Problem Set 1

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1 Problem One. OLS in MATA

1.1 Part 1

In this problem I created the e-class program myreg1. This program takes as input a dependent variable y and a set of independent variables or regressors X_k. The program transform these variables into a vector and matrix respectively and performs the operations necessary to get our OLS estimates and the associated variance-covariance matrix. the output is thus a $b_{(k+1)\times 1}$ vector (OLS estimates) and a $V_{(k+1)\times(k+1)}$ matrix (Variance-covariance).

The log below shows that the results of myreg1 are the same as those obtained using Stata's embed Results with myreg1

```
. myreg1 lnwage hieduc exp exp2
b[4,1]
            c1
r1   .08264541
r2   .02523881
r3  -.00037668
r4   1.3094414
symmetric V[4,4]
            c1          c2          c3          c4
r1   1.195e-06
r2   1.595e-07   .00001683
r3  -4.035e-09  -3.770e-07   8.579e-09
r4  -.00001749  -.00017676   3.899e-06   .00211062
```

```
. quiet reg lnwage hieduc exp exp2
. matrix list e(b)
e(b)[1,4]
         hieduc         exp        exp2       _cons
y1    .08264541   .02523881  -.00037668   1.3094414
. matrix list e(V)
symmetric e(V)[4,4]
             hieduc         exp        exp2       _cons
hieduc    1.195e-06
   exp    1.595e-07   .00001683
  exp2   -4.035e-09  -3.770e-07   8.580e-09
 _cons    -.0000175  -.00017676   3.899e-06   .00211066
```

```
.
. myreg2 lnwage hieduc exp exp2
b[4,1]
            c1
r1   .08264541
r2   .02523881
r3  -.00037668
r4   1.3094414

symmetric V[4,4]
            c1          c2          c3          c4
r1   1.520e-06
r2   1.712e-07   .00001632
r3  -4.045e-09  -3.685e-07   8.451e-09
r4  -.00002216  -.00016979   3.771e-06   .00208194

. quiet reg lnwage hieduc exp exp2, robust
```

```
. quiet reg lnwage hieduc exp exp2, robust

. matrix list e(b)

e(b)[1,4]
        hieduc         exp        exp2       _cons
y1   .08264541   .02523881  -.00037668   1.3094414

. matrix list e(V)

symmetric e(V)[4,4]
            hieduc         exp        exp2       _cons
hieduc   1.520e-06
   exp   1.712e-07   .00001632
  exp2  -4.045e-09  -3.685e-07   8.451e-09
 _cons  -.00002216  -.00016979   3.771e-06   .00208194

.
```

1.2 Part 2

In this part I created the program myreg2 which takes the same inputs as myreg1 and gives the same vector of OLS estimates b. myreg2 takes the variables from Stata and then implements a second program called myols(X,Y), which is the one that actually calculates the OLS estimates and the variance-covariance Matrix V adjusted for arbitrary heteroscedasticity. With respect to the OLS estimates, instead of calculating them with the cross product (and inverse) of the whole X matrix and y vector, it performs the sum of the cross product of each row (observations). The same approach is used for calculating the matrix V.

The log above shows that my results are exactly the same as those obtained using Stata's regress command and "robust" option.

2 Problem Two. Poisson using Maximum Likelihood

If y_i is distributed Poission with mean $exp(X_i'\beta)$, hence the likelihood function for a sample of N observations is given by:

$$L(\beta) = \prod_{i=1}^{N} \frac{1}{y_i!} exp((X^{'}\beta)y_i)exp(-exp(X^{'}\beta))$$

And taking logs we get:

$$lnL(\beta) = \sum_{i}^{N}[-exp(X^{'}\beta) + y_i exp(X^{'}\beta) - ln(y_i!)]$$

Which is the form we use for pur maximum-likelihood estimation I made two .ado files, one containing the generation of the evaluator program and the other one that takes a dependent and independent variables from Stata and performs the Maximum Likelihood Estimation. Those .ado files are attached in the folder.

I show the histogram of the number of awards as well as the mean and variance of the variable. The key assumption of Poisson distribution is that the parameter λ is the mean and variance of y. However, we see in table 2 that the variance is almost twice bigger than the mean, which may reduce the usefulness of Poisson distribution to analyze the behavior of the number of awards.

In the tavle 1 I show the results of the estimation using Stata's command and mypois. I get the same results.

Table 1: Poisson Estimation

	(1) Stata Poisson	(2) mypois
main		
general	0.0000	0.0000
	(.)	(.)
academic	1.0839**	1.0839**
	(0.3583)	(0.3583)
vocation	0.3698	0.3698
	(0.4411)	(0.4411)
math score	0.0702***	0.0702***
	(0.0106)	(0.0106)
Constant	-5.2471***	-5.2471***
	(0.6585)	(0.6585)
Observations	200	200

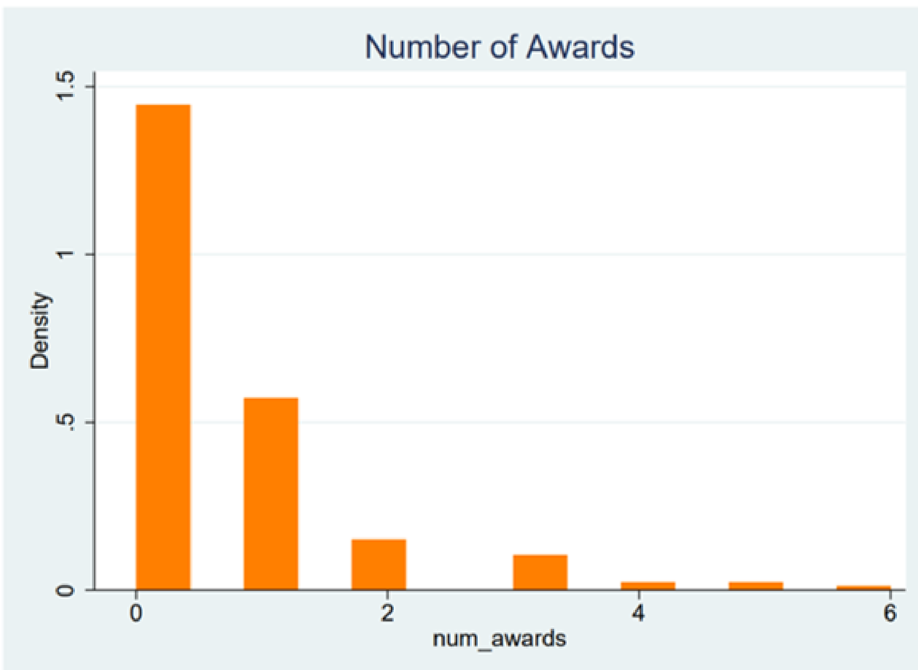
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Number of Awards

	Mean	Variance
Number of awards	0.63	1.11

```
. hist(num_awards), title("Number of Awards") color("or
> ange")
(bin=14, start=0, width=.42857143)
```



3 Problem 3. Mean Squared Error simulation - Sample Size and Distribution

In the first part of the program I create the program OLSPOIS, whose inputs are a number of observations N and a scalar σ that generates a matrix-covariance matrix. My program generates a variable y distributed poisson with mean $exp(2X_{1i} - X_{2i})$. Then it estimates a Poisson and an OLS regression (lny as dependent variable) and returns the average of the squared errors.

I made a loop to run the program 1000 times with N=50,1000 and $\sigma = 0.01, 0.1, 1$ I show the average of the squared error (MSE) obtained in the six cases in the table below. The most salient fact is that MSE is always substantially smaller when using Poisson than with OLS. Additionally, MSE is smaller in both cases when the number of observations is large ($N = 1000$). Also, the smaller sigma (covariance and variance of X_1 and X_2), the smaller the MSE.

Table 3: Average of the squared error (MSE): OLS and Poisson

	0.01 OLS	0.01 POIS	0.1 OLS	0.1 POIS	1 OLS	1 POIS
N=50	.147573	.0070057	.1463649	.0072342	.143837	.0077137
N=1000	.1223382	.000118	.1228836	.0001196	.1214063	.0001158

4 Problem 4. Small number of clusters - Wild Bootstrap

I generate the program randsim that takes as inputs a dependent variable y, an individual or cluster variable "unit" and a time variable "t". It randomly assigns treatment=1 to a unit with probability 0.25 and then generates a variable $y2 = y + 0.05 * treatment$ If it happens that no unit is treated then it assigns the value one to a scalar called $no\_treated$, zero otherwise. It then runs a regression with unit and time fixed effects using clustered standard errors at the unit level. a scalar sig_y takes the value of one if the coefficient of treatment is significant at the 5% level and zero otherwise. The program also calculates the standard error following the wild bootstrap approach using the boottest command. If the coefficient of treatment is significant at the 5% level, the scalar $bsig_y$ takes value 1, and zero otherwise. My program finally returns the 2 scalars.

I run the program 1000 times in two cases: with all (25) and with just a few number of clusters (8). The frequencies of the 4 scalars are reported in tables 4 to 7. These frequencies allow us to see what happens with the recurrence of type 1 and 2 errors with the different standard errors techniques of estimation.

I base my analysis in the following interpretation. Type 1 error means rejecting a null hypothesis that is actually true, whereas Type 2 means failing to reject a false null hypothesis. Our null hypothesis is $H_0 : \beta_{treatment} = 0$. For $lnemp$, treatment is a placebo, so H_0 is actually true. Rejecting it means making the type 1 error. In contrast, for $lnemp2$, H_0 is false: there is a direct relationship between $lnemp2$ and treatment. So failing to reject H_0 would be the type 2 error.

The tables below show the frequencies of ones and zeros of our four scalars. From first row of table 4 we can see the Bootstrap is much better at avoiding type 1 errors than cluster. However, from the second row of table 5 we see that type 2 error is very frequent with bootstrap.

The results for a small number of clusters are shown in tables 6 and 7. Whereas there are no major differences for type 1 error (first row of Table 6), in the second row of table 7 we can see that bootstrap is failing to find significance of treatment with lnemp2. That is, type 2 error becomes more frequent with a small number of clusters

Table 4: Coefficient of treatment significant? Frecuency

	Cluster	Bootstrap
lnemp	1000	52
lnemp2	1000	143

Table 5: Coefficient of treatment insignificant? Frecuency

	Cluster	Bootstrap
lnemp	0	948
lnemp2	0	857

Table 6: Coefficient of treatment significant? Frecuency (few clusters)

	Cluster	Bootstrap
lnemp	918	48
lnemp2	918	0

Table 7: Coefficient of treatment insignificant? Frecuency (few clusters)

	Cluster	Bootstrap
lnemp	0	870
lnemp2	0	918

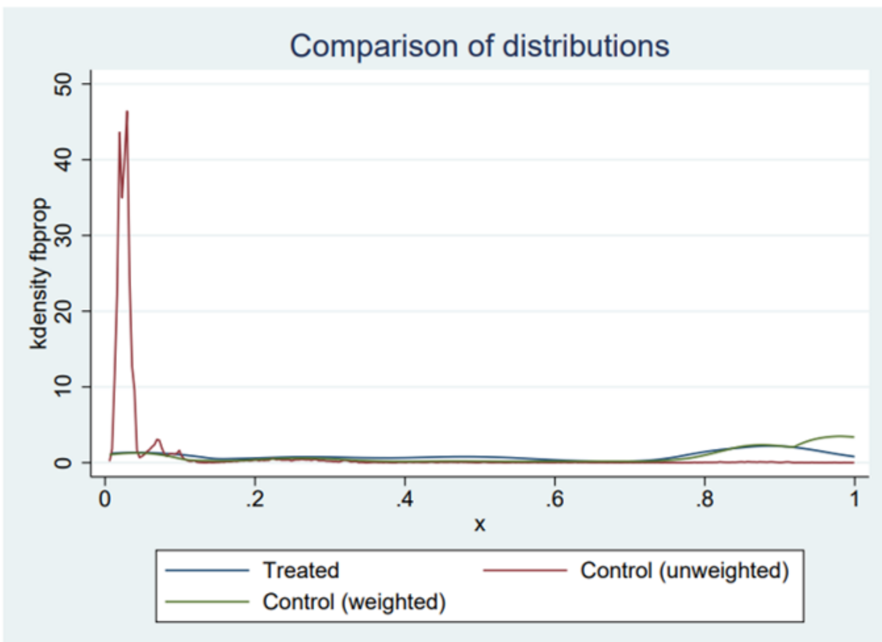
5 Problem 5: Matching

Table 8 presents the estimations for Foreign born with the 8 different estimations method. The table in the page below shows that the covariates are well-balanced under the propensity score method. In the page after there is a figure showing the distribution of of treatment probability for (1) treated, (2) control [unweighted] and (3) control [weighted] sample

.

```
. table fbprop_n FB, c(mean exp mean married mean races
> ing mean hisp mean educ99) row
```

10 quantiles of fbprop	FB 0	FB 1
1	27.28281	27.94118
	.3433456	.3647059
	12.6768331527709961	10.7411766052246094
	0	0
	9.83210086822509766	9.84705924987792969
2	23.30995	24.41
	.4344489	.41
	10.0976362228393555	10.4399995803833008
	0	0
	10.0508136749267578	10.3900003433227539
3	23.61466	23.52756
	.6575066	.5748032
	10.0652074813842773	10
	.0001553	0
	10.4848623275756836	10.7637796401977539
4	19.362	18.91597
	.9292649	.907563
	10.0098628997802734	10
	.0001541	0
	10.0906152725219727	10.2352943420410156
5	22.00368	21.53548
	.7944828	.7612903
	10.181915283203125	10.3741931915283203
	.0009195	0
	11.2148656845092773	11.3161287307739258
6	21.4017	20.81967
	.6885457	.6338798
	10.4786033630371094	10.3825139999389648
	.0011261	.0054645
	12.0387706756591797	12.0819673538208008
7	21.74541	22.2963
	.7948799	.75
	11.6778697967529297	11.435185432434082
	.0012565	0
	12.5068321228027344	12.7685184478759766
8	20.6952	20.10601
	.6223354	.565371
	14.1539926528930664	14.5583038330078125
	.0006363	0
	11.9490928649902344	12.5229682922363281
9	20.43398	20.79415
	.6778761	.6738895
	14.2688493728637695	13.5232934951782227
	.2987611	.5872156
	11.4302654266357422	11.219935417175293
10	21.08562	20.96237
	.6275	.6917505
	17.2250003814697266	22.100402832003125
	.665625	.5724346
	10.364375114440918	8.7969818115234375
Total	22.20966	21.09831
	.6588426	.679933
	11.6240015029907227	19.1085052490234375
	.0474565	.4731183
	11.0315637588500977	9.60829448699951172



Comparison of distributions
kdensity fbprop
0
10
20
30
40
50
0
.2
.4
.6
.8
1
x
Treated
Control (unweighted)
Control (weighted)

Table 8: Estimates of FB

	Bivariate	Simple	Saturated	CEM	PScore	Psmatch_1	Own	IPW
FB	-0.056	0.056		0.050	-0.077	0.006	0.125	0.123
	(0.011)	(0.014)		(0.015)	(0.116)	(0.032)	(0.012)	(0.142)
Obs.	51816	51816	48626	37081	65741	51816	51816	51816
Estimator	OLS Bivariate	OLS Controls	OLS Saturated	CEM	Match	Match	Match	Match

Standard errors in parentheses

Average Treatment On Treated for matching models