Ray Anthony Roderos

APAN K5200

Final Paper

**A Logistic Regression Analysis on the Client Characteristics and Telemarketing Operations on Special Bank Deposit Rates Availment**

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# Description of Data

The Portuguese bank’s direct marketing dataset obtained is multivariate with real numbers. There are 45,211 instances with 9 variables. The variables are categorized into 2: bank client data and details of the call. The research hypothesizes that bank client data and call information have a significant effect on the client for him/her to accept the offer. The study has already excluded some variables deemed not relevant for the study and transformed others to fit the regression model.

# Problem Statement

There is no change of the Problem Statement from the proposal.

1. Client Side: What are the Socio-economic characteristics of the potential client that will entail him/her to avail of the special bank term deposit if telemarketed?
2. Agency Side: What operational and marketing tactics should the bank use to increase their chances of successfully gaining a client through telemarketing?

# Empirical Model

After data cleansing, exclusion and transformation, the model will be employing a logistic regression in which relationships are established between a binary response variable and continuous or binary categorical predictors. This model is best used when the results of the data in which the analysis is being is a binary meaning it can be a 1 or 0, Yes or No or in this case, Accept or Not Accept of the special bank rate deposit.

This will be the proposed model for the logistic regression:

**YB = YB (AC, JC, MC, EC, DF, HF, LF, MO, DO)**

Where:

**YB** = Special Bank Deposit Rate Availment

**YB** = 0 if didn’t availed the Special Rate

= 1 if availed the Special Rate

**AC** = Age of the Client (Years)

**JC** = Employment of the Client (Dummy Variable)

**JC** = 0 if Unemployed

= 1 if Employed

**MC** = Employment of the Client (Dummy Variable)

**MC** = 0 if not married

= 1 if married

**EC** = Education Level of the Client (Dummy Variable)

**EC** = 0 if Primary or Secondary Graduate

= 1 if Tertiary Graduate

**DF** = History of Credit Default of the Client

**DF** = 0 if Client has not defaulted before

= 1 if Client has defaulted before

**HF** = Client has Housing Loan

**HF** = 0 if Client does not have a housing loan

= 1 if Client has a housing loan

**LF** = Client has a Personal Loan

**LF** = 0 if Client does not have a personal loan

= 1 if Client has a personal loan

**MO** = Month of the Year Call was Made (1-12 months)

**DO** = Day of the Month (in 1-30 days)

# Presentation and Analysis of the Nominal Logistic Regression Model

**Nominal Logistic Fit for Y**

**Effect Summary**

| **Source** | **LogWorth** |  | **PValue** |
| --- | --- | --- | --- |
| Housing | 136.086 |  | 0.00000 |
| Loan | 34.389 |  | 0.00000 |
| Education | 28.842 |  | 0.00000 |
| Marital | 27.582 |  | 0.00000 |
| Job | 19.188 |  | 0.00000 |
| Day | 10.420 |  | 0.00000 |
| Age | 8.706 |  | 0.00000 |
| Default | 4.221 |  | 0.00006 |
| Month | 0.087 |  | 0.81841 |

Converged in Gradient, 5 iterations

|  |  |
| --- | --- |
| RSquare (U) | 0.0458 |
| AICc | 31156.3 |
| BIC | 31243.5 |
| Observations (or Sum Wgts) | 45211 |

**Lack Of Fit**

| **Source** | **DF** | **-LogLikelihood** | **ChiSquare** |
| --- | --- | --- | --- |
| Lack Of Fit | 25067 | 11807.427 | 23614.85 |
| Saturated | 25076 | 3760.743 | **Prob>ChiSq** |
| Fitted | 9 | 15568.170 | 1.0000 |

**Parameter Estimates**

| **Term** |  | **Estimate** | **Std Error** | **ChiSquare** | **Prob>ChiSq** |
| --- | --- | --- | --- | --- | --- |
| Intercept |  | 2.38701373 | 0.1024356 | 543.01 | <.0001\* |
| Age |  | -0.0086539 | 0.0014333 | 36.45 | <.0001\* |
| Day |  | 0.01174001 | 0.0017812 | 43.44 | <.0001\* |
| Month |  | -0.0014031 | 0.0061111 | 0.05 | 0.8184 |
| Job[0] |  | -0.2707776 | 0.0285186 | 90.15 | <.0001\* |
| Marital[0] |  | -0.1761576 | 0.0159123 | 122.56 | <.0001\* |
| Education[0] |  | 0.17997481 | 0.0157715 | 130.22 | <.0001\* |
| Default[0] |  | -0.2713901 | 0.0728594 | 13.87 | 0.0002\* |
| Housing[0] |  | -0.3891015 | 0.0158585 | 602.01 | <.0001\* |
| Loan[0] |  | -0.2920817 | 0.025135 | 135.04 | <.0001\* |

For log odds of 0/1

Based from the results of the logistic regression, age, day of the call, employment, marital status, education, history of loan default, housing and personal loans are statistically significant. Only month of the year the call was made was not statistically significant.

The parameter estimates show there is a slight negative relationship for age. It means that as the potential customer is older, there is a decrease in likelihood that he will avail of the special bank deposit rate. Special bank deposits usually have a requirement that a substantial amount of money is withheld in that account for a certain period of time to avail for the rate to take effect, similar to a time deposit but the difference is that money can be withdrawn and deposited in that account so as long as the minimum is met. It is understandable that older people will less likely avail this because as they grow older, they would want to use that money since investing their money on anything that takes time to grow will not benefit them. They will be too old to enjoy the benefits of any investment, including this special bank deposit. Inversely, younger people will likely avail of this special product since they have the time to enjoy the fruits of the increase in interest rate in the near future.

Day of the call has a slight positive relationship with the bank availment meaning that as the call is made later in the month, there is a slight increase in odds that the customer will accept. The reasoning behind this may be as time goes on, people will become more conscious of their funds as they use it throughout the month. So they become more careful of how they spend the money and would like to use it more wisely. Calling them during the time they hold this mindset is a good opportunity for the bank because they will most likely accept the offer in order for them to save more money until the next payday.

Employment and marital status have a negative relationship with the response variable. This means that if the customer currently has no job or not married, there is a higher likelihood that he will avail of the special rate. This may stem from the financial situation of the client when he is not currently employed nor married. If he doesn’t have the job, then the person may be more inclined to find ways to earn some money in any way he can. If the client needs the money, he can withdraw it anytime but this will cancel the special rate. But since an unemployed person has the time while he is applying for work, he can park the money elsewhere. For a person to be married, he will most likely have or is currently planning to start a family. This will involve having dependents such as children and/or a nonworking spouse. There are a lot of expenses that come with having a family so it is very important that financials are fluid. For a product that will require that client to not use that money for a while is not appealing to such a target market. And if that person is not married, he only has to care for himself. Assuming that he is earning the same amount as his counterpart of the same age, he has more savings to be able to avail of the product.

Education has a positive relationship which means that if the customer is a graduate of a tertiary-level education, he will most likely avail of the special bank rate. An explanation of this is that people who have a college degree tend to have better jobs than their secondary and primary level graduate counterparts. Thus, they have more disposable income, more savings and are more financially literate. They have the resources and financial-savvy to understand the benefits of being able to avail of the special rate. For someone, who is not as educated, these people will less likely have an account in a bank, and less money to even avail of the special bank rate as compared to their educated counterparts. They need their cash on hand and the restrictions the special bank deposit rate will not appeal them.

In terms of loans, history of defaulting, currently possessing a housing and personal loan have a negative relationship with the response. This means that if the client has defaulted before, has a housing loan or a personal loan during the time of the call, the client will less likely accept the rate. This is understandable because a client who has defaulted before means that he is having trouble managing his finances and will most likely do not have the funds to avail of the product. The clients who currently have a housing loan or a personal loan have monthly payments to contend with and need their savings ready to be able to pay these. Being able to pay debt is also considered an investment in itself because you are lowering the amount you need to pay in the future. Special bank deposit rates are not attractive enough to them and would rather pay off the loan than deposit it in a bank.

As many articles have pointed out, there is no exact statistical equivalent to the linear regression’s RSquare. There are pseudo-RSquares. SAS JMP has employed the McFadden RSquare for this model. The study has noted that the RSquare is 0.04 but a nominal model rarely has a high RSquare, and it has a RSquare of 1 only when all the probabilities of the events that occur are 1 (SAS JMP).

For the managers’ information, industry jargon and meaning of the variables are included on Appendix 1 as well as the summary statistics of the dataset on Appendix 2.

Other pertinent information about the model that may interest data scientists is included in Appendix 3. The research also created another model that excluded the non-statistically significant variable Month to be able to determine if there are major deviations from the model presented here. Based from the results which can be found on Appendix 4, there are no major differences from the original model. All the variables are still statistically significant and their signs the same.

# Policy Implications

Targeted Customers

The policy implications of the model are clear. Financial organizations that wish to increase their chances of the clients to avail of the special bank deposit rate should target their customers instead of going through their entire client list which can take up a lot of time and resources. They should target younger people who are not married and does not have a job. Recent graduates are the perfect demographic of this. Being young while having experiencing unemployment with no dependents will make them think that they should save more for their future when they’re older and do have a family. They are psychological vulnerable because they don’t have a job right now; it will make them think twice before spending their money save it instead. Call center agents can take advantage of this by directing the conversations toward these facts. They should be made acutely aware of their current situation and the future they want. This should push them to avail of the special rate while they still have the money. Another filter is to look at the debt situation of the client. The bank should first target clients who do not have a history of defaulting and those who are not currently repaying a housing or personal loan. This is understandable since they are preoccupied with using that money to pay back those loans rather than saving them up. Another technique is to call them on the latter part of the month. The agents can make them realize how much they spent throughout the month and they should start saving now or at least get their commitment for the next month.

Training the Agents

Related to the targeting of customers, call center agents can be trained to not only just give a generic sales pitch but they should have prepared lines for various characteristics of the client. Instead of having just one spiel that all the customer agents memorize, there should be several spiels for the most common profiles of the client in which the agent can target. Like mentioned before, there should be a speech for the fact that he/she is married or unmarried, educated or not, employed or not employed, young or old or in debt or not. With the prepared material, the bank can train the agents to be able to use these to full effect. The agent can now know what the profile of the client is and know to mention the appropriate lines when called for. But another problem might arise here; the bank may risk sounding aggressive and brutal for pointing facts that may put the client at unease. This is why it is also important to train the agents to also sound respectful, accommodating and understanding of the client’s situation. The bank already has information about them, so a more personalized and sincere pitch will go a long way.

Changing the Package

Since the current package appeals to clients who are unmarried, do not have a job but are highly educated, do not have a history of defaulting and currently do not have loans, the Portuguese bank can capitalize on this by creating another special bank deposit rate that appeals to people who are married, to clients who have jobs, to potential customers who are not as educated. They can make the mechanics simpler, or create rates more appealing for people whose turnover of funds is quicker. By identifying the typical profile of the customer who is currently taking advantage of the current offerings, the bank can identify the target market they fail to reach. They can then make products that are tailor –fit for them. Couple this with the trained agents and a targeted customer list, future campaigns will surely have a higher success rate.

# Recommendation for Further Studies

One of the strengths of this study is the wealth of information regarding the client and the dataset itself. There are 45,211 rows about the client with several parameters. This study, which aims for model simplicity without sacrificing too much of the parameters that can explain the relationships, opted to remove variables under past marketing campaigns because many of the values were unknown and the model will get too complicated if they are included. One recommendation is to run models that can accommodate the data as is without the use of dummy variables. Models that can do this will be able to fully establish the relationships between the different categories within the factors and the various types of data the predictors have. These models are more complex but it will paint a more accurate picture of the type of clients who avail of the special bank interest rate and

Another recommendation is to employ a model that will be able to take into account predictors with categories labelled as “unknown.” One of the challenges this study encountered is that although the dataset did not have missing values, the original researchers replaced those missing values and put them under the category “unknown.” This research was able to get around this issue by using dummy variables. But for future studies, it is highly recommended that these “unknown” values are replaced with correct data or employ a model that can still explain the relationship accurately despite the numerous unknowns.

Lastly, additional demographics can also be included in the client profile such as family members, rural or urban background and gender. The research recognizes how hard it is to obtain additional data from such an old dataset but it is important to be able to have a bigger overview of the target market that will appeal to future products of similar rates. Being able to know other demographic information, future research will be able to explain how and why these customers avail of the product. Inversely, the bank will be able to find out more about the type of people whom the special bank rate deposit does not appeal to and make better products just for them.

# Conclusion

The study considered seven socio-economic factors and characteristics of the client and two operational factors the bank uses during their telemarketing calls to be able to determine which have an impact on the product availment. In response to the business questions posted in the first part of this study, the results show that age, employment, marital status, education, history of default and housing and personal debt are major factors for a potential client. In terms of the operational side, it was only the day of the month the call was made that had an impact on chances of success for a client to avail of the special bank deposit rate.

# Bibliography

The Logistic Fit Report. (n.d.). SAS JMP. Retrieved from http://www.jmp.com/support/help/The\_Logistic\_Fit\_Report.shtml

# Appendix

## Appendix 1 - Definitions of Variables

1 - age (numeric)

2 - job : type of job (categorical: "admin.","blue-collar","entrepreneur","housemaid","management","retired","self-employed","services","student","technician","unemployed","unknown")

3 - marital : marital status (categorical: "divorced","married","single","unknown"; note: "divorced" means divorced or widowed)

4 - education (categorical: "primary",”secondary”,”tertiary”)

5 - default: has credit in default? (categorical: "no","yes","unknown")

6 - housing: has housing loan? (categorical: "no","yes","unknown")

7 - loan: has personal loan? (categorical: "no","yes","unknown")

8 - contact: contact communication type (categorical: "cellular","telephone")

9 - month: last contact month of year (categorical: "jan", "feb", "mar", ..., "nov", "dec")

10 - day\_of\_week: last contact day of the week (categorical: "mon","tue","wed","thu","fri") in numbers

11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y="no").

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14 - previous: number of contacts performed before this campaign and for this client (numeric)

15 - poutcome: outcome of the previous marketing campaign (categorical: failure", "nonexistent", "success")

16 - y - has the client subscribed a term deposit? (binary: "yes","no")

## Appendix 2 - Descriptive Statistics

|  |  |  |
| --- | --- | --- |
|  | Client Did Not Avail of the Special Bank Deposit Rate | Client Availed of the Special Bank Deposit Rate |
| Age (Mean) | 40.83 | 41.67 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Client Did Not Avail of the Special Bank Deposit Rate | | Client Availed of the Special Bank Deposit Rate | |
|  | Frequency | Percentage | Frequency | Percentage |
| Client Currently Has a Job | 38152 | 84.39% | 4818 | 10.66% |
| Client Currently Does Not Have a Job | 1770 | 3.91% | 471 | 1.04% |
| Total | 39922 | 88.30% | 5289 | 11.70% |
|  |  |  |  |  |
| Client is Currently Married | 24459 | 54.10% | 2755 | 6.09% |
| Client is Not Currently Married | 15463 | 34.20% | 2534 | 5.60% |
| Total | 39922 | 88.30% | 5289 | 11.70% |
|  |  |  |  |  |
| Client is a Tertiary Graduate | 1137 | 2.51% | 2032 | 4.49% |
| Client is Not a Tertiary Graduate | 28595 | 63.25% | 3257 | 7.20% |
| Total | 29732 | 65.76% | 5289 | 11.70% |
|  |  |  |  |  |
| Client Has Not Defaulted in His Debt Before | 763 | 1.69% | 52 | 0.12% |
| Client Has Defaulted in His Debt Before | 39159 | 86.61% | 5237 | 11.58% |
| Total | 39922 | 88.30% | 5289 | 11.70% |
|  |  |  |  |  |
| Client Does Not Have a Housing Loan | 23195 | 51.30% | 1935 | 4.28% |
| Client Has A Housing Loan | 16727 | 37.00% | 3354 | 7.42% |
| Total | 39922 | 88.30% | 5289 | 11.70% |
|  |  |  |  |  |
| Client Has a Personal Loan | 6760 | 14.95% | 484 | 1.07% |
| Client Does Not Have a Personal Loan | 33162 | 73.35% | 4805 | 10.63% |
| Total | 39922 | 88.30% | 5289 | 11.70% |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Year of the Month the Call was Made | Client Did Not Avail of the Special Bank Deposit Rate | | Client Availed of the Special Bank Deposit Rate | |
|  | Frequency | Percentage | Frequency | Percentage |
| January | 1261 | 2.79% | 142 | 0.31% |
| February | 2208 | 4.88% | 441 | 0.98% |
| March | 229 | 0.51% | 248 | 0.55% |
| April | 2355 | 5.21% | 577 | 1.28% |
| May | 12841 | 28.40% | 925 | 2.05% |
| June | 4795 | 10.61% | 546 | 1.21% |
| July | 6268 | 13.86% | 627 | 1.39% |
| August | 5559 | 12.30% | 688 | 1.52% |
| September | 310 | 0.69% | 269 | 0.59% |
| October | 415 | 0.92% | 323 | 0.71% |
| November | 3567 | 7.89% | 403 | 0.89% |
| December | 114 | 0.25% | 100 | 0.22% |
| Total | 39922 | 88.30% | 5289 | 11.70% |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Day of the Month the Call was Made | Client Did Not Avail of the Special Bank Deposit Rate | | Client Availed of the Special Bank Deposit Rate | |
|  |  |  |  |  |
| 1 | 232 | 0.51% | 90 | 0.20% |
| 2 | 1111 | 2.46% | 182 | 0.40% |
| 3 | 901 | 1.99% | 178 | 0.39% |
| 4 | 1215 | 2.69% | 230 | 0.51% |
| 5 | 1695 | 3.75% | 215 | 0.48% |
| 6 | 1751 | 3.87% | 181 | 0.40% |
| 7 | 1660 | 3.67% | 157 | 0.35% |
| 8 | 1641 | 3.63% | 201 | 0.44% |
| 9 | 1382 | 3.06% | 179 | 0.40% |
| 10 | 403 | 0.89% | 121 | 0.27% |
| 11 | 1298 | 2.87% | 181 | 0.40% |
| 12 | 1359 | 3.01% | 244 | 0.54% |
| 13 | 1344 | 2.97% | 241 | 0.53% |
| 14 | 1638 | 3.62% | 210 | 0.46% |
| 15 | 1465 | 3.24% | 238 | 0.53% |
| 16 | 1223 | 2.71% | 192 | 0.42% |
| 17 | 1763 | 3.90% | 176 | 0.39% |
| 18 | 2090 | 4.62% | 228 | 0.50% |
| 19 | 1635 | 3.62% | 122 | 0.27% |
| 20 | 2560 | 5.66% | 192 | 0.42% |
| 21 | 1825 | 4.04% | 201 | 0.44% |
| 22 | 751 | 1.66% | 154 | 0.34% |
| 23 | 813 | 1.80% | 126 | 0.28% |
| 24 | 385 | 0.85% | 62 | 0.14% |
| 25 | 707 | 1.56% | 133 | 0.29% |
| 26 | 919 | 2.03% | 116 | 0.26% |
| 27 | 971 | 2.15% | 150 | 0.33% |
| 28 | 1687 | 3.73% | 143 | 0.32% |
| 29 | 1616 | 3.57% | 129 | 0.29% |
| 30 | 1295 | 2.86% | 271 | 0.60% |
| 31 | 597 | 1.32% | 46 | 0.10% |
| Total | 39932 | 88.32% | 5289 | 11.70% |

## Appendix 3 - Other Pertinent Data on the Logistical Model

**Whole Model Test**

| **Model** | **-LogLikelihood** | | **DF** | | **ChiSquare** | **Prob>ChiSq** |
| --- | --- | --- | --- | --- | --- | --- |
| Difference | 747.307 | | 9 | | 1494.615 | <.0001\* |
| Full | 15568.170 | |  | |  |  |
| Reduced | 16315.477 | |  | |  |  |
| **Measure** | | **Training** | | **Definition** | | | |
| Entropy RSquare | | 0.0458 | | 1-Loglike(model)/Loglike(0) | | | |
| Generalized RSquare | | 0.0633 | | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) | | | |
| Mean -Log p | | 0.3443 | | ∑ -Log(ρ[j])/n | | | |
| RMSE | | 0.3154 | | √ ∑(y[j]-ρ[j])²/n | | | |
| Mean Abs Dev | | 0.1992 | | ∑ |y[j]-ρ[j]|/n | | | |
| Misclassification Rate | | 0.1170 | | ∑ (ρ[j]≠ρMax)/n | | | |
| N | | 45211 | | N | | | |

**Effect Likelihood Ratio Tests**

| **Source** | **Nparm** | **DF** | **L-R ChiSquare** | **Prob>ChiSq** |  |
| --- | --- | --- | --- | --- | --- |
| age | 1 | 1 | 36.0056826 | <.0001\* |  |
| day | 1 | 1 | 43.7119574 | <.0001\* |  |
| month2 | 1 | 1 | 0.05271267 | 0.8184 |  |
| job2 | 1 | 1 | 83.4643769 | <.0001\* |  |
| marital2 | 1 | 1 | 121.751107 | <.0001\* |  |
| education3 | 1 | 1 | 127.507794 | <.0001\* |  |
| default2 | 1 | 1 | 16.0974575 | <.0001\* |  |
| housing2 | 1 | 1 | 619.816434 | <.0001\* |  |
| loan2 | 1 | 1 | 152.873011 | <.0001\* |  |

## Appendix 4 - Logistic Model Excluding the Not Statistically Significant Predictor

**Nominal Logistic Fit for y2**

**Effect Summary**

| **Source** | **LogWorth** |  | **PValue** |
| --- | --- | --- | --- |
| housing2 | 139.722 |  | 0.00000 |
| loan2 | 34.379 |  | 0.00000 |
| education3 | 29.063 |  | 0.00000 |
| marital2 | 27.597 |  | 0.00000 |
| job2 | 19.187 |  | 0.00000 |
| day | 10.439 |  | 0.00000 |
| age | 8.751 |  | 0.00000 |
| default2 | 4.216 |  | 0.00006 |

Converged in Gradient, 5 iterations

**Whole Model Test**

| **Model** | **-LogLikelihood** | **DF** | **ChiSquare** | **Prob>ChiSq** |
| --- | --- | --- | --- | --- |
| Difference | 747.281 | 8 | 1494.562 | <.0001\* |
| Full | 15568.196 |  |  |  |
| Reduced | 16315.477 |  |  |  |

|  |  |
| --- | --- |
| RSquare (U) | 0.0458 |
| AICc | 31154.4 |
| BIC | 31232.9 |
| Observations (or Sum Wgts) | 45211 |

| **Measure** | **Training** | **Definition** |
| --- | --- | --- |
| Entropy RSquare | 0.0458 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.0633 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.3443 | ∑ -Log(ρ[j])/n |
| RMSE | 0.3154 | √ ∑(y[j]-ρ[j])²/n |
| Mean Abs Dev | 0.1992 | ∑ |y[j]-ρ[j]|/n |
| Misclassification Rate | 0.1170 | ∑ (ρ[j]≠ρMax)/n |
| N | 45211 | n |

**Lack Of Fit**

| **Source** | **DF** | **-LogLikelihood** | **ChiSquare** |
| --- | --- | --- | --- |
| Lack Of Fit | 14749 | 7154.313 | 14308.63 |
| Saturated | 14757 | 8413.883 | **Prob>ChiSq** |
| Fitted | 8 | 15568.196 | 0.9951 |

**Parameter Estimates**

| **Term** |  | **Estimate** | **Std Error** | **ChiSquare** | **Prob>ChiSq** |
| --- | --- | --- | --- | --- | --- |
| Intercept |  | 2.38097284 | 0.0989932 | 578.49 | <.0001\* |
| age |  | -0.0086685 | 0.0014318 | 36.65 | <.0001\* |
| day |  | 0.01169878 | 0.0017715 | 43.61 | <.0001\* |
| job2[0] |  | -0.2704275 | 0.028478 | 90.17 | <.0001\* |
| marital2[0] |  | -0.175968 | 0.0158911 | 122.62 | <.0001\* |
| education3[0] |  | 0.18023633 | 0.0157303 | 131.28 | <.0001\* |
| default2[0] |  | -0.271221 | 0.0728557 | 13.86 | 0.0002\* |
| housing2[0] |  | -0.3896444 | 0.0156812 | 617.41 | <.0001\* |
| loan2[0] |  | -0.291957 | 0.0251291 | 134.98 | <.0001\* |

For log odds of 0/1

**Effect Likelihood Ratio Tests**

| **Source** | **Nparm** | **DF** | **L-R ChiSquare** | **Prob>ChiSq** |  |
| --- | --- | --- | --- | --- | --- |
| age | 1 | 1 | 36.2051973 | <.0001\* |  |
| day | 1 | 1 | 43.8003873 | <.0001\* |  |
| job2 | 1 | 1 | 83.4619197 | <.0001\* |  |
| marital2 | 1 | 1 | 121.818694 | <.0001\* |  |
| education3 | 1 | 1 | 128.519287 | <.0001\* |  |
| default2 | 1 | 1 | 16.0780886 | <.0001\* |  |
| housing2 | 1 | 1 | 636.533819 | <.0001\* |  |
| loan2 | 1 | 1 | 152.825332 | <.0001\* |  |