  R^2  Q(20)  11.587  0.929558

> predict(m3,1)
  meanForecast meanError standardDeviation
1  0.0006376837  0.009736079  0.009736079

> m4=gev(ibm,21)
> m4

$n
[1] 89
$data
[1] 0.009855893 0.010407415 0.011350293 0.027677043 0.027500804 0.018913803
.........
[85] 0.043385301 0.019136149 0.013744045 0.023063821 0.011055492
$block
[1] 21

$par.est

xi     sigma     mu
0.258939979 0.008120351 0.018898459
$par.ses
        xi    sigma     mu
0.0900351111   0.0007099667   0.0009714626

> evtVaR(0.258939979, 0.008120351, 0.018898459)
[1] 0.0344539
>
> m5=gpd(ibm,0.01)
> m5
$data
[1] 0.01040741 0.01135029 0.02767704 0.01092416 0.02120533 0.01609265
 ........
[355] 0.01105549

$threshold
[1] 0.01

$n.exceed
[1] 355

$par.est5
        xi    beta
0.144151291  0.008196402

$par.ses
        xi    beta
0.0608365778  0.0006325919

> riskmeasures(m5,c(0.95,0.99))
   p quantile  sfall
[1,] 0.95 0.02208420 0.03369649
[2,] 0.99 0.04008705 0.05473156
>
> m7=gpd(cat,threshold=0.01)
> m7
$data
[1] 0.01460628 0.01218737 0.02654084 0.01062536 0.01852651 0.01137428
 ...........
[547] 0.01065459 0.02828206

$threshold
[1] 0.01

$n.exceed
[1] 548
$par.est$s

<table>
<thead>
<tr>
<th>xi</th>
<th>beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.09241575</td>
<td>0.01324618</td>
</tr>
</tbody>
</table>

$par.ses$s

<table>
<thead>
<tr>
<th>xi</th>
<th>beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0441199028</td>
<td>0.0007989628</td>
</tr>
</tbody>
</table>

> riskmeasures(m7,c(0.95,0.99))

<table>
<thead>
<tr>
<th>p</th>
<th>quantile</th>
<th>sfall</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,]</td>
<td>0.95</td>
<td>0.03548776</td>
</tr>
<tr>
<td>2,]</td>
<td>0.99</td>
<td>0.06256116</td>
</tr>
</tbody>
</table>

#### Problem C ####
> da=read.table("taq-cat-t-jan04t082010.txt",header=T)
> m1=hfchg(da)
> chg=m1$chg
> length(chg)

[1] 155072
> idx=c(1:155072)[chg > 0]
> length(idx)

[1] 27859
> A=rep(0,155072)
> A[idx]=1
> jdx=c(1:155072)[chg < 0]
> length(jdx)

[1] 27510
> A[jdx]=1
> D=rep(0,155072)
> D[idx]=1; D[jdx]=-1

> Ai=A[2:155072]
> Aim1=A[1:155071]
> Di=D[2:155072]
> Dim1=D[1:155071]
> m1=glm(Ai~Aim1+Dim1,family=binomial)
> summary(m1)

Call: glm(formula = Ai ~ Aim1 + Dim1, family = binomial)

Coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -1.053882 | 0.007234 | -145.687 | <2e-16 *** |
| Aim1 | 1.192291 | 0.011177 | 106.675 | <2e-16 *** |
| Dim1 | 0.007944 | 0.008520 | 0.932 | 0.351 |
> m2=glm(Ai~Aim1,family=binomial)
> summary(m2)
Call: glm(formula = Ai ~ Aim1, family = binomial)

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.053882 0.007234 -145.7 <2e-16 ***
Aim1 1.192339 0.011177 106.7 <2e-16 ***
---
Null deviance: 202121 on 155070 degrees of freedom
Residual deviance: 190445 on 155069 degrees of freedom
AIC: 190449

> kdx=c(1:155071)[Ai==1]
> d1=Di[kdx]
> dd=(d1+abs(d1))/2
> dim1=Dim1[kdx]
> aim1=Aim1[kdx]
> m3=glm(dd~dim1+aim1,family=binomial)
> summary(m3)
Call: glm(formula = dd ~ dim1 + aim1, family = binomial)

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.022429 0.012459 1.800 0.0718 .
dim1 -1.146970 0.013592 -84.386 <2e-16 ***
aim1 -0.002733 0.018438 -0.148 0.8821
---
Null deviance: 76756 on 55368 degrees of freedom
Residual deviance: 68417 on 55366 degrees of freedom
AIC: 68423

> m4=glm(dd~dim1,family=binomial)
> summary(m4)
Call: glm(formula = dd ~ dim1, family = binomial)

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.021181 0.009184 2.306 0.0211 *
dim1 -1.147001 0.013591 -84.396 <2e-16 ***
---