

## Консультация перед экзаменом.

### Задача 1.

Let  $Z$  is a random variable with mean  $\mu = E(Z)$  and variance  $\sigma^2 = V(Z)$ . Let we have a sample of size 2,  $z_1 = 0$  and  $z_2 = 4$  from this distribution. We are interested in the parameter  $\theta = \mu^2$ .

- (a) Let the estimator is  $\hat{\theta} = \bar{z}^2 = \left(\frac{z_1 + z_2}{2}\right)^2 = \frac{1}{4}(z_1 + z_2)^2 = 4$ . Find bias of this estimator.
- (b) Explain how you would find a bootstrap-bias-corrected estimator,  $\hat{\theta}_{Boot}$  and calculate its bias.
- (c) Formulate the condition when the bias of  $\hat{\theta}_{Boot}$  is in absolute value smaller than the bias of  $\hat{\theta}$ .

### Задача 2.

Данные по пропускам занятий в 2018 г.

calc1            calculus, 1<sup>st</sup> year (0–100)  
stat1            statistics, 1<sup>st</sup> year (0–100)  
mid2            оценка по мидтерму 2 (2-го года) (0–100)  
na1            число пропусков семинаров до mid1  
na2            число пропусков семинаров от mid1 до mid2  
na12= na1 + na2  
lcalc1 = ln(1+calc1)  
lstat1 = ln(1+stat1)  
lmid2 = ln(1+mid2)

Ниже приведены оценки нескольких моделей.

- (а) (5 баллов) По модели 1 найдите прогноз оценки по второму мидтерму студента с calc1=55, na12=7 и 95%-ный доверительный интервал прогноза. Как изменится оценка при уменьшении количества пропусков на 1?
- (б) (5 баллов) По модели 2 найдите прогноз оценки по второму мидтерму студента с calc1=55, na12=7. Как изменится оценка при уменьшении количества пропусков на 1?
- (в) (5 баллов) По модели 3 найдите вероятность того что студент с calc1=55, na12=7 получит оценку больше 35 (проходной балл). Как изменится эта вероятность при уменьшении количества пропусков на 1?
- (г) (5 баллов) По модели 4 найдите вероятность того что студент с calc1=55, na12=7 получит оценку больше 35 (проходной балл). Как изменится эта вероятность при уменьшении количества пропусков на 1?
- (д) (5 баллов) Интерпретируйте результаты модели 5.

### ----- deskриптивные статистики

.sum calc1 stat1 mid2 na1 na2 na12 lcalc1 lstat1 lmid2

Variable	Obs	Mean	Std. dev.	Min	Max
calc1	222	54.57207	16.07249	21.4	97.2
stat1	222	53.46847	18.87363	16	91
mid2	214	39.41121	20.52021	0	95
na1	222	2.162162	2.259382	0	7
na2	222	3.306306	2.652729	0	7
na12	222	5.468468	4.504035	0	14
lcalc1	222	3.971025	.3174502	3.11	4.59
lstat1	222	3.931668	.3759945	2.83	4.52
lmid2	214	3.473327	.8605712	0	4.56

### Модель 1

```
. reg mid2 na12 calc1
```

Source	SS	df	MS	Number of obs	=	214
Model	53991.0084	2	26995.5042	F(2, 211)	=	159.56
Residual	35698.8047	211	169.188648	Prob > F	=	0.0000
				R-squared	=	0.6020
				Adj R-squared	=	0.5982
Total	89689.8131	213	421.078935	Root MSE	=	13.007

mid2	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
na12	-1.185705	.2274389	-5.21	0.000	-1.634049	-.7373611
calc1	.8001184	.0634011	12.62	0.000	.6751377	.925099
_cons	1.490929	4.297359	0.35	0.729	-6.980329	9.962187

(матрица ковариаций оценок)

```
. matrix list e(V)
```

```
symmetric e(V)[3,3]
```

```
      na12      calc1      _cons
na12   .05172848
calc1   .00678865   .0040197
_cons  -.64858158  -.25792686  18.467295
```

### Модель 2

```
. reg lmid2 na12 lcalc1
```

Source	SS	df	MS	Number of obs	=	214
Model	67.0495207	2	33.5247604	F(2, 211)	=	77.99
Residual	90.6946277	211	.429832359	Prob > F	=	0.0000
				R-squared	=	0.4251
				Adj R-squared	=	0.4196
Total	157.744148	213	.740582857	Root MSE	=	.65562

lmid2	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
na12	-.0534786	.0114449	-4.67	0.000	-.0760397	-.0309176
lcalc1	1.306943	.1623836	8.05	0.000	.9868405	1.627045
_cons	-1.45109	.6789243	-2.14	0.034	-2.789433	-.1127461

### Модель 3

```
. gen pass= (mid2>35) if year==2018
```

```
. probit pass na12 lcalc1
```

```
Probit regression                                Number of obs =    222
                                                LR chi2(2)      =    82.98
                                                Prob > chi2     =    0.0000
Log likelihood = -111.65921                    Pseudo R2      =    0.2709
```

pass	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
na12	-.0633342	.0238393	-2.66	0.008	-.1100585	-.01661
lcalc1	2.335395	.3856257	6.06	0.000	1.579582	3.091207
_cons	-8.809419	1.587522	-5.55	0.000	-11.92091	-5.697932

#### Модель 4

```
. gen grade= pass
. replace grade=grade+1 if (mid2>50)
```

```
. tab grade
```

grade	Freq.	Percent	Cum.
0	102	45.95	45.95
1	45	20.27	66.22
2	75	33.78	100.00
Total	222	100.00	

```
. oprobit grade na12 lcalcl
```

Ordered probit regression

Number of obs = 222

LR chi2(2) = 89.82

Prob > chi2 = 0.0000

Pseudo R2 = 0.1931

Log likelihood = -187.625

grade	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
na12	-.0511547	.0217157	-2.36	0.018	-.0937167	-.0085928
lcalcl	2.347722	.3502968	6.70	0.000	1.661152	3.034291
/cut1	8.937546	1.45024			6.095128	11.77996
/cut2	9.631782	1.464066			6.762266	12.5013

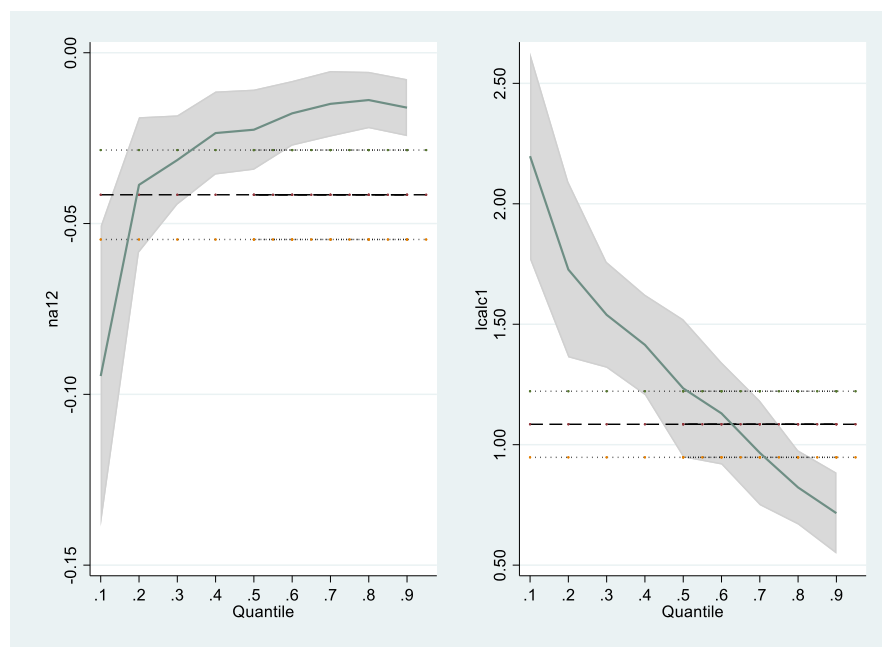
#### Модель 5

```
. sqreg lmid2 na12 lcalcl, q(.1 .2 .3 .4 .5 .6 .7 .8 .9) reps(200)
```

		Coefficient	Bootstrap std. err.	t	P> t	[95% conf. interval]	
q10	na12	-.0838806	.0426027	-1.97	0.050	-.167862	.0001007
	lcalcl	2.426944	.6571186	3.69	0.000	1.131586	3.722303
	_cons	-6.487357	2.814974	-2.30	0.022	-12.03643	-.938281
q20	na12	-.0559812	.0177183	-3.16	0.002	-.0909087	-.0210537
	lcalcl	1.641716	.3300163	4.97	0.000	.9911649	2.292268
	_cons	-3.009746	1.396078	-2.16	0.032	-5.761793	-.2576981
q30	na12	-.0354652	.012701	-2.79	0.006	-.0605024	-.0104281
	lcalcl	1.49511	.1634331	9.15	0.000	1.172939	1.817281
	_cons	-2.365492	.6855298	-3.45	0.001	-3.716857	-1.014128
q40	na12	-.0307546	.0084764	-3.63	0.000	-.0474639	-.0140452
	lcalcl	1.357278	.1743089	7.79	0.000	1.013668	1.700888
	_cons	-1.756461	.7341471	-2.39	0.018	-3.203664	-.3092587
q50	na12	-.0339861	.0096406	-3.53	0.001	-.0529902	-.0149819
	lcalcl	1.207537	.1586549	7.61	0.000	.8947857	1.520289
	_cons	-1.047199	.6704901	-1.56	0.120	-2.368916	.2745188
q60	na12	-.0273181	.0093108	-2.93	0.004	-.0456722	-.008964

	lcalcl1		1.107011	.1254063	8.83	0.000	.8598014	1.354221
	_cons		-.5841629	.5314225	-1.10	0.273	-1.63174	.4634146
-----								
q70								
	na12		-.0224138	.0083664	-2.68	0.008	-.0389063	-.0059214
	lcalcl1		.9942065	.0839169	11.85	0.000	.8287835	1.159629
	_cons		-.0789144	.3660945	-0.22	0.830	-.8005857	.6427569
-----								
q80								
	na12		-.020736	.0090724	-2.29	0.023	-.0386202	-.0028517
	lcalcl1		.920427	.0986422	9.33	0.000	.7259765	1.114877
	_cons		.323837	.4444675	0.73	0.467	-.5523287	1.200003
-----								
q90								
	na12		-.0248994	.0077376	-3.22	0.001	-.0401522	-.0096466
	lcalcl1		.7533497	.1121907	6.71	0.000	.5321915	.9745079
	_cons		1.162592	.4726978	2.46	0.015	.2307763	2.094407
-----								

. grqreg, ci ols ols ci reps(200)



### Задача 3.

Below you can find estimation results from a multinomial logit model. The dependent variable is  
status = 0, if if enrolled in school; (College)  
= 1, if not in school and not working (Home);  
= 2, if working (Work).

Choice 0 (College) is the base choice in the model. Regressors are number of years of education at the current moment (*educ*), experience of employment (*exper*), and its square (*exper*<sup>2</sup>), also a race dummy *black* = 1, if the person is afro American.

Table 1: Multinomial Logit Estimates of School and Labor Market Decisions

Explanatory Variable	Home	Work
	(status=1)	(status=2)
<i>educ</i>	-0.674 (0.070)	-0.315 (0.065)
<i>exper</i>	-0.106 (0.173)	0.849 (0.157)

<i>exper</i> <sup>2</sup>	-0.013 (0.025)	-0.077 (0.023)
<i>black</i>	0.813 (0.303)	0.311 (0.282)
<i>cons</i>	10.28 (1.13)	5.54 (1.09)
# of obs	1717	
% correctly predicted	79.6	
Log-likelihood value	-907.86	
Pseudo- <i>R</i> <sup>2</sup>	0.243	

- (a) Give interpretation of the coefficients at *educ* in both columns of the table (Home, Work). How *educ* influence on the probability to be in school?
- (b) Calculate the marginal effect  $\frac{\partial P(y=0|x)}{\partial educ}$  for a white person with 12 years of schooling and 10 years of experience.
- (c) Describe the model for which the property “Independence of irrelevant alternatives” is relevant. What is “Independence of irrelevant alternatives”?

#### Задача 4.

- (a) Describe the method of estimating the Random Effect Probit model for panel data.
- (b) Describe the underlying idea of estimating Fixed Effect Logit model for panel data. Is it possible to apply same method for estimating Random Effect Probit model for panel data?
- (c) Explain why pooled OLS estimator is not consistent for the panel data dynamic model.
- (e) Describe how you would predict dependent variable in the ordered choice model.