## Homework 6 - Grant Jackson

October 16, 2024

- 0.0.1 HW6: Calculate the marginal effect of the student status on default probability, holding income and balance at their means, using the formula on page 8 of the lecture note 6
  - Note that the student variable is binary

```
[1]: import os
    os.chdir('C:\\Users\gmoor\Documents\Economic Analytics 1\Data')

import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt

raw0 = pd.read_csv('Default.csv')

# drop the observations that contain missing values
raw0.dropna()

raw0.head()
```

```
[1]:
        Unnamed: 0 default student
                                           balance
                                                           income
                         No
                                  No
                                        729.526495
                                                    44361.625074
                  2
     1
                         No
                                 Yes
                                        817.180407
                                                    12106.134700
     2
                  3
                         Nο
                                  Nο
                                      1073.549164
                                                    31767.138947
     3
                  4
                         No
                                  No
                                        529.250605
                                                    35704.493935
     4
                  5
                                       785.655883
                                                    38463.495879
                         No
                                  No
```

```
[2]: raw0.describe(include = 'all')
```

```
[2]:
               Unnamed: 0 default student
                                                   balance
                                                                   income
              10000.00000
                             10000
                                      10000
                                                            10000.000000
     count
                                             10000.000000
                                 2
                                          2
     unique
                      NaN
                                                                      NaN
                                                       NaN
     top
                      NaN
                                No
                                         No
                                                       NaN
                                                                      NaN
                              9667
                                       7056
     freq
                      NaN
                                                                      NaN
                                                       NaN
               5000.50000
                               NaN
                                        NaN
                                               835.374886
                                                            33516.981876
     mean
     std
               2886.89568
                               NaN
                                        NaN
                                               483.714985
                                                            13336.639563
                  1.00000
                               NaN
                                        NaN
                                                  0.000000
                                                               771.967729
     min
     25%
               2500.75000
                               NaN
                                        NaN
                                               481.731105 21340.462903
```

```
50%
              5000.50000
                              NaN
                                      NaN
                                              823.636973 34552.644802
     75%
              7500.25000
                              NaN
                                      {\tt NaN}
                                             1166.308386 43807.729272
     max
             10000.00000
                              NaN
                                      NaN
                                             2654.322576 73554.233495
[3]: raw0.default=(raw0.default=='Yes')*1
     raw0.student=(raw0.student=='Yes')*1
     raw0.head()
[3]:
        Unnamed: 0
                    default
                              student
                                           balance
                                                           income
                 1
                           0
                                    0
                                        729.526495 44361.625074
                 2
     1
                           0
                                    1
                                        817.180407
                                                     12106.134700
     2
                 3
                           0
                                    0
                                      1073.549164 31767.138947
     3
                 4
                           0
                                    0
                                        529.250605 35704.493935
     4
                 5
                           0
                                    0
                                        785.655883 38463.495879
[4]: # Run a logistic regression
     import statsmodels.api as sm # Regular api -> Logit(Y,X)
     import statsmodels.formula.api as smf # Formula api → loqit(default ~ student⊔
     \hookrightarrow+...) (lower-case l)
     # SKlearn -> LogitRegression(X,Y)
     Y = raw0.default
     X = raw0.iloc[:,2:]
     X = sm.add_constant(X)
[5]: X
[5]:
           const
                  student
                                balance
                                                income
     0
             1.0
                        0
                             729.526495
                                         44361.625074
             1.0
     1
                             817.180407
                                         12106.134700
     2
             1.0
                           1073.549164
                                         31767.138947
     3
             1.0
                         0
                             529.250605
                                         35704.493935
     4
             1.0
                             785.655883
                                         38463.495879
     9995
             1.0
                         0
                             711.555020
                                         52992.378914
     9996
             1.0
                         0
                             757.962918
                                         19660.721768
     9997
             1.0
                         0
                             845.411989
                                         58636.156984
     9998
             1.0
                           1569.009053
                                         36669.112365
                         0
     9999
             1.0
                             200.922183
                                         16862.952321
     [10000 rows x 4 columns]
[6]: Y
[6]: 0
             0
```

1

0

```
2 0
3 0
4 0
...
9995 0
9996 0
9997 0
9998 0
9999 0
```

Name: default, Length: 10000, dtype: int32

```
[7]: logitres=sm.Logit(Y,X).fit() # Include Y first; case sensitive: Logit (o)

→ logit(x)

print(logitres.summary())
```

Optimization terminated successfully.

Current function value: 0.078577

Iterations 10

Logit Regression Results

Dep. Variable: default No. Observations: 10000 Model: Logit Df Residuals: 9996 Method: MLE Df Model: Date: Wed, 16 Oct 2024 Pseudo R-squ.: 0.4619 Time: 21:51:10 Log-Likelihood: -785.77 True LL-Null: converged: -1460.3Covariance Type: nonrobust LLR p-value: 3.257e-292

=======	coef	std err	z	P> z	[0.025	0.975]
const	-10.8690	0.492	-22.079	0.000	-11.834	-9.904
student	-0.6468	0.236	-2.738	0.006	-1.110	-0.184
balance	0.0057	0.000	24.737	0.000	0.005	0.006
income	3.033e-06	8.2e-06	0.370	0.712	-1.3e-05	1.91e-05

Possibly complete quasi-separation: A fraction 0.15 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case some parameters will not be identified.

```
[8]: # Extract coefficients from the initial logistic model
beta_0 = logitres.params.iloc[0] # Intercept
beta_student = logitres.params['student']
beta_balance = logitres.params['balance']
beta_income = logitres.params['income']
```

```
print('\nInterecept:', beta_0)
print('\nStudent coefficent:', beta_student)
print('\nBalance coefficent: ', beta_balance)
print('\nIncome coefficent:', beta_income)
```

Interecept: -10.869045212744663

Student coefficent: -0.646775808244028

Balance coefficent: 0.005736505265799081

Income coefficent: 3.0334501193335614e-06

```
[9]: # Define the logistic function
    def logistic_function(x):
        return 1 / (1 + np.exp(-x))
    # Means of balance and income
    mean_balance = raw0['balance'].mean()
    mean_income = raw0['income'].mean()
    # Predicted probabilities when student = 1
    P_student_1 = logistic_function(beta_0 + beta_student * 1 + beta_balance *_u
     # Predicted probabilties when student = 0
    P_student_0 = logistic_function(beta_0 + beta_student * 0 + beta_balance *__

¬mean_balance + beta_income * mean_income)
    # Calculate marginal effect
    marginal_effect = P_student_1 - P_student_0
    print(f"Marginal effect of being a student on default probabilities is:⊔
      →{marginal_effect:.6f}")
```

Marginal effect of being a student on default probabilities is: -0.001205

Marginal effect of being a student on default probabillities is: [-0.00120547]

```
[]:
```