

Handling Large Scale Unit Level Data Using STATA
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Lecture 34

Binary Response Models - III

Welcome friends to this NPTEL MOOC schedule or course on Handling Large Scale Data Using STATA. We are at the particular lecture of understanding binary response models. In the last lecture we already started discussing about Logit model and the theory. The basic premises behind the Logit as against the linear probability model where OLS has been contradicted by the Logit. We are going to validate further also in this particular lecture.

So, today we will emphasize further some other features of Logit, particularly from the last class if you remember correctly that the equation we are emphasizing on the log of odds ratio. That is particularly defining a linear equation in terms of the expected coefficients. That we mentioned.

We are adding some attributes to the Logit model. Even I said earlier, when the probability in the diagram I told you already, it is a sigmoid curve Logit formation follows a sigmoid graph where the probability's value varies from 0 to 1 with the Z value varies from minus infinity to infinity.

So, the Logit that is L goes from minus infinity to infinity and though the probabilities lie between 0 to 1 the logits are not so bounded. So, value in the STATA also we are not going to get any bounded values. We should not be just confused by their coefficients, that's why it is so, why it is not so? We will get to know it for sure.

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FEATURES OF THE LOGIT MODEL

- ❑ As Probability (P) goes from 0 to 1 (i.e. Z varies from $-\infty$ to ∞), the logit L goes from $-\infty$ to ∞ . That is, although the probabilities lie between 0 and 1 the logits are not so bounded.
- ❑ Whereas the LPM assumes that probabilities are linearly related to X, the logit model assumes that the log odds are linearly related to X, the probabilities themselves are not.
- ❑ We can include as many regressors as required.



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- ❑ If L, **the logit**, is **positive**, it means that when the value of the regressor(s) increases, **the odds that the regressand equals 1** (meaning some event of interest happens) **increases**. If L, the logit, is **negative**, the odds that the **regressand equals 1 decreases as the value of X increases**.



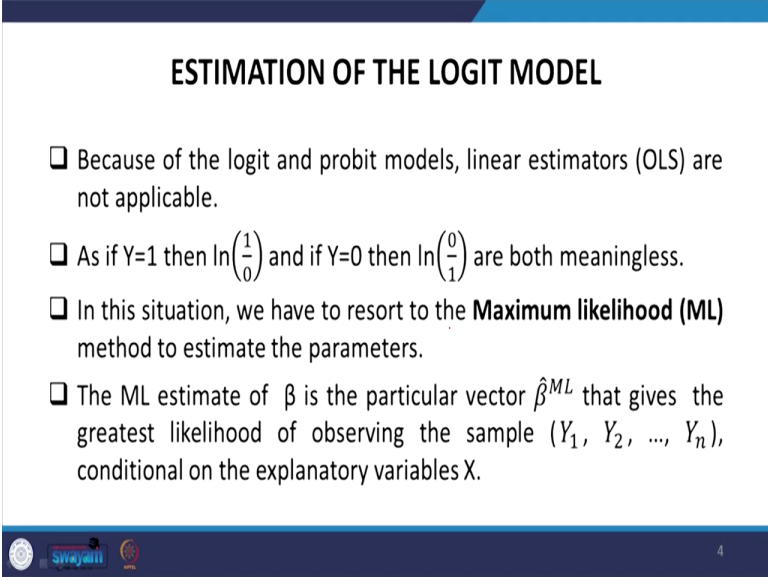
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Whereas the LPM assumes that the probabilities are linearly related to X. The Logit model assumes that the log of odds are linearly related to X. The probabilities themselves are not necessarily linear. We can include as many regressors when so required for the model. So, the L that stands for Logit is positive, means that when the value of the regressor increases the odds of that regressand equals 1, meaning some event of interest happens, also increases.

If L, the Logit is negative the odd of that regressand equals 1 decreases as the value of X increases. So, we are going to also present that odds ratio in terms of comparing with the unit

value. If it is exceeding unit value then it indicates a positive signal. That means the regressor impact the likelihood of the dependent variable positively. If the odds ratio is less than 1 then it is negatively impacting. We are going to emphasize this with help of data.

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ESTIMATION OF THE LOGIT MODEL

- ❑ Because of the logit and probit models, linear estimators (OLS) are not applicable.
- ❑ As if $Y=1$ then $\ln\left(\frac{1}{0}\right)$ and if $Y=0$ then $\ln\left(\frac{0}{1}\right)$ are both meaningless.
- ❑ In this situation, we have to resort to the **Maximum likelihood (ML)** method to estimate the parameters.
- ❑ The ML estimate of β is the particular vector $\hat{\beta}^{ML}$ that gives the greatest likelihood of observing the sample (Y_1, Y_2, \dots, Y_n) , conditional on the explanatory variables X .

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Because the Logit and Probit models and its linear estimation that is OLS are not applicable, so the estimation of the Logit model is different. And since the model itself is not linear so OLS is not applicable in this case. If Y is equal to 1 then the probability with 1 or 0 as the odd ratio. And if it is 0 then the odd ratio is 0 by 1 are both meaningless.

In this situation we have to resort to the maximum likelihood. It is not just the probability with 1 and 0; rather the closeness to 1 or closeness to 0 that is identified through the maximum likelihood estimator is more important than just the probabilities. So, the ML estimate of the beta is a particular vector that is beta hat ML that gives the greatest likelihood of observing the sample of Y_1, Y_2 till Y_n conditional upon the explanatory variable X .

When we say the unit change within the probability limit of 0,1 is very important and the maximum likelihood estimator identifies that so the coefficient itself is not just enough. The absolute coefficient which is scattering to probability of success or failure or odd of success or not success is not enough.

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MARGINAL EFFECTS IN LOGIT MODEL

- ❑ In linear regression model, the slope coefficient measures the change in the average value of the regressand for a unit change in the value of a regressor.
- ❑ The actual coefficients in a logit or probit analysis are limited in their immediate interpretability.
- ❑ The signs are meaningful, but the magnitudes may not be, particularly when the variables are in different metrics.
- ❑ We can not interpret the coefficients directly in terms of units of change in Y for a unit change in X, as in regression analysis.



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- ❑ The coefficients of the logit function is quite difficult to interpret since it follows a logistic distribution function.
- ❑ As a results we compute the **odds ratio** and the **marginal effects**
- ❑ Marginal effects gives the derivative of the probability that the dependent variable equals one with respect to a particular conditioning variable.

$$\frac{\partial P(Y=1)}{\partial X} = \frac{\partial F(\hat{\beta}_0 + \hat{\beta}_1 X)}{\partial X} \hat{\beta}_1 = \frac{\hat{\beta}_1 e^{-(\hat{\beta}_0 + \hat{\beta}_1 X)}}{[1 + e^{-(\hat{\beta}_0 + \hat{\beta}_1 X)}]^2}$$

The derivative is non- linear and depends on the value of X.



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The derivative is non- linear and depends on the value of X.

Rather in that case the unit change value or the maximum likelihood estimator of its unit change expressed through marginal effects is very important. Since the dependent variable is with 1 and 0 means binary so the unit change the very fractional change and its interpretation is very relevant. So, that is the reason why we are sticking to marginal effects.

In linear regression model the slope coefficient measures the change or the average value of the regressand for the unit change in the value of the regressor. The actual coefficients in the Logit or Probit analysis are limited because of their immediate interpretability. The signs are meaningful but the magnitude may not be. The magnitude of the coefficient is not meaningful particularly when the variables are in different metrics.

We cannot interpret the coefficients directly in terms of units of change in Y with the unit change in X in the regression analysis. Rather the coefficient of the Logit function is quite difficult to interpret since it follows a Logistic distribution function. It is not a continuous series. There are fractional change in the probabilistic structure with the change in the Z values from minus infinity to infinity. So, as a result of this we compute the odds ratio and also the marginal effects.

Marginal effects give the derivative. Basically when we say marginal that means we have to take the derivative of the dependent with respect to the derivative of the independent. So, in the independent we have X as the set of, or vector of independent variables, the regressors. So, if you take the partial derivative because we have so many independent variables, you take partial

derivative with respect to X here then in that case it is important to find out, so it is important to locate how partial it is and with the unit change in this.

So, let me just fix the pen here. Whether it is coming? It was there earlier. Let me just check. I hope it is not been set. It is probably here alright it is the pen mode. So, touch is active, alright. So, I will operate through this. Here now I am discussing about the partial derivative of the dependent variable with respect to the independent variable.

When we take the first derivative it will be certainly be of the dy/dx in the right hand side. You look at this carefully. dy/dx , dy is nothing but the cumulative distribution function, logistic distribution function with this. And when we take it, since X is here and this is a constant alright. So, the derivative will be, the others are constant so β_1 is left. That will be simply multiplied.

After that, what is that function of that logistic? We have already mentioned that $\beta_1 X$ is nothing but in the logistic function This is separated and we are left with. So, the function is e to the power minus Z . So, 1 upon E to the power minus Z .

So, what we will do? If you take the derivative it will be like here. If I just take the derivative, it will be, in the denominator it will be if it is in terms of ratio the denominator will be simply square of it, in the first derivative will be square of it. Then basically e , that is in terms of square is there in the denominator and in the numerator it is simply e to the power minus Z , e to the power minus Z and 1 plus this term, this is of square. So, this is what we have derived.

The derivative is in fact nonlinear and depends on the value of X . So, what is the meaning of it? That means the marginal effect or the impact of this we wanted to find out is whatever the marginal effect of Y observed through the X . So, Z here we already defined in the last class that it is dependent upon X . Coming to the example, the real life example of testing Logit function, the Logistic estimation; there are slight difference between Logistic and Logit because of the ratio or the coefficient we are going to estimate. That we are mentioning in a short while.

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EXAMPLE: LOGIT REGRESSION MODEL

- ❑ We are using the same dataset (BCM_practice.dta) and same variables (check lecture on LPM for variable description) as in LPM model.
- ❑ running the same model (i.e. what factors explain the choices of women being a necessity entrepreneur) with logit regression approach.

Note!
We are not summarizing and describing the data as we have already done this in previous lecture. So, directly running the model.

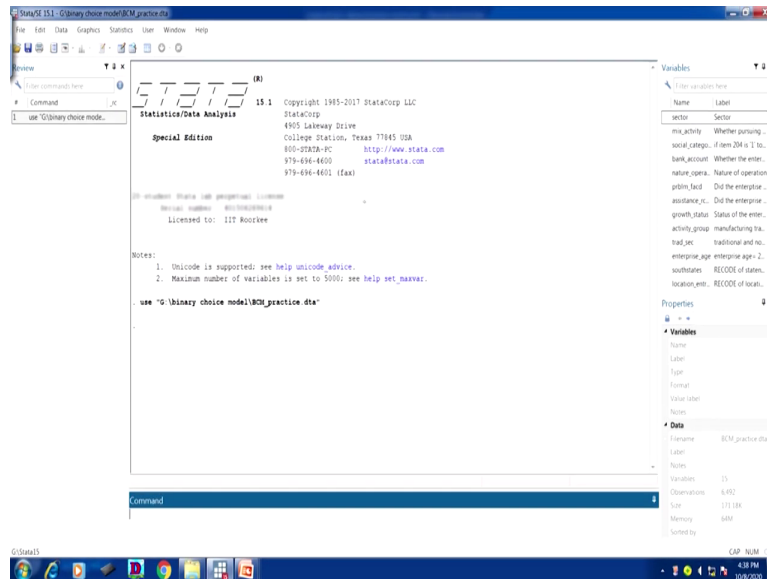
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The example we are going to cite is through our data. That is we are providing the sample data to you from 73rd NSS data. So, we have mentioned the title of the data as BCM, binary choice model for practice. And same variables we are linking with the LPM as well as for other Logit and Probit. We are going to compare.

So, running the same model what factors explain the choices of women being necessity entrepreneur. That we already started discussing in the LPM. We are again discussing the Logit function as well. So, which factor explain the choice of women being a necessity entrepreneur. So, that is what we are going to mention.

So, we are not summarizing or describing the data as we have already done it in the previous lecture and we have seen broadly that the data consists of bytes not in string; so in numeric, numbers. It is composed of categorical and non categorical as well as in continuous series. But the dependent variable is in binary. And that we have already seen it.

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So, straightaway we are going to run the model. Once we use the model in the STATA, let me open the STATA for you quickly. I am going to open the BCM data. So, it is here, so I am just going to open the data BCM practice data. I told you already. , this has already been opened on the screen.

(Refer Slide Time: 13:47)

use "BCM_practice.dta", clear

logit *enterprise_type* *enterprise_age* *age_square* *i.sector*
i.mix_activity *i.prblm_facd* *i.assistance_rcvd* *i.trad_sec*
i.southstates *i.location_entrprise* *i.social_category*
i.bank_account *i.growth_status* *i.activity_group*

The *i.* before some variables denotes that these variables are **dummy** or **categorical variables**, and that it should be included in the model as a **series of indicator variables**.

This *i.* syntax was introduced in stata 11.

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```

1. This code is supported: see help unsmooth.
2. Maximum number of variables is set to 5000; see help set_maxvar.

. use "G:\binary choice model\BCM_practice.dta"

. logit enterprise_type enterprise_age age_square i sector i mix_activity i pblm_facid i assistance_cvd i trad_sec i southstates
> i location_enterprise i social_category i bank_account i growth_status i activity_group

Iteration 0: log likelihood = -3203.0881
Iteration 1: log likelihood = -2225.0495
Iteration 2: log likelihood = -2110.0416
Iteration 3: log likelihood = -2106.6903
Iteration 4: log likelihood = -2106.6862
Iteration 5: log likelihood = -2106.6862

Logistic regression              Number of obs   =    4,492
                                LR chi2(19)      =   2193.00
                                Prob > chi2       =    0.0000
                                Pseudo R2          =    0.3423

Log likelihood = -2106.6862

+-----+-----+-----+-----+-----+-----+
| enterprise_type |   Coef. |   Std. Err. |    z |   P>|z| | [95% Conf. Interval] |
+-----+-----+-----+-----+-----+-----+
| enterprise_age |  0.019257 |  0.153023 |  0.13 |  0.890 | - 0.287662 |  0.319176 |
| age_square     | -0.003199 |  0.003996 | -0.80 |  0.423 | - 0.011032 |  0.004633 |
+-----+-----+-----+-----+-----+-----+
| sector         |         |         |         |         |         |         |
| urban         | -2.62724 |  0.825251 | -3.18 |  0.001 | - 4.244702 | -1.009778 |
+-----+-----+-----+-----+-----+-----+
| mix_activity   |         |         |         |         |         |         |
| No            |         |         |         |         |         |         |
| 1             |  0.122468 |  2.024046 |  0.07 |  0.948 | - 3.83479 |  4.099325 |
| 2             |  2.981787 |  0.89519 |  2.88 |  0.004 |  0.827257 |  4.336337 |
| 3             |  0.793318 |  0.895206 |  0.21 |  0.837 | - 0.752947 |  0.839584 |
+-----+-----+-----+-----+-----+-----+
| trad_sec      |         |         |         |         |         |         |
+-----+-----+-----+-----+-----+-----+

```

Now, from the data we will now first operate the simple Logit function, the Logit model. So, that Logit model we will estimate quickly. So, it is here. Let me operate all the variables that has been listed and we are running it. So, once I ran all those variables with Logit enterprise, this gives result very quickly. The Logit function has generated the values in front of us, the coefficient values in front of us.

As we already mentioned about R square and regarding pseudo R square, the coefficient already been highlighted, the Chi square value whether that is significant or not, even earlier models we did mention. Once again it is significantly defined. So, most importantly the likelihood function as I mentioned, this was taken 5 iterations. It kept on iterating all its variable with different forms of sample within the model by observing how they are varying.

At the end it has iterated with the likelihood value of minus 2106 but this is important to note here whether the module is fit or not, module is fine or not? Whether we go with the model? Because the probability of the significance level of that Chi square value is 0.0000. So, it is not going to be problematic. It rests on which variable are important and how we are going to interpret.

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	coef.	std. Err.	z	P> z	[95% Conf. Interval]
Log likelihood = -2106.6862					
enterprise_type					
enterprise_age	0.019237	0.133023	0.13	0.900	-0.2890662 0.3195176
age_square	-0.003199	0.003396	-0.90	0.423	-0.011032 0.004633
sector					
urban	-2.62724	0.825251	-3.18	0.001	-4.244702 -1.009178
mix_activity					
no	0.132268	2.024046	0.07	0.948	-3.83479 4.099325
2.pblm_facd	2.581797	0.89519	2.88	0.004	0.827257 4.336337
2.assistance_rcvd	0.793018	3.85206	0.21	0.837	-6.752947 4.839384
lead_sec					
nontraditional	3.688896	1.67583	2.19	0.040	0.35209 6.72463
2.southstates	1.871851	0.82531	2.27	0.023	0.241744 3.483986
location_enterprise					
outsidem	-2.405317	0.905855	-2.65	0.000	-4.208862 -0.227773
social_category					
sc	8.228426	1.788989	4.57	0.000	4.702452 11.75444
oac	4.470788	1.805955	2.48	0.001	1.921826 7.029712
others	-0.852442	1.277821	-0.67	0.501	-3.363705 1.645221
bank_account					
enterprise_age	-1.431724	1.8954	-0.75	0.451	-4.199277 1.335829

From the model itself coefficients are given. I have said in the features itself that in Logit, even in Probit also, the coefficient is not important. The odds ratio is important and the marginal effect is very important.

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use "BCM_practice.dta", clear

*logit enterprise_type enterprise_age age_square i.sector
i.mix_activity i.pblm_facd i.assistance_rcvd i.trad_sec
i.southstates i.location_enterprise i.social_category
i.bank_account i.growth_status i.activity_group*

The i. before some variables denotes that these variables are **dummy** or **categorical variables**, and that it should be included in the model as a **series of indicator variables**.

This i. syntax was introduced in stata 11.

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So, we are going to discuss that right now. After doing so as you can see very clearly some of the variables are categorical and some of the variables are dummy. So, dummy variables we already

defined in our previous lectures. If you simply take the dummy as an average without having any specification of the dummy, then average of dummy you will not have any correct interpretation.

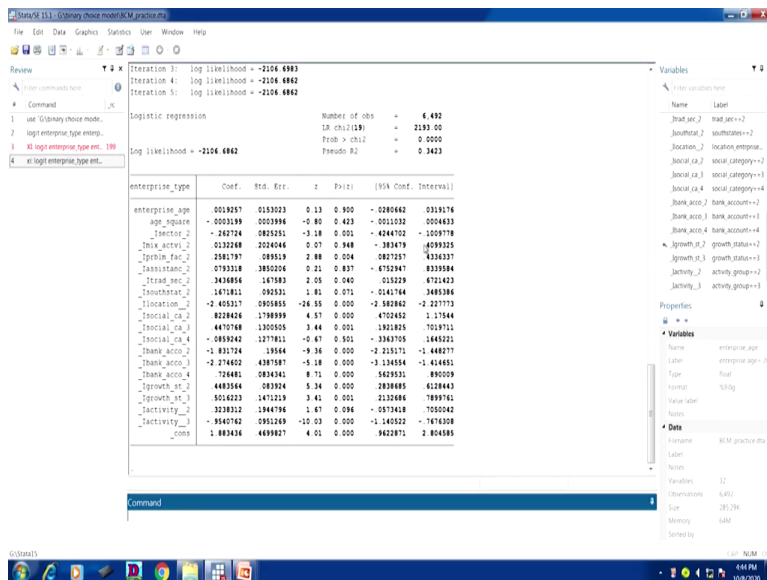
So, for that you have to take a base value in the dummy. Like to identify the base value we have gone through a command that is this `i dot`, alright. So, `i dot` before some variable denotes that these variables are the dummy or categorical, that it should be included in the model as a series of indicator variables, series of indicator variables. So, this `i dot` syntax was introduced in STATA 11, alright, 11 onwards this has been introduced.

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- ❑ You can also use **xi: prefix** before `logit` (**xi: logit**) which gives exactly the same result but the coefficients are reported slightly differently and the names correspond directly to the newly generated dummy/indicator variables in the dataset.
- ❑ This prefix was earlier used and it still works but if you don't want to create new indicator variable you don't have to use it.
- ❑ If you don't specify stata which category to take as reference, by default it takes first category as a reference category.

The screenshot shows the STATA interface with a logit regression output window and a command window. The output window displays coefficients for various variables, including categorical variables like `social_category`, `bank_account`, `growth_status`, and `activity_group`. The command window shows the command used to run the regression: `xi: logit enterprise_type enterprise_age_age_square i sector i mix_activity i public_faced i assistance_cvd i trad_sec i southsta > > > i location enterprise i social_category i bank_account i growth_status i activity_group`. The command window also shows the error message: `command xi not defined by xt ado`.

Variable	Coefficient	Std. Err.	z	P > z	95% Conf. Interval
trad_sec	3438856	1475893	2.05	0.040	0.05229 - 6721423
nontraditional	1471911	992931	1.48	0.071	-0.24764 - 3489386
location_enterprise_outside	-2.453517	0.958855	-2.55	0.000	-2.582862 - -2.227773
social_category					
sc	8228426	1788999	4.57	0.000	4.702452 - 1.75144
onc	4470748	1302805	3.44	0.001	1.921829 - 7019711
others	-2859242	1277821	-2.24	0.025	-3.363705 - -1445231
bank_account					
both	-1.831744	1.88644	-0.97	0.000	-2.215171 - -1.448277
noaccounts	-2.274402	4387587	-0.52	0.000	-3.244554 - -1.424251
growth_status					
2	4483564	883924	5.07	0.000	2.838485 - 6128443
3	5014223	1471219	3.41	0.001	2.132486 - 7899741
activity_group					
Trade	3238332	1344794	2.41	0.016	-0.573418 - 7050042
services	-3540742	6951249	-0.51	0.000	-1.140522 - -7476308
_cons	1.883436	4493827	0.42	0.000	-9422871 - 2.804885



Those who have earlier version, you might be in trouble. So, you have to take help command for the patching of any extra version of it or extra operated solution to it. We can use xi also, xi from the very beginning, that conditioning for the model with this categorcal variable. So, like prefixing xi logit which gives exactly the same result but the coefficients are reported slightly different and the names corresponding directly to newly generated dummy or indicator variable in the data set.

So, we will just show it. Like if you just go by this command, xi command we can go for it. That we can show it here also in the STATA directly. With the same command it is there. This xi colon, if we add xi colon we will get. The look is different. It is in capital. You can make it in small. So, the capital entry as we already mentioned that STATA is very case sensitive so you have to take small letters.

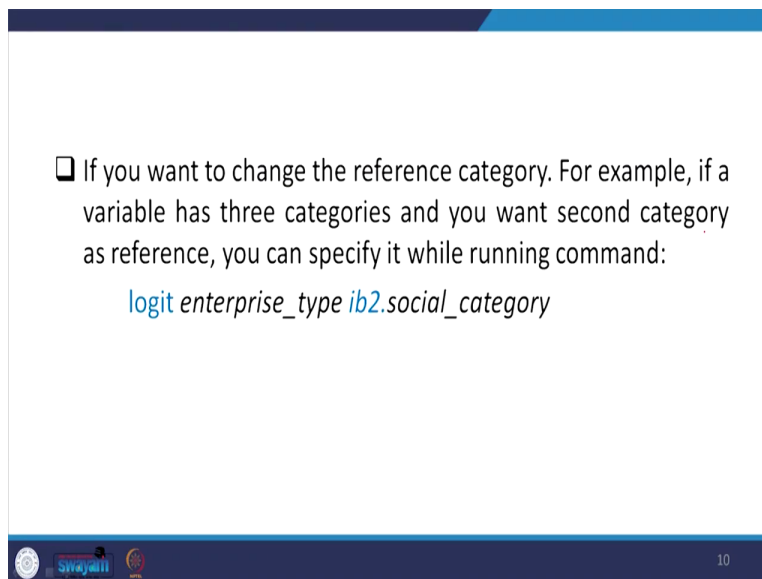
Look at the coefficients, here are interpreted against the exact non-reference category. But in the previous case we just see, look at this. The reference category value is also mentioned or not? Let me see. Only, so even i dot command we have taken. again in the sector, rural and urban so urban value is presented.

Look at this. In the mixed activity also only three are presented. here only one. Each, against each, where is it? In the sector, only the category 2, that category itself is mentioned. It is nowhere mentioning the base category, isn't it? So, that is the only difference. Suppose you want

to get small table I think this is more useful, alright. So, these are also generated as well and defining the other categories as against to the base.

Now, let us go by the detailing here. Coming to the interpretation further, this prefix was earlier used and it still works. But if you do not want to create new indicator variable, basically in the variables itself it identifies the indicator variables, which are the indicator variables, and these are added in the dataset itself. But in the earlier case it is not showing the indicator variables or not added at all. If you do not specify STATA which category to take as reference, by default it takes the first category as the reference category.

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❑ If you want to change the reference category. For example, if a variable has three categories and you want second category as reference, you can specify it while running command:

```
logit enterprise_type ib2.social_category
```

The slide footer contains logos for 'Sreyas' and 'SRM Institute of Science and Technology' on the left, and the number '10' on the right.

But there are techniques. If we add, it gives the particular category as the base category. Like in rural or urban by default rural was 1 for us, 2 for urban. So, 1 considers as the base category by default. If you specify `ib2 dot`, `ib2` that means it specifies the second one as the base. So, if you want to change the reference category you can accordingly specify. Rest of the details are the same.

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```

logit enterprise_type enterprise_age age_square i_sector i_mia_activity i_probim_fact i_m
> stata: lsm1 location_entrprave i_social_category i_bank_account i_growth_status i_activi
Iteration 0: log likelihood = -3203.1881
Iteration 1: log likelihood = -2229.0639
Iteration 2: log likelihood = -2110.0616
Iteration 3: log likelihood = -2106.6862
Iteration 4: log likelihood = -2106.6862
Iteration 5: log likelihood = -2106.6862
Logistic regression              Number of obs   =    6,492
                                LR chi2(19)      =   2193.00
                                Prob > chi2         =    0.0000
                                Pseudo R2         =    0.3423
Log likelihood = -2106.6862

```

enterprise_type	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
enterprise_age	0.0530257	0.1530223	0.13	0.900	-0.2806462 0.3191764
age_square	-0.0003159	0.0003996	-0.80	0.423	-0.0010332 0.0004633
sector					
urban	-2.62724	0.8252051	-3.18	0.001	-4.284702 -1.009778
mia_activity					
mi	0.122248	0.2048464	0.07	0.948	-0.309479 0.599322
i_probim_fact	2.861797	0.890513	2.88	0.004	0.827257 4.36337
i_akkastatac_code	0.793318	0.850206	0.21	0.837	-0.702947 0.339584
trade_act					
nonconditional	3436856	1475803	2.05	0.040	0.152279 6721423

```

i_southstates 1.671811 0.92531 1.81 0.071 -0.241764 3.685286
location_entrprave
outsidahr -2.405317 0.905885 -2.65 0.000 -2.582862 -2.227773
social_category
sc 8228426 1798999 4.57 0.000 4702452 1.17544
cbc 4470768 1300505 3.44 0.001 1921825 7019711
others -0.859242 1.277811 -0.67 0.501 -3363705 1645221
bank_account
enterprisename -1.831724 1.9564 -0.93 0.000 -2.215171 -1.448277
both -2.274602 4387587 -5.18 0.000 -3.134554 -1.414651
noaccounts -7.26481 0.834341 8.71 0.000 5.629531 890009
growth_status
2 4483564 0.89324 5.34 0.000 2838685 6128443
3 5016223 1.471219 3.41 0.001 2132486 7899761
activity_group
trade 3238312 1944736 1.67 0.096 -0.573418 7050042
services -9540762 0.951269 -10.03 0.000 -1.140522 -7676308
_cons 1.883436 4699827 4.01 0.000 9622871 2.804585

```

Maximizing the log likelihood function

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- ❑ In the result, we can see that the iteration log likelihood indicating how quickly the model converged. The log likelihood is used to compare nested models.
- ❑ The likelihood ratio chi-square of 189.65 with a p-value 0.0000 explains that our model as a whole fits significantly better than a model with no predictors.
- ❑ Like other regression model, the logit regression also displays coefficients, their standard errors, the z-statistics, associated p-value and the 95% confidence interval of the coefficients.

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We are going to discuss also, we have already discussed about the maximizing of the log likelihood functions, so 5 iterations we already discussed and some other interpretation we already shown to you. So, in the result that we can see that the alteration of log likelihood indicating how quickly the model converged. The log likelihood is used to compare the nested models. If you have any other nested models that likelihood estimator can also be useful for comparison.

The likelihood ratio with Chi square value, we have already shown you Chi square value of 189.65 with a P value that is 0.000. It indicates significant at one portion level explain that our model as a whole fits significantly better than a model with no predictors. So, like other regression model the Logit regression also displays coefficients. So, coefficients that I mentioned. Their standard errors also, standard error next to their coefficients, standard errors are there.

Then the Z statistics also, then the probability limit, the P values, that we can find out which variable is significant. Like in urban it is significant at 1 percent level. These two are not significant. First two are not significant. Then sector urban is significant. In the mixed activities also, the middle one, that is problem faced is significant. Similarly you can interpret other coefficients. So, the confidence interval values are also defined.

(Refer Slide Time: 23:01)

❑ Pseudo R^2 :

- ❑ Analogous to the R^2 .
- ❑ Expresses the predictive quality of the model with explanatory variables relative to the predictive quality of the sample proportion p of cases where $Y_i = 1$.
- ❑ Pseudo $R^2 = 1 - \frac{\ln L_{ur}}{\ln L_r}$,

Where, $\ln L_{ur}$ is the value of the log likelihood at the ML estimates (the 'unrestricted' model) and $\ln L_r$ is the log likelihood value for a 'restricted' model in which the only 'explanatory' variable is a constant.

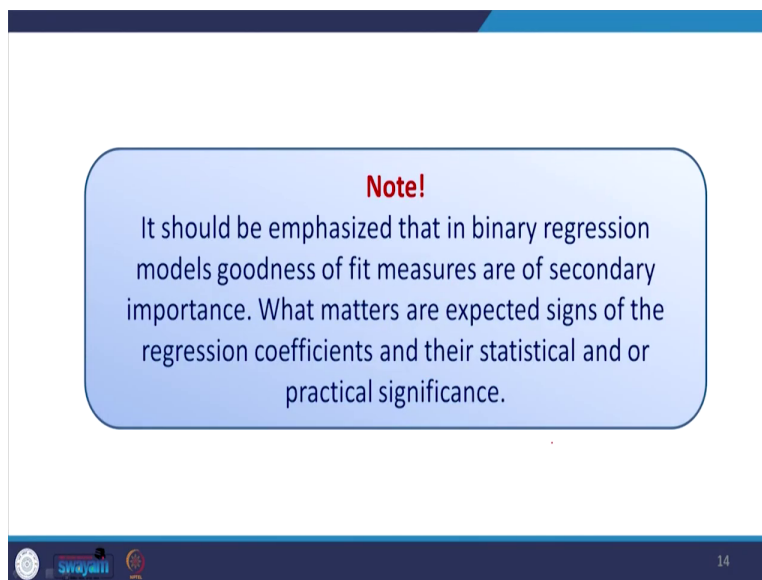
- ❑ Stata computes McFadden's pseudo R^2 .

Coming to the interpretation of R square in the model and specifically we clarified in our previous lecture about pseudo R square again, I am emphasizing on the pseudo R square that it is not similar to the R square values we used to have in the continuous case or in the regression model, normal or ordinary least square method but this pseudo R square is analogous to the R square we studied. This expresses the predictive quality of the model with explanatory variables relative to the predictive quality of the sample proportion of cases where Y is equal to success and that is 1.

So, pseudo R square in this case using the likelihood ratio basically takes the log likelihood ratio and with unadjusted or unrestricted and the restricted model. In this case L_{ur} so the pseudo R square is equal to 1 minus log likelihood with unrestricted and log of restricted. In the numerator it is unrestricted.

So, L_{ur} is the value of log likelihood at the ML estimates, that is unrestricted model and the log restricted, R is the log likelihood value of the restricted model which the only explanatory variable is a constant. So, that is important. You can take a note of it. So, STATA computes, already mentioned the McFadden technique of estimating R square that is also called pseudo R square in this case STATA adopts in this kind of model.

(Refer Slide Time: 24:56)



Note!

It should be emphasized that in binary regression models goodness of fit measures are of secondary importance. What matters are expected signs of the regression coefficients and their statistical and or practical significance.

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It should be emphasized that in binary regression models, goodness of fit measures are of secondary importance. What matters are the expected sign. The sign, the relationship is more important. Sign of the coefficient is more important and their practical and statistical significance with which we have already discussed is more important than that of R square. So, if R square value is low you may not worry especially in these kinds of models.

(Refer Slide Time: 25:26)

- ❑ **Interpretation of coefficients:** Among sectors, as compare to rural, women entrepreneurs in urban sector decreases the log odds of choosing necessity entrepreneurship by 0.262.
- ❑ The coefficients of the logit function is quite difficult to interpret since it follows a logistic distribution function.
- ❑ As a results we compute the **odds ratio** and the **marginal effects**.
- ❑ Stata does this task by specifying simple command:
“logistic” command outputs odds ratios instead of log odds. Use logistic command instead of logit command.

```
logit enterprise_type enterprise_age age_square i.sector i.mia_activity i.prbld_fad i.
> thataster i.location_enterprise i.social_category i.bank_account i.growth_status i.acti

Iteration 0: log likelihood = -3203.1881
Iteration 1: log likelihood = -2225.0595
Iteration 2: log likelihood = -2110.0416
Iteration 3: log likelihood = -2106.6980
Iteration 4: log likelihood = -2106.6862
Iteration 5: log likelihood = -2106.6862

Logistic regression      Number of obs   =   4,492
                        LR chi2(18)              =  2193.00
                        Prob > chi2              =   0.0000
                        Pseudo R2               =   0.3423

log likelihood = -2106.6862

+-----+-----+-----+-----+-----+-----+
| enterprise_type |   Coef. | Std. Err. |   z | P>|z| | [95% Conf. Interval] |
+-----+-----+-----+-----+-----+-----+
| enterprise_age |  0019257 |  0159023 |  0.13 | 0.900 | -0.280642 |  0319176 |
| age_square     | -0003139 |  0003936 | -0.80 | 0.423 | -0.011032 |  0004633 |
| sector         |         |         |         |         |         |         |
|   urban        |  -262724 |  0825201 | -3.18 | 0.001 | -4284702 | -1009778 |
| mia_activity   |         |         |         |         |         |         |
|   No          |  0132248 |  2024046 |  0.07 | 0.948 | -383479 |  4093325 |
| i.prbld_fad    |  2981797 |  090519 |  2.89 | 0.004 |  0827257 |  4336337 |
| i.assistance_crd |  0793318 |  3892206 |  0.21 | 0.837 | -6782347 |  8339584 |
| tead_rec       |         |         |         |         |         |         |
| nontraditional |  3436856 |  147583 |  2.05 | 0.040 |  018229 |  6721423 |

+-----+-----+-----+-----+-----+-----+
| 2.southstates |  1671811 |  092531 |  1.81 | 0.071 | -0141764 |  3485386 |
| location_enterprise |         |         |         |         |         |         |
|   outsideMH    | -2.405317 |  0905895 | -2.65 | 0.000 | -2.582862 | -2.227773 |
| social_category |         |         |         |         |         |         |
|   BC           |  8228426 |  1798999 |  4.57 | 0.000 |  4702452 |  117544 |
|   CBC          |  4470768 |  1300505 |  3.44 | 0.001 |  1921825 |  7019711 |
|   others       | -0859242 |  1277811 | -0.67 | 0.501 | -3363705 |  1645221 |
| bank_account   |         |         |         |         |         |         |
| enterprise_name |         |         |         |         |         |         |
|   both        | -2.274602 |  4387587 | -5.18 | 0.000 | -3.134554 | -1.414651 |
|   noaccounts  |  .726481 |  0834341 |  0.71 | 0.000 |  .5629531 |  .890009 |
| growth_status  |         |         |         |         |         |         |
|   2           |  4483564 |  083924 |  5.34 | 0.000 |  2836685 |  6128443 |
|   3           |  5016223 |  1471219 |  3.41 | 0.001 |  2132686 |  7899761 |
| activity_group |         |         |         |         |         |         |
|   trade       |  3238312 |  1944796 |  1.67 | 0.096 | -0573418 |  7050042 |
|   services    | -3540762 |  0951269 | -10.03 | 0.000 | -1.140522 | -7676308 |
|   _cons       |  1.889436 |  4699827 |  4.01 | 0.000 |  9622871 |  2.804585 |
```

```
❑ logistic enterprise_type enterprise_age age_square i.sector  
i.mix_activity i.prblm_facd i.assistance_rcvd i.trad_sec  
i.southstates i.location_entrprise i.social_category  
i.bank_account i.growth_status i.activity_group
```

❑ Or simply add 'or' option with logit command.

```
logit enterprise_type enterprise_age age_square i.sector  
i.mix_activity i.prblm_facd i.assistance_rcvd i.trad_sec  
i.southstates i.location_entrprise i.social_category  
i.bank_account i.growth_status i.activity_group,or
```



Coming to the interpretation of coefficients further among sectors as compared to rural women entrepreneurs and urban sector decrease the log of odds of choosing necessity entrepreneurs by 0.262. So, like we have already said here. Here it is 0 point in this case. The log of odds is negative related to the necessity entrepreneurs. That means enterprise or the women entrepreneurs to be necessity entrepreneurs being in urban area is negatively linked with a coefficient of minus, coefficient of 0.262, 0.263 roughly.

Similarly, the coefficient of the Logit function is quite difficult to interpret since it follows a logistic distribution function. So, the coefficient which we have said, it is somewhere linking to average. Average coefficient is not suggested to be interpreted. Since the function is logistic it has to be in favor towards success or failure or probabilistic structures is attached. So, likelihood of estimation is attached. So, we should not interpret the coefficient as such. Rather it is suggested to interpret the odd ratio and the marginal effect.

So, STATA does this task by specifying simple command logistic instead of just logit. And so the command is here. We can just operate. Basically whatever we operated it is more or less same but it gives only odds ratio. So, odds ratio logistic command if you simply add here that gives, but if you only logit, till this if you do not add this, it is not going to give odds ratio at all. It only gives coefficient. But if you simply comma add with 'or', or stands for odds ratio. This certainly boils down to the odds ratio of it.

(Refer Slide Time: 27:45)

Logistic regression results showing coefficients, odds ratios, and p-values for various predictors. The model includes variables like enterprise_type, age_square, sector, mix_activity, and location_entreprise. A blue box highlights the interpretation of the odds ratio for the 'urban' sector variable, stating it is 0.76 times less likely to choose necessity entrepreneurship compared to the rural sector.

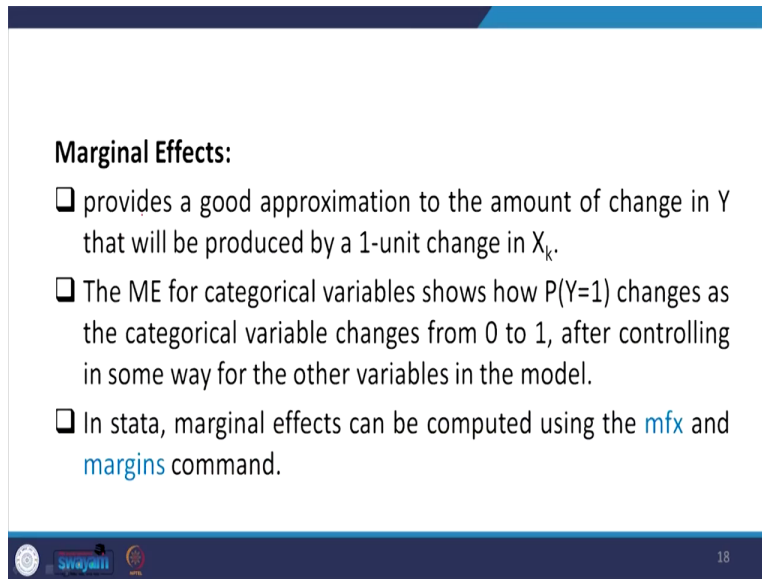
Interpretation of odds ratio: women entrepreneurs in urban sector is 0.76 times less likely to choose necessity entrepreneurship as compare to rural sector.

The results are like this, the way we have shown earlier but I think this is more or less repetitive. You should not operate much. You can operate on your own. The interpretation is like earlier we have seen coefficients but now it is not coefficients. The command here is logistic, more importantly you have to check this first. Then this is not that important. You may not be worried about this pseudo R square but still here it seems 34 percent fitting to the model. It is a good fitting.

Then coming to the interpretation of the coefficient. Wherever it is exceeding 1 that means those variables are positively linked to the dependent variable or the regressand. And those who are less than 1, 1 we are taking as stands for probability of success and so whichever are less they are negative related, whichever are less than 1 they are negative related to the regressand. So, like here these variables, we have already seen that was of minus of 0.262.

But here now look at this. This is negatively linked because as I told you since these are in odd ratio the probability in favor of success or failure, and this is saying that being urban women entrepreneurs is having a likelihood of minus, negatively linked to being a necessity entrepreneur. So, likelihood of the woman to be necessity entrepreneur is negative. The interpretation exactly is that it is 0.7 times less likely to choose or to be a necessity entrepreneur, so being in urban area, alright. Similarly you can interpret other variables, whichever is more than 1 that is, it is positively and otherwise it is negatively linked.

(Refer Slide Time: 30:07)



Marginal Effects:

- ❑ provides a good approximation to the amount of change in Y that will be produced by a 1-unit change in X_k .
- ❑ The ME for categorical variables shows how $P(Y=1)$ changes as the categorical variable changes from 0 to 1, after controlling in some way for the other variables in the model.
- ❑ In stata, marginal effects can be computed using the `mf` and `margins` command.

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So, marginal effect is very very important. I suggest many times that coefficients are not to be interpreted, better to avoid that. So, straight away come to the interpret of marginal effect. This provides a good approximation to the amount of change in Y given the unit change in X . We have already defined this derivative. So, derivative values of Y with respect to X that the marginal effect depends upon change in X . So, it is important.

The ME that is marginal effect so for categorical variables shows that how the P with value 1 changes as categorical variable changes from 0 to 1, after controlling in some way or the other variables in the model. In STATA marginal effects can be computed using a `mf` or the `margins` command.

(Refer Slide Time: 31:00)

mfX command:

- obtains marginal effect or elasticities after estimation.

```
help mfx                                     dialog: 41
-----
mfx has been superseded by margins.  margins can do everything that mfx did and more.  margins syntax differs from mfx: see margins.  mfx continues to work
but does not support factor variables and will often fail if you do not run your estimation command under version control, with the version set to less than
11.  This help file remains to assist those who encounter an mfx command in old do-files and programs.
```

margins command:

- calculate predicted probabilities.
- According to stata manual, Margins are statistics calculated from predictions of a previously fit model at fixed values of some covariates and averaging or otherwise integrating over the remaining covariates.

Capabilities include estimated marginal means, least-squares means, average and conditional marginal and partial effects (which may be reported as derivatives or as elasticities), average and conditional adjusted predictions, and predictive margins.

- Was introduced in stata 11.

After running the logit model:

margins, atmeans

Atmeans option estimate the margins at the mean of covariates.

So, you can take the help search mfx command from the STATA. So, many suggestions will be there. You can get it .Out of that we are going to operate with any of the command. We are going to operate with the margins command. So, since we have taken dy/dx so somewhere we are linking to elasticity of their estimation. So, in margins command also helps in giving the predicted probabilities.

According to STATA manual margins are statistics calculated from predictions of a previously fit model at fixed values of some covariates and averaging or otherwise integrating over remaining variables. Basically it is calculated from the predictions of the fitted variables or values. The

capabilities of the marginal effect include estimated marginal means. Like it is estimated at means value, then least square means also, alright, average, then conditional marginal, partial effects. There are so many way of interpretation of the marginal values, so which may be also reported as derivatives or elasticities.

Average and conditional adjusted predictions and predictive margins. There are so many ways of interpreting the MEs. So, this was introduced as I mentioned since STATA 11 version. After running the Logit, once we run the Logit model then we can go for margins at means one of the way of interpreting ME. So, atmeans option estimates the margins at the means of the covariates.

(Refer Slide Time: 33:20)

STATA 11.1: Company choice model (BCM_practice.dta)

Review

Command

```

1 use "Company choice model"
2 logit entrepr11-ge
3 nl_1 logit entrepr11-ge, nll(1)
4 nl_2 logit entrepr11-ge, nll(2)
5 margins, atmeans

```

Adjusted predictions

Number of obs = 6,492

Model VCE = OIM

Expression = Pr(entrepr11-ge) predict()

at

entrepr11-ge	=	10.36445	(mean)
age_square	=	151.6562	(mean)
_sector_2	=	5150955	(mean)
_mix_activ-2	=	9705792	(mean)
_indus_fa-2	=	6797397	(mean)
_ass1tab-2	=	89322	(mean)
_itrad_sec-2	=	2466359	(mean)
_trouhtst-2	=	651191	(mean)
_location-2	=	1665770	(mean)
_social_c-2	=	1166551	(mean)
_social_c-3	=	4882886	(mean)
_social_c-4	=	2392374	(mean)
_bank_acc-2	=	6320316	(mean)
_bank_acc-3	=	608626	(mean)
_bank_acc-4	=	5198706	(mean)
_growh_y-2	=	5468659	(mean)
_growh_y-3	=	107289	(mean)
_activity-2	=	2147258	(mean)
_activity-3	=	2208072	(mean)

Delta-method					
	Margin	Std. Err.	z	P> z	[95% Conf. Interval]
_atmeans	8902236	6049878	1.48	0.000	8804477 8999995

Variables

Name	Label
entrepr11-ge	entrepr11-ge
social_fa	RECODE of social_fa
location_est	RECODE of location_est
age_square	entrepr11-ge
entrepr11-ge	RECODE of entrepr11-ge
_sector_2	sector+2
_mix_activ-2	mix_activ+2
_indus_fa-2	indus_fa+2
_ass1tab-2	ass1tab+2
_itrad_sec-2	itrad_sec+2
_trouhtst-2	trouhtst+2
_location-2	location+2
_social_c-2	social_c+2
_social_c-3	social_c+3
_social_c-4	social_c+4
_bank_acc-2	bank_acc+2
_bank_acc-3	bank_acc+3
_bank_acc-4	bank_acc+4
_growh_y-2	growh_y+2
_growh_y-3	growh_y+3
_activity-2	activity+2
_activity-3	activity+3

Properties

Variables

Name	Label	Type	Format	Value labels
entrepr11-ge	entrepr11-ge	float	%9.0g	

Data

Filename	Label	Notes
BCM_practice.dta	BCM_practice.dta	

Variables: 12
Observations: 6,492
Size: 281,274
Memory: 6482
Sorted by:

The probability of enterprise type = 1 is 89% given that all predictors are set to their mean values.

```

margin, atmeans
-----
Adjusted predictions      Number of obs   =   6,492
Model VCE      :   OIM

Expression   :   Pr(enterprise type)   predict()
of           :   enterprise type       -   10.36445 (mean)
age square   -   137.5042 (mean)
1.sector     -   -0.64545 (mean)
2.sector     -   -0.51095 (mean)
1.mia actvty -   -0.29420 (mean)
2.mia actvty -   -0.70279 (mean)
1.pblm fact  -   -0.32243 (mean)
2.pblm fact  -   -0.79759 (mean)
1.assistancd -   -0.0079 (mean)
2.assistancd -   -0.9122 (mean)
1.trad acc  -   -0.73364 (mean)
2.trad acc  -   -0.24439 (mean)
1.southatara -   -0.44959 (mean)
2.southatara -   -0.51191 (mean)
1.locationw -   -0.65421 (mean)
2.locationw -   -0.44579 (mean)
1.social cvy -   -0.15989 (mean)
2.social cvy -   -0.16601 (mean)
3.social cvy -   -0.48248 (mean)
4.social cvy -   -0.91374 (mean)
1.bank acct -   -0.43944 (mean)
2.bank acct -   -0.32234 (mean)
3.bank acct -   -0.08426 (mean)
4.bank acct -   -0.15970 (mean)
1.growth sva -   -0.44544 (mean)
2.growth sva -   -0.44829 (mean)
3.growth sva -   -0.17289 (mean)
1.activitytp -   -0.54389 (mean)
2.activitytp -   -0.21421 (mean)
3.activitytp -   -0.21987 (mean)

-----
Delta-method
Margin   Std. Err.   z   P>|z|   [95% Conf. Interval]
-----+-----
_cons   -0.02216   0.049878   178.48   0.000   -0.04477   -0.00055

```

That we just wanted to show you, alright. So, it is here. We simply get that to the model, to the STATA. Since we have already derived the result, we simply take atmeans value. So, margin atmeans, then we go to the STATA window. Then since STATA as already we run the Logit regression. This has given the result.

At the means, margin at its average or the average value or means is derived. So, I am going to discuss it so 0.89 is very very important. And also that predicted values of each of these entries are also equally important for our interpretation. Likewise this is what we derive.

Here the probability of the enterprise with code 1 that is necessity enterprise is of 89 which we have shown that is 89 percent. Given that all the predictors are set to their mean values. All the predictors it is highlighted here variables at means values. You can just have a check. Variables at mean values and everywhere mean is mentioned. So, when all the variables are set at its mean what is the probability of enterprise to be of necessity type? That is of 89; nearly 90 percent is having the probability of to be necessity driven or necessity enterprises.

(Refer Slide Time: 34:57)

Command: `margins sector, atmeans`

Holding all variables at their mean values, the probability of enterprise type = 1:

- 90% among those who are in rural areas
- 88% among those who are in urban areas

Similarly, you can run this command for all factor variables.

Caution!

Margin command does not accept continuous variables as factor variable. (such as age and age squared). It requires certain value of these variables at which it will calculate margin

```
margin sector, atmeans
Adjusted predictions      Number of obs   =   6,492
Model VCE      : OIM

Expression   : Pr(enterprise_type) _p{predict()}
at
  1. enterprise_type = 10.16443 (mean)
  2. age             = 127.5562 (mean)
  3. sector          = 4848043 (mean)
  4. need           = 5151895 (mean)
  5. mba            = 6284208 (mean)
  6. mba_activity   = 9705792 (mean)
  7. pblm_faid     = 3222409 (mean)
  8. pblm_faid     = 4797059 (mean)
  9. socialize_0    = .00878 (mean)
 10. socialize_0    = .99122 (mean)
 11. trad_soc      = 7233643 (mean)
 12. trad_soc      = 2446359 (mean)
 13. socialize_0    = 3488959 (mean)
 14. socialize_0    = 6511091 (mean)
 15. socialize_0    = 6574221 (mean)
 16. socialize_0    = 3445779 (mean)
 17. socialize_0    = 1219889 (mean)
 18. socialize_0    = 1144051 (mean)
 19. socialize_0    = 4482484 (mean)
 20. socialize_0    = 2993376 (mean)
 21. bank_accr_0   = 438464 (mean)
 22. bank_accr_0   = 6320394 (mean)
 23. bank_accr_0   = 698262 (mean)
 24. bank_accr_0   = 5188704 (mean)
 25. growth_s_0    = 3453643 (mean)
 26. growth_s_0    = 3488269 (mean)
 27. growth_s_0    = 1072089 (mean)
 28. activity_p_0   = 5641889 (mean)
 29. activity_p_0   = 2147259 (mean)
 30. activity_p_0   = 2228872 (mean)

-----+-----
              Delta-method
              Std. Err.   z      P>|z|   [95% Conf. Interval]
-----+-----
sector
rural   90.90277   0.00221   409.94   0.000   89.93961   91.86594
urban   87.17141   0.00761   113.23   0.000   86.38994   87.95287
```

Coming to specific command emphasizing sector and their margin, particular sector-wise, which sector has higher probability, rural or urban? If you specify with margins with a sector with means. Initially we said only margins atmeans that gives the total model, isn't it? When we specify to a particular categorical variable, we just wanted to know difference between rural and urban probabilities. It has given the value. The result we can easily get with the same command if you can try.

For the rural and urban; rural it has given 90.902767. So, that means 90 percent probability are there with the rural entrepreneur to be necessity driven or necessity type of enterprises whereas in the urban areas of 87. So, even it is understood and logical that in urban areas the likelihood of the enterprises to be necessity driven is very less, should be less than that of the rural areas because of many other problems or facilities or shortage of access specially financial access as well, transport and financial access as well.

So, coming to the understanding relating to the margin command this does not accept continuous variable. That is more important because we are comparing with categories. So, this does not accept continuous variable as a factor variable such as age or age square is not going to be interpreted at all or is not going to be considered. It requires certain values of these variables at which it will calculate the margin. It will compare from one to another one. There must be some

discrete difference from one category to another category then only the margin could be derived. Then only the derivative could be derived.

So, let us come to the understanding of the change in the probability. What are the change in the probability when the predictor of the independent variable increases by 1 unit? So, if there is, we simply say the absolute probability of a particular category when we keep other variables to be at their average value.

(Refer Slide Time: 37:15)

To show the change in probability when the predictor or independent variable increases by one unit.

margins, dydx(*) **atmeans**

dydx estimate average marginal effect of variables in varlist

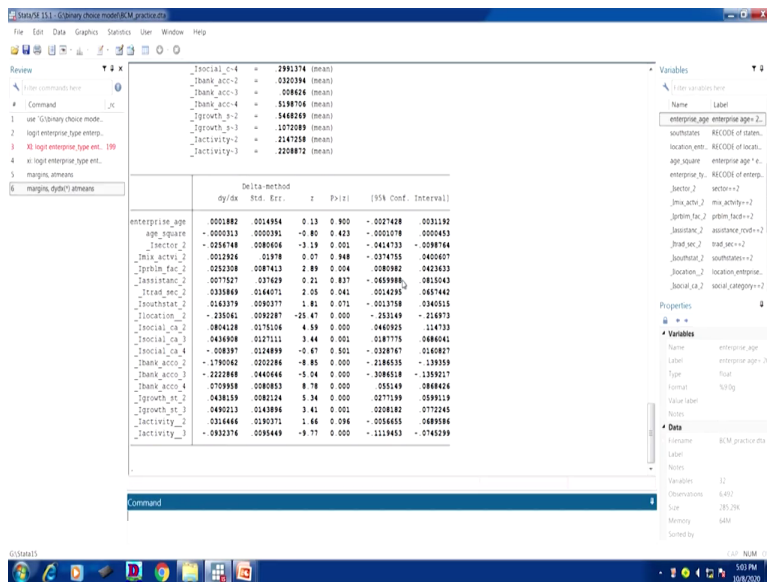
If we want conditional marginal effects for all covariates, we have to specify (*) or (_all) with dydx, both mean the same thing.

The atmeans option gives result for conditional marginal effect conditioned at means of the variables.

The change in the probability for one instant change in age is .02 percentage points (pp), in age square .003 pp. none of the effects here are significant

	Delta-method				[95% Conf. Interval]	
	dy/dx	Std. Err.	z	P> z		
enterprise age	.001882	.0014954	0.13	0.900	-.0027428	.0031192
age square	-.0000313	.0000391	-0.80	0.423	-.0001078	.0000453
sector						
urban	-.025626	.0080395	-3.19	0.001	-.0413831	-.0098689
mix activity						
No	.0012989	.0199728	0.07	0.948	-.0378471	.0404449
2,public land	.0261843	.0094129	2.78	0.005	.0077354	.0446331
2,assistance road	.0079918	.0399403	0.20	0.842	-.0703382	.0603217
read soc						
nonfunctional	.0315991	.0145279	2.18	0.030	.0012149	.0600733
2,nonfunctional	.0146699	.0094201	1.55	0.076	.0017795	.0311233
location enterprise						
notinBHR	-.3225801	.013592	-23.73	0.000	-.34922	-.2959403
social category						
SC	.0733839	.0140372	4.57	0.000	.0419123	.1048555
OBC	.0407771	.0144621	3.12	0.002	.0119389	.0705142
others	-.0104828	.0156712	-0.68	0.495	-.0413977	.0200321
bank account						
enterprisebank	-.3648904	.0475964	-7.71	0.000	-.4601775	-.2706033
both	-.4703459	.1031932	-4.61	0.000	-.677461	-.2709009
nocraccounts	.0481644	.0080647	8.45	0.000	.0523553	.0839775
growth status						
2	.0465695	.0091084	5.11	0.000	.0287173	.0644217
3	.0510939	.0135544	3.77	0.000	.0245277	.0776401
activity group						
trade	.0248316	.0140439	1.77	0.077	-.0024939	.052357
services	-.128051	.0125734	-8.90	0.000	-.1474094	-.0942018

Being from urban area decreases the probability of necessity entrepreneur by 2.5 percentage points and is highly statistically significant. Other values are interpreted in the same way.



We are saying, what is their marginal unit change. In that case we have to take the dy/dx . So, dy/dx if you can take it that will be giving result like this. We can find it also. So, let us have a check. So, dy/dx and this is going to be more useful throughout your papers. While you write for assignment or papers it will be very useful.

This has given the marginal effect which we are trying to interpret. Against against each predictor variable we have now derived this marginal effect, the unit change, the individual derivative of each variable on the dependent variable. So, the marginal change is highlighted and these coefficients should be interpreted. Those were positive, negative very clearly understood. Generally it is highly linked with the coefficient values but the coefficient values if you interpret, that is misleading. So, better stick to this.

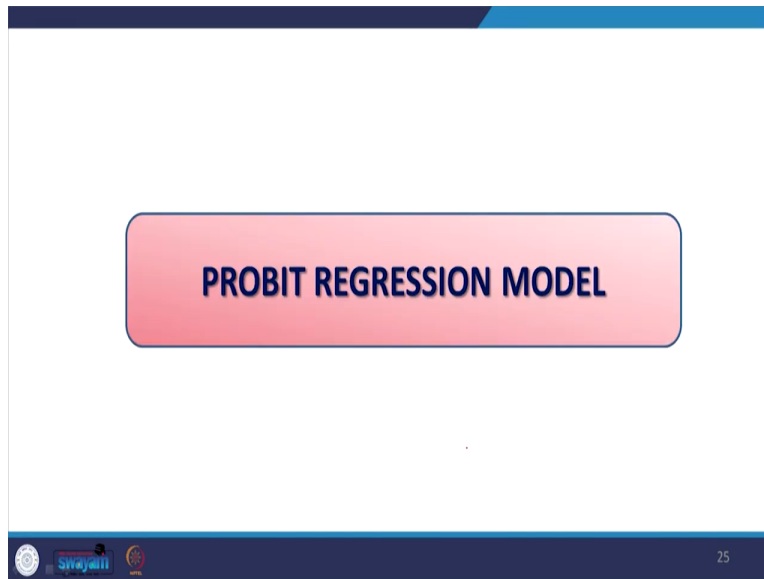
dy/dx estimate average marginal effect of variables because we have set at mean values, so average marginal effect is derived. If we want conditional marginal effect for all covariates we have to specify with the star or all with dy/dx , underscore all with dy/dx . Both mean the same thing. Either this or this refer to the same interpretation. So, if you simply go by this that will give you the conditional marginal effects. The `atmeans` option gives result of conditional marginal effect conditioned at the means of the variables. That is the conditional aspect we are referring to. Then we have to specify it.

In this case the change in the probability of one instant change in particularly age here. Age is basically minus of 0.0003. So, the change in percentage is of 0.02 alright. So, age is here. The

first one is age. Second one is age square. When the second one square case is age square that is of here, that is 0.003. The first one is 0.001882 so roughly around 0.02 point.

So, coming to the discussion of urban area as against to the rural, in this case, urban it is negatively linked to the necessity entrepreneur. In percentage point it is of 2.5 percent lesser points. So, being from urban area decrease the probability of necessity entrepreneurship by 2.5 percent and is highly statistically significant. That we wanted to check. This is statistically significant. Similarly, you can understand this is statistical significant. Even these are statistically significant at different levels. Then these variables, I am just mentioning. You can understand all three. Similarly other you can compare.

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Alright, so from the next class we will try to understand Probit and Tobit. I think it is very clearly understood to you that how Logit is operated and how marginal effect at conditional mean is understood and it is important for interpretation. And please go and practice with any other dataset but sticking to the kind of specification with the dependent variable and independent variable. Then that really works better. So, let us explore Probit regression model from the next class. Thank you so much.