# <u>Quantitative Methods in Finance</u>

## Tutorial, Part 14:
## *Binomial discrete choice models. Maximum likelihood estimation.*

**<u>Example 1:</u>** A survey on eating habits concerning chicken meat was conducted on a sample of 419 individuals. Among others, the data on the following variables were collected (Stata data file `chicken.dta`):

- *butcher*: dichotomous variable for a person buying chicken meat at the butcher's instead of in the supermarket: 1 – the person is buying chicken meat at the butcher, 0 – the person is not buying chicken meat at the butcher;
- *expense_chicken*: money spent on chicken meat in an average week;
- *safe_butcher*: the butcher is selling safe meat (variable measured on a 7-level Likert scale: 1 – completely disagree, …, 7 – completely agree);
- *supermarket*: dichotomous variable for a person having trust in the information from the supermarket: 0 – no, 1 – yes;
- *age*: person's age;
- *hhsize*: number of household members.

a) Explore the data. What kind of variables are there in the data set?
b) Assess the probability that a person is buying chicken meat at the butcher's. Assess the probability that a person is buying chicken meat at the butcher's if they completely agree that the butcher is selling safe meat. How about if they completely disagree? Assess the probability that a person is buying chicken meat at the butcher's if they do not trust the information from supermarket.
c) By applying the least squares estimator, estimate a simple linear probability model with *butcher* as the dependent variable and all the other variables as regressors. Interpret the coefficients. Does the trust into supermarket information affect the probability of buying chicken meat at the butcher's? Test the hypothesis that the probability of buying chicken meat at the butcher's does not depend on age.
d) Calculate the predicted probabilities for the regression in c). Do they have meaningful values? How does the distribution of residuals look like?
e) By applying the maximum likelihood estimator, estimate a probit model using the same variables as in c). Calculate and interpret the marginal effects at the means of explanatory variables (centroid).
f) By applying the maximum likelihood estimator, estimate a logit model using the same variables as in c). Again, calculate and interpret the marginal effects at the means of explanatory variables (centroid).
g) Compare the regression coefficients of probit and logit models. Compare the marginal effects of probit and logit models. What do you find out?
h) What is the hit ratio (classification accuracy or percentage correctly classified) of the logit model from f)?
i) Calculate the hit ratio for a logit model without insignificant explanatory variables. What do you find out?

*Computer printout of the results in Stata:*

*Part a)*

```
. summarize

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
     butcher |        419    .3412888    .4747089          0          1
expense_ch~n |        419    69.77804    218.6385          0       1199
safe_butcher |        419    4.940334    1.728946          1          7
 supermarket |        419    .8186158    .3857969          0          1
         age |        419    45.70644    15.72711         18         87
-------------+---------------------------------------------------------
      hhsize |        419    2.682578    1.287391          1          7
```

```
. tab butcher

  Buying at |
  butcher's |      Freq.     Percent        Cum.
------------+-----------------------------------
         no |        276       65.87       65.87
        yes |        143       34.13      100.00
------------+-----------------------------------
      Total |        419      100.00
```

```
. tab safe_butcher

    Meat at butcher's safe |      Freq.     Percent        Cum.
---------------------------+-----------------------------------
      Completely disagree |         23        5.49        5.49
          Mostly disagree |         22        5.25       10.74
        Somewhat disagree |         28        6.68       17.42
Neither agree nor disagree |         99       23.63       41.05
           Somewhat agree |         52       12.41       53.46
             Mostly agree |        102       24.34       77.80
         Completely agree |         93       22.20      100.00
---------------------------+-----------------------------------
                     Total |        419      100.00
```

*Part b)*

```
. tab butcher

  Buying at |
  butcher's |      Freq.     Percent        Cum.
------------+-----------------------------------
         no |        276       65.87       65.87
        yes |        143       34.13      100.00
------------+-----------------------------------
      Total |        419      100.00
```

```
. tab butcher if safe_butcher==7

  Buying at |
  butcher's |      Freq.     Percent        Cum.
------------+-----------------------------------
         no |         50       53.76       53.76
        yes |         43       46.24      100.00
------------+-----------------------------------
      Total |         93      100.00
```

```
. tab butcher if safe_butcher==1

  Buying at |
  butcher's |      Freq.     Percent        Cum.
------------+-----------------------------------
         no |         21       91.30       91.30
        yes |          2        8.70      100.00
------------+-----------------------------------
      Total |         23      100.00

. tab butcher if supermarket==0

  Buying at |
  butcher's |      Freq.     Percent        Cum.
------------+-----------------------------------
         no |         46       60.53       60.53
        yes |         30       39.47      100.00
------------+-----------------------------------
      Total |         76      100.00
```

*Part c)*

```
. regress butcher expense_chicken safe_butcher supermarket age hhsize

      Source |       SS       df       MS              Number of obs =     419
-------------+------------------------------           F(  5,   413) =   10.92
       Model |  11.0014909     5  2.20029818           Prob > F      =  0.0000
    Residual |  83.1942132   413  .201438773           R-squared     =  0.1168
-------------+------------------------------           Adj R-squared =  0.1061
       Total |  94.1957041   418  .225348574           Root MSE      =  .44882

------------------------------------------------------------------------------
        butcher |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
expense_chicken |  -.0001362   .0001017    -1.34   0.181     -.000336    .0000637
   safe_butcher |   .0782508   .0127748     6.13   0.000     .0531391    .1033625
    supermarket |  -.0711321   .0571179    -1.25   0.214    -.1834102    .0411459
            age |   .0041666     .00141     2.96   0.003      .001395    .0069382
         hhsize |   .0212159   .0173183     1.23   0.221    -.0128271     .055259
          _cons |   -.224919   .1118267    -2.01   0.045    -.4447395   -.0050985
------------------------------------------------------------------------------

. test supermarket=0

 ( 1)  supermarket = 0

       F(  1,   413) =    1.55
            Prob > F =    0.2137

. test age=0

 ( 1)  age = 0

       F(  1,   413) =    8.73
            Prob > F =    0.0033
```

*Part d)*

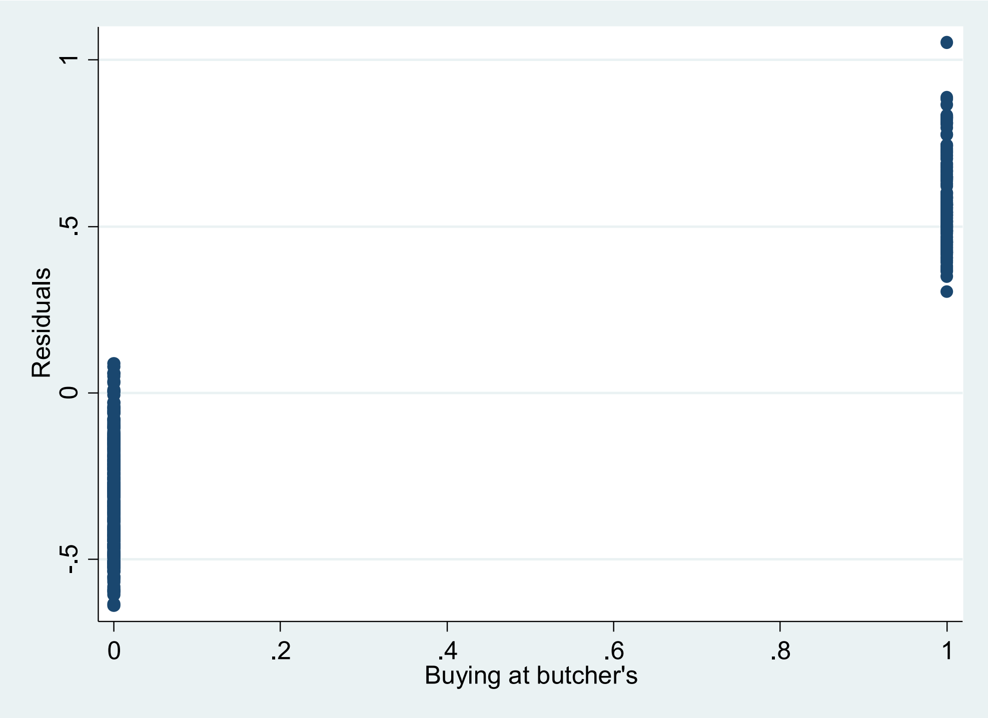
```
. predict prob_hat
(option xb assumed; fitted values)
```

```
. summarize prob_hat

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    prob_hat |        419    .3412888    .1622324  -.0886773   .6956753

. predict resid, resid

. scatter resid butcher
```




*Part e)*

```
. probit butcher expense_chicken safe_butcher i.supermarket age hhsize

Iteration 0:   log likelihood = -268.95049
Iteration 1:   log likelihood = -242.52865
Iteration 2:   log likelihood = -242.40975
Iteration 3:   log likelihood = -242.40974

Probit regression                               Number of obs     =        419
                                                LR chi2(5)        =      53.08
                                                Prob > chi2       =     0.0000
Log likelihood = -242.40974                     Pseudo R2         =     0.0987

---------------------------------------------------------------------------------
        butcher |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
expense_chicken |  -.0004295   .0003209    -1.34   0.181    -.0010584    .0001994
   safe_butcher |   .2487339   .0426283     5.83   0.000     .1651839    .3322838
  1.supermarket |  -.2092815   .1699843    -1.23   0.218    -.5424446    .1238815
            age |   .0117166   .0042426     2.76   0.006     .0034012     .020032
         hhsize |   .0626871   .0520667     1.20   0.229    -.0393618     .164736
          _cons |  -2.195304   .3582204    -6.13   0.000    -2.897403   -1.493205
---------------------------------------------------------------------------------
```

```
. margins, dydx(expense_chicken safe_butcher supermarket age hhsize) atmeans

Conditional marginal effects                      Number of obs   =        419
Model VCE    : OIM

Expression   : Pr(butcher), predict()
dy/dx w.r.t. : expense_chicken safe_butcher 1.supermarket age hhsize
at           : expense_ch~n    =    69.77804 (mean)
               safe_butcher    =    4.940334 (mean)
               0.supermar~t    =    .1813842 (mean)
               1.supermar~t    =    .8186158 (mean)
               age             =    45.70644 (mean)
               hhsize          =    2.682578 (mean)

------------------------------------------------------------------------------
                |            Delta-method
                |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
expense_chicken |  -.0001539   .0001149    -1.34   0.180     -.000379    .0000713
   safe_butcher |      .0891   .0150122     5.94   0.000     .0596767    .1185234
  1.supermarket |  -.0770337   .0640196    -1.20   0.229    -.2025097    .0484424
            age |   .0041971   .0015205     2.76   0.006      .001217    .0071771
         hhsize |   .0224554   .0186437     1.20   0.228    -.0140855    .0589964
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

*Parts f) and g)*

```
. logit butcher expense_chicken safe_butcher i.supermarket age hhsize

Iteration 0:   log likelihood = -268.95049
Iteration 1:   log likelihood = -242.93034
Iteration 2:   log likelihood = -242.40049
Iteration 3:   log likelihood = -242.39982
Iteration 4:   log likelihood = -242.39982

Logistic regression                               Number of obs   =        419
                                                  LR chi2(5)      =      53.10
                                                  Prob > chi2     =     0.0000
Log likelihood = -242.39982                       Pseudo R2       =     0.0987

------------------------------------------------------------------------------
        butcher |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
expense_chicken |  -.0007484   .0005721    -1.31   0.191    -.0018697    .0003729
   safe_butcher |   .4148784   .0735383     5.64   0.000     .2707461    .5590108
  1.supermarket |  -.3484696   .2804421    -1.24   0.214     -.898126    .2011867
            age |   .0197676   .0070855     2.79   0.005     .0058803    .0336549
         hhsize |   .1072604   .0863361     1.24   0.214    -.0619552    .2764759
          _cons |  -3.674573   .6202249    -5.92   0.000    -4.890191   -2.458954
------------------------------------------------------------------------------

. margins, dydx(expense_chicken safe_butcher supermarket age hhsize) atmeans

Conditional marginal effects                      Number of obs   =        419
Model VCE    : OIM

Expression   : Pr(butcher), predict()
dy/dx w.r.t. : expense_chicken safe_butcher 1.supermarket age hhsize
at           : expense_ch~n    =    69.77804 (mean)
               safe_butcher    =    4.940334 (mean)
               0.supermar~t    =    .1813842 (mean)
               1.supermar~t    =    .8186158 (mean)
```

```
              age             =    45.70644 (mean)
              hhsize          =    2.682578 (mean)

------------------------------------------------------------------------------
               |            Delta-method
               |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
expense_chicken |  -.0001618   .0001234    -1.31   0.190    -.0004038    .0000801
   safe_butcher |   .0897076   .0153309     5.85   0.000     .0596595    .1197556
  1.supermarket |  -.0781375   .0648243    -1.21   0.228    -.2051908    .0489158
            age |   .0042743   .0015281     2.80   0.005     .0012793    .0072692
         hhsize |   .0231925   .0186461     1.24   0.214    -.0133531    .0597381
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

*Part h)*

```
. qui logit butcher expense_chicken safe_butcher i.supermarket age hhsize

. predict probability_hat
(option pr assumed; Pr(butcher))

. summarize probability_hat

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
probabilit~t |       419    .3412888    .1645072    .044734   .7285379

. generate butcher_hat=0
. replace butcher_hat=1 if probability_hat>=0.5
(80 real changes made)

. tabulate butcher butcher_hat

 Buying at |      butcher_hat
 butcher's |         0          1 |     Total
-----------+----------------------+----------
        no |       239         37 |       276
       yes |        92         51 |       143
-----------+----------------------+----------
     Total |       331         88 |       419

. scalar hit_ratio=(239+51)/419
. display hit_ratio*100
69.212411
```

*Part i)*

```
. logit butcher safe_butcher age

Iteration 0:   log likelihood = -268.95049
Iteration 1:   log likelihood = -245.30396
Iteration 2:   log likelihood = -244.86245
Iteration 3:   log likelihood = -244.86208
Iteration 4:   log likelihood = -244.86208

Logistic regression                               Number of obs   =        419
                                                  LR chi2(2)      =      48.18
                                                  Prob > chi2     =     0.0000
Log likelihood = -244.86208                       Pseudo R2       =     0.0896
```

```
------------------------------------------------------------------------------
     butcher |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
safe_butcher |   .4096279   .0729168     5.62   0.000     .2667135    .5525423
         age |   .0186308   .0069548     2.68   0.007     .0049996    .0322621
       _cons |  -3.634732   .5076558    -7.16   0.000    -4.629719   -2.639745
------------------------------------------------------------------------------

. predict probability_h
(option pr assumed; Pr(butcher))

. summarize probability_h

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
probabilit~h |       419    .3412888    .1568919   .0595617   .7013106

. generate butcher_h=0
. replace butcher_h=1 if probability_h>=0.5
(80 real changes made)

. tabulate butcher butcher_h

 Buying at |       butcher_h
 butcher's |         0          1 |     Total
-----------+----------------------+----------
        no |       238         38 |       276 
       yes |       101         42 |       143 
-----------+----------------------+----------
     Total |       339         80 |       419 

. scalar hit_ratio1=(238+42)/419
. display hit_ratio1*100
66.825776
```

■

**Example 2:** In Stata data file `holiday.dta` there are data on several variables concerning the main annual holidays:

- *abroad*: dichotomous variable for a person spending holidays abroad: 1 – abroad, 0 – in the home country;
- *log_income*: logarithm of annual family net income per household member;
- *age*: person's age;
- *pet*: dichotomous variable for the presence of pets in the family: 1 – yes, 0 – no.

a) Estimate the probit model for the *abroad* variable as the dependent variable and all the other variables as regressors. Do the signs of regression coefficients make sense?
b) Reproduce the likelihood ratio test statistic for testing the statistical significance of the regression model as a whole. How is the pseudo $R^2$ coefficient calculated?
c) Calculate automatically and manually the marginal effects at the means of explanatory variables (centroid). Interpret the calculated marginal effects.
d) Estimate the logit model and compare the results to those from a).
e) Again, calculate automatically and manually the marginal effects at the means of explanatory variables (centroid). Interpret the calculated marginal effects.
f) Calculate (automatically and manually) and interpret the odds ratios from the logit model.

## *Computer printout of the results in Stata:*

*Part a)*

```
. summarize

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      abroad |        40         .55    .5038315          0          1
      income |        40     10779.5    4936.733       3360      27940
  log_income |        40    9.193383    .4326685   8.119697   10.23781
         age |        40       47.85    12.01185         26         72
         pet |        40          .3    .4640955          0          1

. probit abroad log_income age i.pet

Iteration 0:   log likelihood = -27.525553
Iteration 1:   log likelihood = -16.890274
Iteration 2:   log likelihood = -16.783332
Iteration 3:   log likelihood = -16.782923
Iteration 4:   log likelihood = -16.782923

Probit regression                                 Number of obs   =         40
                                                  LR chi2(3)      =      21.49
                                                  Prob > chi2     =     0.0001
Log likelihood = -16.782923                       Pseudo R2       =     0.3903

------------------------------------------------------------------------------
      abroad |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_income |   2.546419   .8138292     3.13   0.002     .9513429    4.141495
         age |  -.0610703   .0249326    -2.45   0.014    -.1099373   -.0122034
       1.pet |  -1.361899    .611138    -2.23   0.026    -2.559708   -.1640909
       _cons |   -19.8639    6.81757    -2.91   0.004    -33.22609   -6.501707
------------------------------------------------------------------------------
```

*Part b)*

```
. ereturn list

scalars:
               e(rank) =  4
                  e(N) =  40
                 e(ic) =  4
                  e(k) =  4
               e(k_eq) =  1
               e(k_dv) =  1
          e(converged) =  1
                 e(rc) =  0
                 e(ll) =  -16.78292322495001
         e(k_eq_model) =  1
               e(ll_0) =  -27.52555254854354
               e(df_m) =  3
               e(chi2) =  21.48525864718707
                  e(p) =  .0000834653961897
              e(N_cdf) =  0
              e(N_cds) =  0
               e(r2_p) =  .3902784260060915

macros:
            e(cmdline) : "probit abroad log_income age pet"
                e(cmd) : "probit"
          e(estat_cmd) : "probit_estat"
            e(predict) : "probit_p"
```

```
              e(title) : "Probit regression"
           e(chi2type) : "LR"
                e(opt) : "moptimize"
                e(vce) : "oim"
               e(user) : "mopt__probit_d2()"
          e(ml_method) : "d2"
          e(technique) : "nr"
              e(which) : "max"
             e(depvar) : "abroad"
         e(properties) : "b V"

matrices:
                  e(b) :  1 x 4
                  e(V) :  4 x 4
                e(mns) :  1 x 4
              e(rules) :  1 x 4
               e(ilog) :  1 x 20
           e(gradient) :  1 x 4

functions:
             e(sample)
```

```
. scalar LR=-2*(e(ll_0)-e(ll))
. display LR
21.485259

. display chi2tail(3,LR)
.00008347

. scalar pR2=1-e(ll)/e(ll_0)
. display pR2
.39027843
```

*Part c)*

```
. margins, dydx(log_income age pet) atmeans

Conditional marginal effects                      Number of obs   =         40
Model VCE    : OIM

Expression   : Pr(abroad), predict()
dy/dx w.r.t. : log_income age 1.pet
at           : log_income      =    9.193383 (mean)
               age             =       47.85 (mean)
               0.pet           =          .7 (mean)
               1.pet           =          .3 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_income |   .9925525   .3120236     3.18   0.001     .3809974    1.604108
         age |  -.0238042   .0097122    -2.45   0.014    -.0428398   -.0047687
       1.pet |  -.5034006    .190536    -2.64   0.008    -.8768442    -.129957
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

. qui probit abroad log_income age pet

. matrix B_probit=e(b)
```

```
. matrix list B_probit

B_probit[1,4]
        abroad:     abroad:     abroad:     abroad:
    log_income         age         pet       _cons
y1    2.546419  -.06107035  -1.3618994  -19.863898

. scalar b_probit_log_income=B_probit[1,1]
. scalar b_probit_age=B_probit[1,2]
. scalar b_probit_pet=B_probit[1,3]
. scalar b_probit_cons=B_probit[1,4]

. summarize log_income

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  log_income |        40    9.193383    .4326685   8.119697   10.23781

. scalar mean_log_income=r(mean)

. summarize age

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         age |        40       47.85    12.01185         26         72

. scalar mean_age=r(mean)

. summarize pet

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         pet |        40          .3    .4640955          0          1

. scalar mean_pet=r(mean)

. scalar Xb_probit=b_probit_cons+b_probit_log_income*mean_log_income+
  b_probit_age*mean_age+b_probit_pet*mean_pet

. display Xb_probit
.21552118

. display normalden(Xb_probit)
.38978373

. display normalden(Xb_probit)*b_probit_log_income
.99255269

. display normalden(Xb_probit)*b_probit_age
-.02380423

. display normal(Xb_probit-b_probit_pet*mean_pet+b_probit_pet)-
  normal(Xb_probit-b_probit_pet*mean_pet)
-.50340064
```

*Part d)*

```
. logit abroad log_income age i.pet

Iteration 0:   log likelihood = -27.525553
Iteration 1:   log likelihood = -17.032774
Iteration 2:   log likelihood = -16.960203
Iteration 3:   log likelihood = -16.959864
Iteration 4:   log likelihood = -16.959864
```

```
Logistic regression                               Number of obs   =         40
                                                  LR chi2(3)      =      21.13

                                                  Prob > chi2     =     0.0001
Log likelihood = -16.959864                       Pseudo R2       =     0.3839

------------------------------------------------------------------------------
      abroad |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_income |   4.250643   1.449276     2.93   0.003     1.410114    7.091172
         age |  -.1004235   .0442162    -2.27   0.023    -.1870858   -.0137613
       1.pet |  -2.278437   1.075051    -2.12   0.034    -4.385498    -.171377
       _cons |  -33.26217   12.14418    -2.74   0.006    -57.06433   -9.460013
------------------------------------------------------------------------------
```

*Part e)*

```
. margins, dydx(log_income age pet) atmeans

Conditional marginal effects                      Number of obs   =         40
Model VCE    : OIM

Expression   : Pr(abroad), predict()
dy/dx w.r.t. : log_income age 1.pet
at           : log_income      =    9.193383 (mean)
               age             =       47.85 (mean)
               0.pet           =          .7 (mean)
               1.pet           =          .3 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_income |   1.034782    .350304     2.95   0.003     .3481992    1.721365
         age |  -.0244472   .0108509    -2.25   0.024    -.0457146   -.0031799
       1.pet |  -.5135038   .1927674    -2.66   0.008     -.891321   -.1356866
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.

. qui logit abroad log_income age pet

. matrix B_logit=e(b)
. matrix list B_logit

B_logit[1,4]
        abroad:     abroad:     abroad:     abroad:
    log_income         age         pet       _cons
y1   4.2506429  -.10042354  -2.2784374  -33.262172

. scalar b_logit_log_income=B_logit[1,1]
. scalar b_logit_age=B_logit[1,2]
. scalar b_logit_pet=B_logit[1,3]
. scalar b_logit_cons=B_logit[1,4]

. scalar Xb_logit=b_logit_cons+b_logit_log_income*mean_log_income+
  b_logit_age*mean_age+b_logit_pet*mean_pet

. display Xb_logit
.32681861

. display logisticden(Xb_logit), logistic(Xb_logit)*(1-logistic(Xb_logit))
.24344141 .24344141
```

```
. display logisticden(Xb_logit)*b_logit_log_income
1.0347825

. display logisticden(Xb_logit)*b_logit_age
-.02444725

. display logistic(Xb_logit-b_logit_pet*mean_pet+b_logit_pet)-
  logistic(Xb_logit-b_logit_pet*mean_pet)
-.5135038
```

*Part f)*

```
. logistic abroad log_income age pet

Logistic regression                               Number of obs   =         40
                                                  LR chi2(3)      =      21.13
                                                  Prob > chi2     =     0.0001
Log likelihood = -16.959864                       Pseudo R2       =     0.3839

------------------------------------------------------------------------------
      abroad | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_income |    70.1505   101.6674     2.93   0.003     4.096423    1201.314
         age |   .9044543   .0399916    -2.27   0.023     .8293726    .9863329
         pet |   .1024442   .1101327    -2.12   0.034     .0124567    .8425039
       _cons |   3.58e-15   4.35e-14    -2.74   0.006     1.65e-25    .0000779
------------------------------------------------------------------------------

. scalar OR_log_income=exp(b_logit_log_income)
. display OR_log_income
70.150496

. scalar OR_age=exp(b_logit_age)
. display OR_age
.90445426

. scalar OR_pet=exp(b_logit_pet)
. display OR_pet
.10244416
```

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