

# ADVANCED ECONOMETRICS I

## Practice Exercises (2/2)

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# Illustration 5

## Aims:

- Study the determinants of the choice between 2 tomato ketchup brands: Heinz and Hunts
- In particular, investigate whether the promotional activities developed by both brands have any impact on the probability of consumers choosing one instead of the other

## Sample:

- 2798 purchases made during a period of about two years in Springfield, Missouri
- Purchase data were collected automatically using an optical scanner; the shelf price of the other brand was also stored
- It was also registered if at the time of purchase the brands had ongoing promotional activities

# Illustration 5

Promotional activities:

- Display only
- Newspaper feature only
- Both

Model:

$$\begin{aligned} &Pr(Heinz = 1 | \dots) \\ &= G \left[ \beta_0 + \beta_1 Dhei + \beta_2 Fhei + \beta_3 DFhei + \beta_4 Dhun \right. \\ &\quad \left. + \beta_5 Fhun + \beta_6 DFhun + \beta_7 \log \left( \frac{Phei}{Phun} \right) \right] \end{aligned}$$

Details:

- Franses and Paap (2001), ch. 4.4

# Illustration 5 – Question 1

. describe

-----				
	storage	display	value	
variable name	type	format	label	variable label
-----				
Family	int	%8.0g		Family id
Heinz	byte	%8.0g		=1 Heinz chosen
Hunts	byte	%8.0g		=1 Hunts chosen
Phei	float	%9.0g		Heinz price (US\$/oz)
Phun	float	%9.0g		Hunts price (US\$/oz)
Dhei	byte	%8.0g		=1 if Heinz was on display but not featured
Dhun	byte	%8.0g		=1 if Hunts was on display but not featured
Fhei	byte	%8.0g		=1 if Heinz was featured but not on display
Fhun	byte	%8.0g		=1 if Hunts was featured but not on display
DFhei	byte	%8.0g		=1 if Heinz was on display and featured
DFhun	byte	%8.0g		=1 if Hunts was on display and featured
-----				

# Illustration 5 – Question 2

```
. summarize Heinz Hunts Dhei Dhun Fhei Fhun DFhei DFhun Phei Phun
```

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
Heinz	2798	.8902788	.3125978	0	1
Hunts	2798	.1097212	.3125978	0	1
Dhei	2798	.159757	.366446	0	1
Dhun	2798	.0353824	.1847774	0	1
Fhei	2798	.124732	.3304738	0	1
-----+-----					
Fhun	2798	.0364546	.1874519	0	1
DFhei	2798	.0375268	.1900828	0	1
DFhun	2798	.0092924	.0959651	0	1
Phei	2798	.0348276	.0089737	.001	.061
Phun	2798	.0335547	.0053069	.003	.087

# Illustration 5 – Question 3

```
. gen lpp=ln(Phei/Phun)
. logit Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp
```

Logistic regression	Number of obs	=	2798
	LR chi2(7)	=	584.96
	Prob > chi2	=	0.0000
Log likelihood = -675.43973	Pseudo R2	=	0.3022

Heinz	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Dhei	.5474406	.2427129	2.26	0.024	.071732	1.023149
Dhun	-.6207141	.2449583	-2.53	0.011	-1.100824	-.1406047
Fhei	.5785839	.3165889	1.83	0.068	-.041919	1.199087
Fhun	-.9971683	.3466031	-2.88	0.004	-1.676498	-.3178388
DFhei	.4452738	.4431288	1.00	0.315	-.4232427	1.31379
DFhun	-1.940127	.4802308	-4.04	0.000	-2.881362	-.9988919
lpp	-6.110695	.3858905	-15.84	0.000	-6.867026	-5.354363
_cons	3.27461	.1423418	23.01	0.000	2.995625	3.553595

```
. estimates store logit
```

# Illustration 5 – Question 3 (cont.)

```
. probit Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp
```

```
Probit regression                                Number of obs   =          2798
                                                LR chi2(7)      =          591.39
                                                Prob > chi2     =          0.0000
Log likelihood = -672.22516                    Pseudo R2       =          0.3055
```

Heinz	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Dhei	.2768603	.1226386	2.26	0.024	.0364931	.5172275
Dhun	-.3599038	.1455494	-2.47	0.013	-.6451753	-.0746322
Fhei	.2396884	.1549172	1.55	0.122	-.0639437	.5433206
Fhun	-.5526825	.1904251	-2.90	0.004	-.9259089	-.1794561
DFhei	.2486314	.2282668	1.09	0.276	-.1987634	.6960262
DFhun	-1.068493	.2749	-3.89	0.000	-1.607287	-.5296985
lpp	-3.348536	.2094459	-15.99	0.000	-3.759042	-2.938029
_cons	1.840782	.0723702	25.44	0.000	1.698939	1.982625

```
. estimates store probit
```

# Illustration 5 – Question 3 (cont.)

```
. cloglog Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp
```

```
Complementary log-log regression      Number of obs      =      2798
                                      Zero outcomes         =       307
                                      Nonzero outcomes       =      2491

                                      LR chi2(7)            =      589.99
                                      Prob > chi2           =      0.0000

Log likelihood = -672.92517
```

Heinz	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Dhei	.2088229	.0936429	2.23	0.026	.0252863	.3923596
Dhun	-.3518195	.1501518	-2.34	0.019	-.6461116	-.0575275
Fhei	.1227095	.1145124	1.07	0.284	-.1017307	.3471497
Fhun	-.4820495	.164347	-2.93	0.003	-.8041638	-.1599353
DFhei	.209065	.1765308	1.18	0.236	-.136929	.5550589
DFhun	-1.077127	.3208661	-3.36	0.001	-1.706013	-.448241
lpp	-2.802396	.1883769	-14.88	0.000	-3.171608	-2.433184
_cons	1.270849	.0566031	22.45	0.000	1.159909	1.381789

```
. estimates store cloglog
```



# Illustration 5 – Question 3 (cont.)

```
. estimates table logit probit cloglog, b star(0.1 0.05 0.01)
```

Variable	logit	probit	cloglog
Dhei	.54744056**	.27686031**	.20882294**
Dhun	-.62071414**	-.35990375**	-.35181954**
Fhei	.57858393*	.23968844	.12270948
Fhun	-.99716835***	-.55268247***	-.48204954***
DFhei	.4452738	.24863139	.20906496
DFhun	-1.9401271***	-1.0684927***	-1.0771271***
lpp	-6.1106949***	-3.3485359***	-2.8023956***
_cons	3.2746098***	1.8407819***	1.2708491***

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

# Illustration 5 – Question 3 (cont.)

## Main conclusions:

- There is no clear evidence on whether the promotional activities undertaken by Heinz increase significantly the probability of consumers purchasing its ketchup
- The promotional activities made by Hunts decrease significantly the probability of consumers purchasing Heinz ketchup → clearly, because Hunts is a smaller and less known brand, it benefits a lot from promotional activities, especially when display and feature activities are held at the same time
- Increasing the relative price of Heinz ketchup decreases the probability of consumers purchasing its ketchup

# Illustration 5 – Question 4

```
. estimates restore logit
. predict XB1, xb
. gen XB12=XB1^2
. quietly logit Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp XB12
. test XB12
( 1)  [Heinz]XB12 = 0
```

```
chi2( 1) = 9.35
Prob > chi2 = 0.0022
```

→ The null hypothesis of a well-specified functional form is rejected

```
. estimates restore probit
. predict XBp, xb
. gen XBp2=XBp^2
. quietly probit Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp XBp2
. test XBp2
( 1)  [Heinz]XBp2 = 0
```

```
chi2( 1) = 0.73
Prob > chi2 = 0.3933
```

→ The null hypothesis of a well-specified functional form cannot be rejected

# Illustration 5 – Question 4 (cont.)

```
. estimates restore cloglog
. predict XBcl, xb
. gen XBcl2=XBcl^2
. quietly cloglog Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp XBcl2
. test XBcl2
( 1)  [Heinz]XBcl2 = 0
```

```
chi2( 1) = 9.63
Prob > chi2 = 0.0019
```

→ The null hypothesis of a well-specified functional form is rejected

# Illustration 5 – Question 5.1

```
. quietly probit Heinz Dhei Dhun Fhei Fhun DFhei DFhun lpp XBp2
```

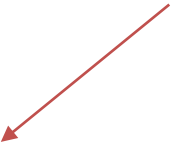
```
. estimates store probitR
```

```
. lrtest probit probitR
```

Likelihood-ratio test

(Assumption: probit nested in probitR)

LR chi2(1)	=	0.73
Prob > chi2	=	0.3922



The null hypothesis of a well-specified functional form is not rejected

# Illustration 5 – Question 5.2

```
. estimates restore probit  
(results probit are active now)
```

```
. estat classification
```

Probit model for Heinz

----- True -----					
Classified		D	~D		Total
-----+-----+-----					
+		2462	232		2694
-		29	75		104
-----+-----+-----					
Total		2491	307		2798

Classified + if predicted  $\Pr(D) \geq .5$

True D defined as Heinz  $\neq 0$

(continues on the next slide)

# Illustration 5 – Question 5.2 (cont.)

-----		
Sensitivity	$\Pr(+ D)$	98.84% → % 1's correctly predicted
Specificity	$\Pr(- \sim D)$	24.43% → % 0's correctly predicted
Positive predictive value	$\Pr(D +)$	91.39%
Negative predictive value	$\Pr(\sim D -)$	72.12%
-----		
False + rate for true $\sim D$	$\Pr(+ \sim D)$	75.57%
False - rate for true $D$	$\Pr(- D)$	1.16%
False + rate for classified +	$\Pr(\sim D +)$	8.61%
False - rate for classified -	$\Pr(D -)$	27.88%
-----		
Correctly classified		90.67% → % correct predictions
-----		

# Illustration 5 – Question 6.1

```
. summarize Phei Phun
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Phei	2798	.0348276	.0089737	.001	.061
Phun	2798	.0335547	.0053069	.003	.087

```
. scalar lppm=log(0.0348276/0.0335547)
```

```
. display normal(_b[_cons]+_b[lpp]*lppm)  
.9569286
```

```
. display normal(_b[_cons]+_b[DFhei]+_b[lpp]*lppm)  
.97527763
```

```
. display normal(_b[_cons]+_b[DFhun]+_b[lpp]*lppm)  
.74138217
```

```
. display normal(_b[_cons]+_b[DFhei]+_b[DFhun]+_b[lpp]*lppm)  
.81493872
```



# Illustration 5 – Question 6.1 (cont.)

	I	II	III	IV
Dhei	0	0	0	0
Fhei	0	0	0	0
DFhei	0	1	0	1
Dhun	0	0	0	0
Fhun	0	0	0	0
DFhun	0	0	1	1
Phei	3.48	3.48	3.48	3.48
Phun	3.36	3.36	3.36	3.36
$Pr(Heinz = 1   \dots)$	95.69	97.53	74.14	81.49

# Illustration 5 – Question 6.2

```
. margins, dydx(_all)
```

Average marginal effects

Number of obs = 2798

Model VCE : OIM

Expression : Pr(Heinz), predict()

dy/dx w.r.t. : Dhei Dhun Fhei Fhun DFhei DFhun lpp

-----						
		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
Dhei		.0363993	.0161128	2.26	0.024	.0048189 .0679798
Dhun		-.0473172	.0190541	-2.48	0.013	-.0846626 -.0099719
Fhei		.0315123	.020376	1.55	0.122	-.008424 .0714486
Fhun		-.0726622	.024952	-2.91	0.004	-.1215672 -.0237572
DFhei		.032688	.0299977	1.09	0.276	-.0261065 .0914825
DFhun		-.1404768	.0358536	-3.92	0.000	-.2107485 -.070205
lpp		-.4402384	.024884	-17.69	0.000	-.48901 -.3914667
-----						

# Illustration 5 – Question 6.3

```
. margins, dydx(DFhun) at(Dhei=0 Fhei=0 DFhei=0 Dhun=0 Fhun=0 DFhun=0 lpp=0)
```

```
Conditional marginal effects      Number of obs   =       2798
Model VCE      : OIM
```

```
Expression      : Pr(Heinz), predict()
dy/dx w.r.t.    : DFhun
at              : Dhei      =      0
                  Dhun      =      0
                  Fhei      =      0
                  Fhun      =      0
                  DFhei     =      0
                  DFhun     =      0
                  lpp       =      0
```

-----						
	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
DFhun	-.0783219	.0220713	-3.55	0.000	-.1215808	-.0350629
-----						

# Illustration 5 – Question 6.4

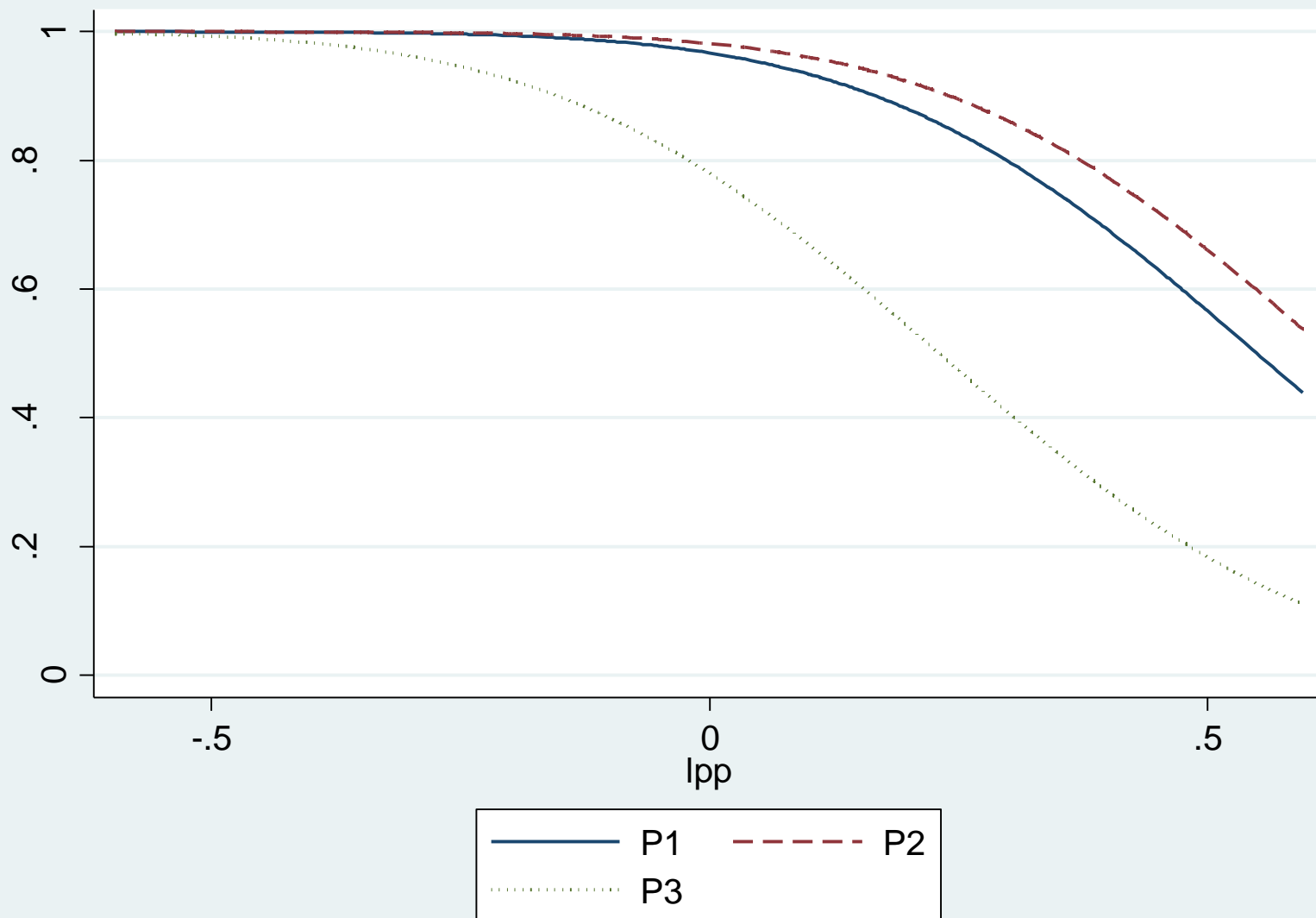
```
. gen P1=normal(_b[_cons]+_b[lpp]*lpp)

. gen P2=normal(_b[_cons]+_b[DFhei]+_b[lpp]*lpp)

. gen P3=normal(_b[_cons]+_b[DFhun]+_b[lpp]*lpp)

. line P1 P2 P3 lpp if lpp > -0.6 & lpp < 0.6, lpattern(solid dash dot)
```

# Illustration 5 – Question 6.4 (cont.)



# Illustration 5 – Question 6.4 (cont.)

## Main conclusions:

- The higher the price of Heinz relative to Hunts, the less the probability of Heinz being purchased (and vice-versa)
- Heinz promotional activities do not allow this brand to substantially increase its price or market share
- Hunts promotional activities are more effective, with two possible effects:
  - If Hunts does not change its price, the probability of consumers purchasing its ketchup increases substantially
  - If Hunts opts for keeping its market share, it is able to sell the same quantity but at a higher price

# Illustration 6

Aim:

- Studying the probability of an individual with health insurance have at least one contact with a medical doctor per year

Model:

$$\begin{aligned} &Pr(dmdu = 1 | \dots) \\ &= G(\beta_0 + \beta_1 lcoins + \beta_2 ndisease + \beta_3 female \\ &+ \beta_4 age + \beta_5 lfam + \beta_6 child + \alpha_i) \end{aligned}$$

Details:

- Cameron and Trivedi (2010), ch. 18.4

# Illustration 6 – Question 1.1

```
. xtset id year
      panel variable:  id (unbalanced)
      time variable:  year, 1 to 5, but with gaps
                  delta:  1 unit

. xtdescribe
      id:  125024, 125025, ..., 632167          n =          5908
      year:  1, 2, ..., 5                      T =           5
      Delta(year) = 1 unit
      Span(year)  = 5 periods
      (id*year uniquely identifies each observation)
```

Distribution of T <sub>i</sub> :	min	5%	25%	50%	75%	95%	max
	1	2	3	3	5	5	5

(continue in the next slide)



# Illustration 6 – Question 1.1 (cont.)

Freq.	Percent	Cum.		Pattern
-----+-----				
3710	62.80	62.80		111..
1584	26.81	89.61		11111
156	2.64	92.25		1....
147	2.49	94.74		11...
79	1.34	96.07		..1..
66	1.12	97.19		.11..
33	0.56	97.75		..111
33	0.56	98.31		.1111
29	0.49	98.80		...11
71	1.20	100.00		(other patterns)
-----+-----				
5908	100.00			XXXXX

# Illustration 6 – Question 1.1 (cont.)

```
. describe
```

```
  obs:      20,186
```

```
 vars:         13
```

---

	storage	display	value	
variable name	type	format	label	variable label
coins	float	%9.0g		coinsurance -- medical
year	float	%9.0g		study year
id	float	%9.0g		person id, leading digit is sit
age	float	%9.0g		age that year
female	float	%9.0g		=1 if female
med	float	%9.0g		medical expenditures (dollars)
mdu	float	%9.0g		number face-to-face md visits
num	float	%9.0g		family size
ndisease	float	%9.0g		count of chronic diseases
child	float	%9.0g		=1 if child
lfam	float	%9.0g		log of family size
lcoins	float	%9.0g		log(coinsurance+1)
dmdu	float	%9.0g		= 1 if mdu > 0

---

# Illustration 6 – Question 1.2

```
. xtsum lcoins ndisease female age lfam child
```

Variable		Mean	Std. Dev.	Min	Max	Observations
-----+-----						
lcoins	overall	2.383588	2.041713	0	4.564348	N = 20186
	between		2.045796	0	4.564348	n = 5908
	within		0	2.383588	2.383588	T-bar = 3.41672
ndisease	overall	11.2445	6.741647	0	58.6	N = 20186
	between		6.712985	0	58.6	n = 5908
	within		0	11.2445	11.2445	T-bar = 3.41672
female	overall	.5169424	.4997252	0	1	N = 20186
	between		.4997557	0	1	n = 5908
	within		0	.5169424	.5169424	T-bar = 3.41672
age	overall	25.71844	16.76759	0	64.27515	N = 20186
	between		16.97265	0	63.27515	n = 5908
	within		1.086687	23.46844	27.96844	T-bar = 3.41672
lfam	overall	1.248404	.5390681	0	2.639057	N = 20186
	between		.5372082	0	2.639057	n = 5908
	within		.0730824	.3242075	2.44291	T-bar = 3.41672
child	overall	.4014168	.4901972	0	1	N = 20186
	between		.4820984	0	1	n = 5908
	within		.1096116	-.3985832	1.201417	T-bar = 3.41672

# Illustration 6 – Question 1.3

```
. xttab dmdu
```

dmdu	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
0	6308	31.25	3193	54.05	58.61
1	13878	68.75	5164	87.41	78.17
Total	20186	100.00	8357	141.45	70.70

(n = 5908)

- Overall, 68,75% of observations concern cases where occurred at least one annual contact with a medical doctor
- 87,41% of individuals (5164 out of 5908) had a contact with a medical doctor in at least one year
- 78,17% of those 5164 individuals had a contact with a medical doctor in every year

# Illustration 6 – Question 2

```
. logit dmdu lcoins ndisease female age lfam child, vce(cluster id)
(...)
```

```
Logistic regression                                Number of obs   =       20186
                                                    Wald chi2(6)    =       488.18
                                                    Prob > chi2     =       0.0000
Log pseudolikelihood = -11973.392                Pseudo R2      =       0.0450
```

(Std. Err. adjusted for 5908 clusters in id)

-----						
		Robust				
dmdu		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
lcoins		-.1572107	.0109064	-14.41	0.000	-.1785869    -.1358345
ndisease		.050301	.0039657	12.68	0.000	.0425285    .0580735
female		.3091573	.0445772	6.94	0.000	.2217876    .396527
age		.0042689	.0022307	1.91	0.056	-.0001032    .008641
lfam		-.2047573	.0470287	-4.35	0.000	-.2969317    -.1125828
child		.0921709	.0728107	1.27	0.206	-.0505355    .2348773
_cons		.6039411	.1107712	5.45	0.000	.3868335    .8210486
-----						

```
. estimates store POOLED
```

# Illustration 6 – Question 2 (cont.)

```
. xtlogit dmdu lcoins ndisease female age lfam child
```

```
Iteration 3:   log likelihood = -10878.687
```

```
(...)
```

```
Log likelihood   = -10878.687          Wald chi2(6)      =      549.76
                                          Prob > chi2       =      0.0000
```

	dmdu	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lcoins		-.2403864	.0162836	-14.76	0.000	-.2723017	-.208471
ndisease		.078151	.0055456	14.09	0.000	.0672819	.0890201
female		.4631005	.0663209	6.98	0.000	.3331138	.5930871
age		.0073441	.0031508	2.33	0.020	.0011687	.0135194
lfam		-.3021841	.0644721	-4.69	0.000	-.4285471	-.175821
child		.1935357	.1002267	1.93	0.053	-.002905	.3899763
_cons		.8629898	.1568968	5.50	0.000	.5554778	1.170502
/lnsig2u		1.225652	.0490898			1.129438	1.321866
sigma_u		1.84564	.045301			1.758953	1.936599
rho		.5087003	.0122687			.4846525	.532708

```
Likelihood-ratio test of rho=0: chibar2(01) = 2189.41 Prob >= chibar2 = 0.000
```

```
. estimates store RE
```

# Illustration 6 – Question 2 (cont.)

```
. xtlogit dmdu lcoins ndisease female age lfam child, fe
```

```
note: 3459 groups (11161 obs) dropped because of all positive or  
all negative outcomes.
```

```
(...)
```

```
Conditional fixed-effects logistic regression    Number of obs    =    9025  
Group variable: id                            Number of groups  =    2449
```

```
Obs per group: min =    2  
                avg  =    3.7  
                max  =    5
```

```
Log likelihood   = -3395.5996  
LR chi2(3)       =    10.74  
Prob > chi2      =    0.0132
```

-----						
dmdu	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
lcoins	0	(omitted)				
ndisease	0	(omitted)				
female	0	(omitted)				
age	-.0341815	.0183827	-1.86	0.063	-.070211	.001848
lfam	.478755	.2597327	1.84	0.065	-.0303116	.9878217
child	.270458	.1684974	1.61	0.108	-.0597907	.6007068
-----						

```
. estimates store FE
```

# Illustration 6 – Question 2 (cont.)

```
. estimates table POOLED RE FE, b star(0.1 0.05 0.01)
```

Variable	POOLED	RE	FE
dmdu			
lcoins	-.15721065***	-.24038638***	(omitted)
ndisease	.05030099***	.07815098***	(omitted)
female	.30915732***	.46310045***	(omitted)
age	.0042689*	.00734407**	-.03418147*
lfam	-.20475725***	-.30218405***	.47875505*
child	.09217092	.19353567*	.27045805
_cons	.60394105***	.86298976***	
lnsig2u			
_cons		1.2256522***	

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01



# Illustration 7

## Sample:

- Credit ratings assigned by Standard and Poor's to 921 North-American firms in 2005
- Two rating scales:
  - 1 (D – lowest rating) to 7 (AAA – highest rating)
  - 'investment grade' (rating 4 / BBB or superior) and 'speculative grade': (rating 3 / BB or inferior)

## Aim:

- Explaining firm's credit rating as a function of a set of explanatory variables

## Details:

- Verbeek (2008), ch. 7.2.3

# Illustration 7 – Question 1

```
. describe
```

```
    obs:          921
   vars:           7
   size:        25,788
```

```
-----
               storage  display      value
variable name  type    format      label      variable label
-----
booklev        float   %9.0g                Book leverage
ebit           float   %9.0g                EBIT / Total assets
invgrade       float   %9.0g                Investment grade
logsales       float   %9.0g                Log(Sales)
rating         float   %9.0g                Credit rating
reta          float   %9.0g                Retained earnings / Total assets
wka           float   %9.0g                Working capital / Total assets
-----
```

# Illustration 7 – Question 2

```
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
booklev	921	.2931868	.1735339	0	.9992067
ebit	921	.0938921	.0843643	-.3841692	.6515085
invgrade	921	.4723127	.4995041	0	1
logsales	921	7.995754	1.497413	1.100278	12.70142
rating	921	3.499457	1.134561	1	7
reta	921	.1569942	.300684	-.9958922	.9799219
wka	921	.1404142	.1503398	-.4120839	.7480223

# Illustration 7 – Question 3.1

```
. logit invgrade booklev ebit logsales reta wka
```

Logistic regression

Number of obs = 921

LR chi2(5) = 591.80

Prob > chi2 = 0.0000

Log likelihood = -341.07758

Pseudo R2 = 0.4645

-----						
invgrade	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
booklev	-4.427266	.7714185	-5.74	0.000	-5.939218	-2.915313
ebit	4.354735	1.439922	3.02	0.002	1.532539	7.176931
logsales	1.081593	.0956839	11.30	0.000	.8940558	1.26913
reta	4.116108	.4885083	8.43	0.000	3.158649	5.073566
wka	-4.012492	.7479141	-5.36	0.000	-5.478377	-2.546607
_cons	-8.214321	.8668543	-9.48	0.000	-9.913324	-6.515317
-----						

# Illustration 7 – Question 3.2

```
. ologit rating booklev ebit logsales reta wka
```

Ordered logistic regression

Number of obs = 921

LR chi2(5) = 862.87

Prob > chi2 = 0.0000

Log likelihood = -965.30716

Pseudo R2 = 0.3089

rating	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
booklev	-2.751598	.4773028	-5.76	0.000	-3.687094	-1.816101
ebit	4.731324	.944758	5.01	0.000	2.879632	6.583015
logsales	.9405595	.0588423	15.98	0.000	.8252308	1.055888
reta	3.559983	.302294	11.78	0.000	2.967498	4.152468
wka	-2.580078	.482632	-5.35	0.000	-3.526019	-1.634136
/cut1	-.3694825	.6332452			-1.61062	.8716554
/cut2	4.880646	.5208171			3.859864	5.901429
/cut3	7.625999	.5511597			6.545746	8.706252
/cut4	9.88504	.5916376			8.725452	11.04463
/cut5	12.88296	.673386			11.56315	14.20277
/cut6	14.78264	.7841076			13.24582	16.31947

# Illustration 7 – Question 4

Binary logit model:

$$Pr(invgrade_i = 1|x_i) = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

Ordered logit model:

$$Pr(rating_i \geq 4|x_i) = 1 - \frac{e^{\gamma_2 - x_i'\beta}}{1 + e^{\gamma_2 - x_i'\beta}}$$

```
. summarize booklev ebit logsales reta wka
```

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
booklev	921	.2931868	.1735339	0	.9992067
ebit	921	.0938921	.0843643	-.3841692	.6515085
logsales	921	7.995754	1.497413	1.100278	12.70142
reta	921	.1569942	.300684	-.9958922	.9799219
wka	921	.1404142	.1503398	-.4120839	.7480223

# Illustration 7 – Question 4 (cont.)

```
. quietly logit invgrade booklev ebit logsales reta wka

. scalar xblogit = _b[_cons] + _b[booklev]*0.2931868 + _b[ebit]*0.0938921 +
_b[logsales]*7.995754 + _b[reta]*0.1569942 + _b[wka]*0.1404142

. display exp(xblogit)/(1+exp(xblogit))
.40793294

. quietly ologit rating booklev ebit logsales reta wka

. scalar xborden = _b[booklev]*0.2931868 + _b[ebit]*0.0938921 +
_b[logsales]*7.995754 + _b[reta]*0.1569942+_b[wka]*0.1404142

. display 1-exp(_b[/cut3]-xborden)/(1+exp(_b[/cut3]-xborden))
.43256406
```

# Illustration 8

## Sample:

- 210 observations concerning travel mode choice for travel between Sydney and Melbourne

## Travel modes:

- Air
- Train
- Bus
- Car

## Details:

- Greene (2003), ch. 21



# Illustration 8 – Question 1

```
. describe
```

```
obs:           840
vars:           6                      11 Apr 2014 14:04
size:          19,320
```

```
-----
      storage  display      value
variable name  type  format  label      variable label
-----
id             int    %8.0g              Identification
Modealt        str5   %9s                Travel mode alternatives
Mode           float  %9.0g              =1 if travel mode chosen
Ttme           float  %9.0g              Terminal time
GC             float  %9.0g              Cost of travel (transport cost and amount of
                                         time spent travelling)
Hinc           float  %9.0g              Household income
-----
```

```
Sorted by:  id  Modealt
```

# Illustration 8 – Question 2.1

```
. summarize Mode Ttme GC Hinc if Modealt=="air"
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Mode	210	.2761905	.4481805	0	1
Ttme	210	61.00952	15.71943	5	99
GC	210	102.6476	30.57503	56	197
Hinc	210	34.54762	19.71132	2	72

```
. summarize Mode Ttme GC Hinc if Modealt=="bus"
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Mode	210	.1428571	.3507633	0	1
Ttme	210	41.65714	12.07737	5	60
GC	210	115.2571	44.93441	45	222
Hinc	210	34.54762	19.71132	2	72

# Illustration 8 – Question 2.1 (cont.)

```
. summarize Mode Ttme GC Hinc if Modealt=="car"
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Mode	210	.2809524	.4505383	0	1
Ttme	210	0	0	0	0
GC	210	95.41429	46.82743	30	238
Hinc	210	34.54762	19.71132	2	72

```
. summarize Mode Ttme GC Hinc if Modealt=="train"
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Mode	210	.3	.4593526	0	1
Ttme	210	35.69048	12.27922	1	99
GC	210	130.2	58.23454	42	269
Hinc	210	34.54762	19.71132	2	72

# Illustration 8 – Question 2.2

```
. summarize Ttme GC Hinc if Modealt=="air" & Mode==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Ttme	58	46.53448	24.38882	5	99
GC	58	113.5517	33.19753	58	197
Hinc	58	41.72414	19.11534	4	70

```
. summarize Ttme GC Hinc if Modealt=="train" & Mode==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Ttme	63	28.52381	19.35397	1	99
GC	63	106.619	49.60113	42	211
Hinc	63	23.06349	17.28683	4	72

# Illustration 8 – Question 2.2 (cont.)

```
. summarize Ttme GC Hinc if Modealt=="bus" & Mode==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Ttme	30	25.2	14.91909	5	60
GC	30	108.1333	43.24408	45	201
Hinc	30	29.7	16.85056	2	60

```
. summarize Ttme GC Hinc if Modealt=="car" & Mode==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Ttme	59	0	0	0	0
GC	59	89.08475	49.83292	30	238
Hinc	59	42.22034	17.68505	4	70

# Illustration 8 – Question 3

- ‘Long form’ database:

	id	Modealt	Mode	Ttme	GC	Hinc
1.	1	air	0	69	70	35
2.	1	bus	0	35	70	35
3.	1	car	1	0	30	35
4.	1	train	0	34	71	35
5.	2	air	0	64	68	30
6.	2	bus	0	53	85	30
7.	2	car	1	0	50	30
8.	2	train	0	44	84	30
9.	3	air	0	69	129	40
10.	3	bus	0	35	149	40
11.	3	car	1	0	101	40
12.	3	train	0	34	195	40

- This is the data format necessary to estimate a conditional logit model (it may include  $x_i$ -type variables) using Stata

# Illustration 8 – Question 3 (cont.)

- ‘Wide form’ database:

	id	Modeair	Ttmeair	GCair	Modebus	Ttmebus	GCbus	Modecar	Ttmecar
1.	1	0	69	70	0	35	70	1	0
2.	2	0	64	68	0	53	85	1	0
3.	3	0	69	129	0	35	149	1	0
4.	4	0	64	59	0	53	81	1	0
5.	5	0	64	82	0	53	94	1	0
6.	6	0	69	70	0	35	58	0	0
7.	7	1	45	160	0	35	167	0	0
8.	8	0	69	137	0	35	146	1	0
9.	9	0	69	70	0	35	70	1	0
10.	10	0	69	65	0	35	68	1	0
11.	11	0	64	68	0	53	73	1	0
12.	12	0	64	79	0	53	91	1	0

- This is the data format necessary to estimate a multinomial logit model using Stata when there are only  $x_i$ -type variables

# Illustration 8 – Question 3 (cont.)

- From 'long form' to 'wide form':

```
. reshape wide Ttme GC Mode, i(id) j(Modealt) string
```

- After reshaping the data once, it is possible to alternate between the two formats using the following commands:

```
. reshape long
```

```
. reshape wide
```



# Illustration 8 – Question 3.1

```
. gen Y=0 if Modeair==1  
(152 missing values generated)
```

```
. replace Y=1 if Modetrain==1  
(63 real changes made)
```

```
. replace Y=2 if Modebus==1  
(30 real changes made)
```

```
. replace Y=3 if Modecar==1  
(59 real changes made)
```

# Illustration 8 – Question 3.1 (cont.)

```
. mlogit Y Hinc, baseoutcome(0)
```

Multinomial logistic regression

Number of obs = 210

LR chi2(3) = 44.03

Prob > chi2 = 0.0000

Log likelihood = -261.74506

Pseudo R2 = 0.0776

-----							
	Y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
0		(base outcome)					
-----+-----							
1							
	Hinc	-.059059	.0116784	-5.06	0.000	-.0819482	-.0361698
	_cons	1.963424	.4195611	4.68	0.000	1.141099	2.785749
-----+-----							
2							
	Hinc	-.0353522	.0128212	-2.76	0.006	-.0604814	-.010223
	_cons	.5991669	.4909705	1.22	0.222	-.3631176	1.561452
-----+-----							
3							
	Hinc	.0014204	.0098938	0.14	0.886	-.0179711	.0208118
	_cons	-.0425218	.454562	-0.09	0.925	-.9334469	.8484034
-----							

# Illustration 8 – Question 3.2

```
. reshape long
```

```
. asclogit Mode Ttme GC, case(id) alternatives(Modealt) casevars(Hinc) basealternative(air)
(...)
```

		Mode	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Modealt							
	Ttme		-.0954606	.0104732	-9.11	0.000	-.1159876    -.0749335
	GC		-.0109274	.0045878	-2.38	0.017	-.0199192    -.0019355
air		(base alternative)					
bus							
	Hinc		-.0232107	.0162306	-1.43	0.153	-.055022    .0086006
	_cons		-1.744529	.6775004	-2.57	0.010	-3.072406    -.4166531
car							
	Hinc		.0053735	.0115294	0.47	0.641	-.0172237    .0279707
	_cons		-5.874813	.8020903	-7.32	0.000	-7.446882    -4.302745
train							
	Hinc		-.0511884	.0147352	-3.47	0.001	-.0800689    -.0223079
	_cons		-.3249561	.5763335	-0.56	0.573	-1.454549    .8046369

# Illustration 9

## Aim:

- Explaining annual health care expenditures ( $med$ ) and the annual number of medical consultations ( $mdu$ ) as a function of health insurance characteristics ( $lcoins$ ), socio-economic factors ( $female, age, lfam, child$ ) and health status variables ( $ndisease$ )

## Details:

- Cameron and Trivedi (2005), ch. 16.6

# Illustration 9 – Question 1

```
. summarize med
```

Variable	Obs	Mean	Std. Dev.	Min	Max
med	20186	171.5892	698.2689	0	39182.02

```
. summarize med if med>0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
med	15733	220.1551	784.1543	.4276146	39182.02

- Non-negative outcome
- High proportion of zeros: 4453 observations (22.1% of the sample units)

# Illustration 9 – Question 2.1

```
. drop if year!=1  
(14548 observations deleted)
```

```
. poisson med lcoins ndisease female age lfam child, robust  
(...)
```

-----						
		Robust				
med		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
lcoins		-.0478877	.0245805	-1.95	0.051	-.0960646 .0002892
ndisease		.0281757	.0060746	4.64	0.000	.0162696 .0400817
female		.2263111	.1192456	1.90	0.058	-.007406 .4600282
age		.0097846	.003701	2.64	0.008	.0025307 .0170384
lfam		-.0928784	.0882497	-1.05	0.293	-.2658446 .0800879
child		-.4112285	.2444742	-1.68	0.093	-.8903892 .0679321
_cons		4.631177	.2039135	22.71	0.000	4.231514 5.03084
-----						

```
. estimates store poisson
```

# Illustration 9 – Question 2.2

```
. poisson med lcoins ndisease female age lfam child if med>0, robust  
(...)
```

Poisson regression	Number of obs	=	4451
	Wald chi2(6)	=	66.48
	Prob > chi2	=	0.0000
Log pseudolikelihood = -1087511.2	Pseudo R2	=	0.0657

-----							
		Robust					
med		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
lcoins		-.0200287	.0246889	-0.81	0.417	-.068418	.0283606
ndisease		.0210867	.0062785	3.36	0.001	.0087812	.0333923
female		.1474704	.1177851	1.25	0.211	-.0833842	.3783249
age		.0087803	.0036967	2.38	0.018	.0015349	.0160258
lfam		-.0823594	.0902764	-0.91	0.362	-.2592978	.0945791
child		-.3678983	.2481063	-1.48	0.138	-.8541777	.1183811
_cons		4.91825	.2098069	23.44	0.000	4.507036	5.329464
-----							

```
. estimates store poisson0
```

# Illustration 9 – Question 2.3

```
. gen lmed=log(med)
```

```
(1187 missing values generated)
```

```
. regress lmed lcoins ndisease female age lfam child if med>0, robust
```

```
(...)
```

-----							
		Robust					
lmed		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
lcoins		-.054901	.0099633	-5.51	0.000	-.0744341	-.0353679
ndisease		.030717	.0030927	9.93	0.000	.0246537	.0367803
female		.1199091	.0417646	2.87	0.004	.0380298	.2017885
age		.0072817	.0020791	3.50	0.000	.0032055	.0113578
lfam		-.1357759	.0442937	-3.07	0.002	-.2226136	-.0489382
child		-.4972463	.0737896	-6.74	0.000	-.6419107	-.3525819
_cons		3.954487	.1043663	37.89	0.000	3.749877	4.159096
-----							

```
. estimates store log0
```



# Illustration 9 – Question 2.4

```
. gen lmed1=log(med+1)

. regress lmed1 lcoins ndisease female age lfam child, robust
(...)
```

-----							
		Robust					
lmed1		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
lcoins		-.1485372	.0126915	-11.70	0.000	-.1734174	-.1236569
ndisease		.0584591	.0039132	14.94	0.000	.0507878	.0661304
female		.3064252	.0535977	5.72	0.000	.201353	.4114974
age		.0089512	.0027704	3.23	0.001	.0035202	.0143821
lfam		-.1806985	.0556686	-3.25	0.001	-.2898305	-.0715666
child		-.4759264	.0946324	-5.03	0.000	-.6614425	-.2904103
_cons		3.000465	.1346348	22.29	0.000	2.736529	3.264401
-----							

```
. estimates store log1
```

# Illustration 9 – Question 2 (summary)

```
. estimates table poisson poisson0, b star(0.1 0.05 0.01)
```

Variable	poisson	poisson0
lcoins	-.04788772*	-.0200287
ndisease	.02817566***	.02108674***
female	.22631112*	.14747037
age	.00978456***	.00878032**
lfam	-.09287836	-.08235938
child	-.41122852*	-.3678983
_cons	4.6311773***	4.9182498***

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

```
. estimates table log0 log1, b star(0.1 0.05 0.01)
```

Variable	log0	log1
lcoins	-.05490096***	-.14853716***
ndisease	.03071698***	.0584591***
female	.11990912***	.3064252***
age	.00728165***	.00895117***
lfam	-.13577591***	-.18069853***
child	-.4972463***	-.47592639***
_cons	3.9544865***	3.0004653***

# Illustration 9 – Question 3.1

```
. summarize mdu
```

Variable	Obs	Mean	Std. Dev.	Min	Max
mdu	5638	2.877971	4.332918	0	69

```
. tabulate mdu
```

number			
face-to-fac			
e md visits	Freq.	Percent	Cum.
0	1,729	30.67	30.67
1	1,047	18.57	49.24
2	814	14.44	63.68
3	511	9.06	72.74
4	385	6.83	79.57
5	271	4.81	84.37
6	188	3.33	87.71
7	156	2.77	90.48
8	134	2.38	92.85
9	80	1.42	94.27
10	56	0.99	95.26
11	56	0.99	96.26
12	32	0.57	96.83

(...)

# Illustration 9 – Question 3.2.1

```
. poisson mdu lcoins ndisease female age lfam child
```

Poisson regression	Number of obs	=	5638
	LR chi2(6)	=	2296.50
	Prob > chi2	=	0.0000
Log likelihood = -17173.058	Pseudo R2	=	0.0627

-----						
mdu	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
lcoins	-.0682563	.0038214	-17.86	0.000	-.0757462	-.0607665
ndisease	.03538	.0010286	34.40	0.000	.0333639	.037396
female	.1276798	.0164078	7.78	0.000	.0955211	.1598386
age	.0041167	.0007841	5.25	0.000	.0025798	.0056536
lfam	-.141855	.0154716	-9.17	0.000	-.1721789	-.1115312
child	.056673	.0278998	2.03	0.042	.0019903	.1113557
_cons	.7463066	.0385653	19.35	0.000	.67072	.8218932
-----						

```
. estimates store cpoissonml
```

# Illustration 9 – Question 3.2.2

```
. poisson mdu lcoins ndisease female age lfam child, robust
```

Poisson regression	Number of obs	=	5638
	Wald chi2(6)	=	388.20
	Prob > chi2	=	0.0000
Log pseudolikelihood = -17173.058	Pseudo R2	=	0.0627

		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
mdu							
lcoins		-.0682563	.0094538	-7.22	0.000	-.0867854	-.0497273
ndisease		.03538	.002696	13.12	0.000	.0300959	.0406641
female		.1276798	.04043	3.16	0.002	.0484385	.2069211
age		.0041167	.0019155	2.15	0.032	.0003624	.007871
lfam		-.141855	.0336317	-4.22	0.000	-.207772	-.0759381
child		.056673	.0625248	0.91	0.365	-.0658734	.1792194
_cons		.7463066	.0861806	8.66	0.000	.5773956	.9152175

```
. estimates store cpoissonqml
```

# Illustration 9 – Question 3.2.3

```
. nbreg mdu lcoins ndisease female age lfam child, dispersion(constant)
```

Negative binomial regression	Number of obs	=	5638
	LR chi2(6)	=	529.02
Dispersion = constant	Prob > chi2	=	0.0000
Log likelihood = -12128.041	Pseudo R2	=	0.0213

-----						
mdu	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
lcoins	-.076432	.0069326	-11.02	0.000	-.0900197	-.0628442
ndisease	.0309127	.0019493	15.86	0.000	.0270922	.0347333
female	.1447002	.029679	4.88	0.000	.0865305	.2028699
age	.0027029	.0014494	1.86	0.062	-.0001378	.0055436
lfam	-.1235042	.0276393	-4.47	0.000	-.1776761	-.0693323
child	-.0049686	.0499784	-0.10	0.921	-.1029245	.0929873
_cons	.8537349	.0697031	12.25	0.000	.7171195	.9903504
-----+-----						
/lndelta	1.278115	.0319841			1.215427	1.340802
-----+-----						
delta	3.589865	.1148187			3.371733	3.822109
-----						

Likelihood-ratio test of delta=0:  $\chi^2(01) = 1.0e+04$  Prob>= $\chi^2 = 0.000$

```
. estimates store cnegbin1
```

Overdispersion test:  
the hypothesis of  
correct specification  
of the Poisson model  
is rejected

# Illustration 9 – Question 3.2.4

```
. nbreg mdu lcoins ndisease female age lfam child, dispersion(mean)
```

```
Negative binomial regression      Number of obs   =       5638
                                LR chi2(6)             =       459.10
Dispersion      = mean           Prob > chi2        =       0.0000
Log likelihood = -12163.001      Pseudo R2          =       0.0185
```

```
-----+-----
            mdu |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      lcoins |   -.0719827   .0083402    -8.63   0.000    -.0883292   -.0556362
    ndisease |    .0391488   .002618     14.95   0.000     .0340175    .0442801
      female |    .1229883   .0350213     3.51   0.000     .0543479    .1916288
         age |    .0035899   .0017692     2.03   0.042     .0001223    .0070574
        lfam |   -.1834739   .036481     -5.03   0.000    -.2549754   -.1119723
       child |    .0842864   .0621692     1.36   0.175    -.0375631    .2061359
        _cons |    .7638038   .087809      8.70   0.000     .5917012    .9359063
-----+-----
    /lnalpha |    .2193579   .0274111                .1656333    .2730826
-----+-----
        alpha |    1.245277   .0341344                1.18014    1.314009
-----+-----
```

```
Likelihood-ratio test of alpha=0:  chibar2(01) = 1.0e+04 Prob>=chibar2 = 0.000
```

```
. estimates store cnegbin2
```

Overdispersion test:  
the hypothesis of  
correct specification  
of the Poisson model  
is rejected

# Illustration 9 – Question 3.2 (summary)

```
. estimates table cpoissonml cpoissonqml cnegbin1 cnegbin2, b star(0.1 0.05 0.01)
```

Variable	cpoissonml	cpoissonqml	cnegbin1	cnegbin2
mdu				
lcoins	-.06825635***	-.06825635***	-.07643198***	-.0719827***
ndisease	.03537998***	.03537998***	.03091273***	.03914881***
female	.12767984***	.12767984***	.1447002***	.12298834***
age	.0041167***	.0041167**	.0027029*	.00358987**
lfam	-.14185505***	-.14185505***	-.1235042***	-.18347387***
child	.05667301**	.05667301	-.00496864	.0842864
_cons	.74630658***	.74630658***	.85373493***	.76380377***
lndelta				
_cons			1.2781147***	
lnalpha				
_cons				.21935795***

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01



# Illustration 9 – Question 3.3

```
. estimates restore cpoissonml  
(results cpoissonml are active now)
```

Formulas:

$$Pr(Y_i = y|x_i) = \frac{e^{-\lambda_i} \lambda_i^y}{y!}, \quad \lambda_i = E(Y|X) = \exp(x_i' \beta)$$

- $Pr(Y_i = 0|x_i) = e^{-\lambda_i}$
- $Pr(Y_i = 1|x_i) = e^{-\lambda_i} \lambda_i$
- $Pr(Y_i \geq 2|x_i) = 1 - Pr(Y_i = 0|x_i) - Pr(Y_i = 1|x_i)$

```
. scalar lambda0 = exp(_b[_cons] + _b[lcoins]*log(1) + _b[age]*50 +  
_b[lfam]*log(3))
```

```
. scalar lambda1 = exp(_b[_cons] + _b[lcoins]*log(51) + _b[age]*50 +  
_b[lfam]*log(3))
```

```
. scalar lambda2 = exp(_b[_cons] + _b[lcoins]*log(101) + _b[age]*50 +  
_b[lfam]*log(3))
```

# Illustration 9 – Question 3.3 (cont.)

```
. display lambda0
```

```
2.2173168
```

```
. display lambda1
```

```
1.695412
```

```
. display lambda2
```

```
1.6181549
```

```
. display exp(-lambda0)
```

```
.10890092
```

```
. display exp(-lambda1)
```

```
.18352361
```

```
. display exp(-lambda2)
```

```
.19826418
```

```
. display exp(-lambda0)*lambda0
```

```
.24146784
```

```
. display exp(-lambda1)*lambda1
```

```
.31114812
```

```
. display exp(-lambda2)*lambda2
```

```
.32082215
```

```
. display 1-0.10890092-0.24146784
```

```
.64963124
```

```
. display 1-0.18352361-0.31114812
```

```
.50532827
```

```
. display 1-0.19826418-0.32082215
```

```
.48091367
```

# Illustration 9 – Question 3.3 (cont.)

<i>coins:</i>	0	50	100
$E(mdu   \dots)$	2.2	1.7	1.6
$Pr(mdu = 0   \dots)$	10.9	18.4	19.8
$Pr(mdu = 1   \dots)$	24.1	31.1	32.1
$Pr(mdu \geq 2   \dots)$	65.0	50.5	48.1

# Illustration 9 – Question 4.1

```
. xtset id year
      panel variable:  id (unbalanced)
      time variable:  year, 1 to 5, but with gaps
                  delta:  1 unit
```

```
. xtdescribe
      id:  125024, 125025, ..., 632167          n =          5908
      year:  1, 2, ..., 5                      T =             5
      Delta(year) = 1 unit
      Span(year)  = 5 periods
      (id*year uniquely identifies each observation)
```

Distribution of T_i:							
	min	5%	25%	50%	75%	95%	max
	1	2	3	3	5	5	5

Freq.	Percent	Cum.	Pattern
3710	62.80	62.80	111..
1584	26.81	89.61	11111
156	2.64	92.25	1....
147	2.49	94.74	11...
79	1.34	96.07	..1..
66	1.12	97.19	.11..
33	0.56	97.75	..111
33	0.56	98.31	.1111
29	0.49	98.80	...11
71	1.20	100.00	(other patterns)
5908	100.00		XXXXX

# Illustration 9 – Question 4.2.1

```
. poisson mdu lcoins ndisease female age lfam child, vce(cluster id)
```

Poisson regression	Number of obs	=	20186
	Wald chi2(6)	=	476.93
	Prob > chi2	=	0.0000
Log pseudolikelihood = -62579.401	Pseudo R2	=	0.0609

(Std. Err. adjusted for 5908 clusters in id)

-----						
		Robust				
mdu		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+						
lcoins		-.0808023	.0080013	-10.10	0.000	-.0964846    -.0651199
ndisease		.0339334	.0026024	13.04	0.000	.0288328    .039034
female		.1717862	.0342551	5.01	0.000	.1046473    .2389251
age		.0040585	.0016891	2.40	0.016	.000748    .0073691
lfam		-.1481981	.0323434	-4.58	0.000	-.21159    -.0848062
child		.1030453	.0506901	2.03	0.042	.0036944    .2023961
_cons		.748789	.0785738	9.53	0.000	.5947872    .9027907
-----						

```
. estimates store pooled
```

# Illustration 9 – Question 4.2.2

```
. xtpoisson mdu lcoins ndisease female age lfam child, re  
(...)
```

mdu	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
lcoins	-.0878258	.0068682	-12.79	0.000	-.1012873	-.0743642
ndisease	.0387629	.0022046	17.58	0.000	.034442	.0430839
female	.1667192	.0286298	5.82	0.000	.1106058	.2228325
age	.0019159	.0011134	1.72	0.085	-.0002663	.0040982
lfam	-.1351786	.0260022	-5.20	0.000	-.186142	-.0842152
child	.1082678	.0341477	3.17	0.002	.0413396	.1751961
_cons	.7574177	.0618346	12.25	0.000	.6362241	.8786112
/lnalpha	.0251256	.0209586			-.0159526	.0662038
alpha	1.025444	.0214919			.984174	1.068444

```
Likelihood-ratio test of alpha=0: chibar2(01) = 3.9e+04 Prob>=chibar2 = 0.000
```

```
. estimates store RE
```

# Illustration 9 – Question 4.2.3

```
. xtpoisson mdu lcoins ndisease female age lfam child, fe
note: 265 groups (265 obs) dropped because of only one obs per group
note: 666 groups (2130 obs) dropped because of all zero outcomes
note: lcoins dropped because it is constant within group
note: ndisease dropped because it is constant within group
note: female dropped because it is constant within group
(...)
```

```
Log likelihood = -24173.211      Wald chi2(3)      =      19.24
                                Prob > chi2      =      0.0002
```

-----							
mdu		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
age		-.0112009	.0039024	-2.87	0.004	-.0188494	-.0035523
lfam		.0877134	.0554606	1.58	0.114	-.0209874	.1964141
child		.1059867	.0437744	2.42	0.015	.0201905	.1917829
-----							

```
. estimates store FE
```

# Illustration 9 – Question 4.2 (summary)

```
. estimates table pooled RE FE, b star(0.1 0.05 0.01)
```

-----+-----				
Variable		pooled	RE	FE
-----+-----				
mdu				
lcoins		-.08080226***	-.08782576***	
ndisease		.0339334***	.03876295***	
female		.17178621***	.16671918***	
age		.00405853**	.00191594*	-.01120087***
lfam		-.1481981***	-.13517858***	.08771336
child		.10304526**	.10826785***	.10598669**
_cons		.74878896***	.7574177***	
-----+-----				
lnalpha				
_cons			.02512562	
-----+-----				

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01



1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027, 2028, 2029, 2030, 2031, 2032, 2033, 2034, 2035, 2036, 2037, 2038, 2039, 2040, 2041, 2042, 2043, 2044, 2045, 2046, 2047, 2048, 2049, 2050, 2051, 2052, 2053, 2054, 2055, 2056, 2057, 2058, 2059, 2060, 2061, 2062, 2063, 2064, 2065, 2066, 2067, 2068, 2069, 2070, 2071, 2072, 2073, 2074, 2075, 2076, 2077, 2078, 2079, 2080, 2081, 2082, 2083, 2084, 2085, 2086, 2087, 2088, 2089, 2090, 2091, 2092, 2093, 2094, 2095, 2096, 2097, 2098, 2099, 2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2108, 2109, 2110, 2111, 2112, 2113, 2114, 2115, 2116, 2117, 2118, 2119, 2120, 2121, 2122, 2123, 2124, 2125, 2126, 2127, 2128, 2129, 2130, 2131, 2132, 2133, 2134, 2135, 2136, 2137, 2138, 2139, 2140, 2141, 2142, 2143, 2144, 2145, 2146, 2147, 2148, 2149, 2150, 2151, 2152, 2153, 2154, 2155, 2156, 2157, 2158, 2159, 2160, 2161, 2162, 2163, 2164, 2165, 2166, 2167, 2168, 2169, 2170, 2171, 2172, 2173, 2174, 2175, 2176, 2177, 2178, 2179, 2180, 2181, 2182, 2183, 2184, 2185, 2186, 2187, 2188, 2189, 2190, 2191, 2192, 2193, 2194, 2195, 2196, 2197, 2198, 2199, 2200, 2201, 2202, 2203, 2204, 2205, 2206, 2207, 2208, 2209, 2210, 2211, 2212, 2213, 2214, 2215, 2216, 2217, 2218, 2219, 2220, 2221, 2222, 2223, 2224, 2225, 2226, 2227, 2228, 2229, 2230, 2231, 2232, 2233, 2234, 2235, 2236, 2237, 2238, 2239, 2240, 2241, 2242, 2243, 2244, 2245, 2246, 2247, 2248, 2249, 2250, 2251, 2252, 2253, 2254, 2255, 2256, 2257, 2258, 2259, 2260, 2261, 2262, 2263, 2264, 2265, 2266, 2267, 2268, 2269, 2270, 2271, 2272, 2273, 2274, 2275, 2276, 2277, 2278, 2279, 2280, 2281, 2282, 2283, 2284, 2285, 2286, 2287, 2288, 2289, 2290, 2291, 2292, 2293, 2294, 2295, 2296, 2297, 2298, 2299, 2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2315, 2316, 2317, 2318, 2319, 2320, 2321, 2322, 2323, 2324, 2325, 2326, 2327, 2328, 2329, 2330, 2331, 2332, 2333, 2334, 2335, 2336, 2337, 2338, 2339, 2340, 2341, 2342, 2343, 2344, 2345, 2346, 2347, 2348, 2349, 2350, 2351, 2352, 2353, 2354, 2355, 2356, 2357, 2358, 2359, 2360, 2361, 2362, 2363, 2364, 2365, 2366, 2367, 2368, 2369, 2370, 2371, 2372, 2373, 2374, 2375, 2376, 2377, 2378, 2379, 2380, 2381, 2382, 2383, 2384, 2385, 2386, 2387, 2388, 2389, 2390, 2391, 2392, 2393, 2394, 2395, 2396, 2397, 2398, 2399, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2421, 2422, 2423, 2424, 2425, 2426, 2427, 2428, 2429, 2430, 2431, 2432, 2433, 2434, 2435, 2436, 2437, 2438, 2439, 2440, 2441, 2442, 2443, 2444, 2445, 2446, 2447, 2448, 2449, 2450, 2451, 2452, 2453, 2454, 2455, 2456, 2457, 2458, 2459, 2460, 2461, 2462, 2463, 2464, 2465, 2466, 2467, 2468, 2469, 2470, 2471, 2472, 2473, 2474, 2475, 2476, 2477, 2478, 2479, 2480, 2481, 2482, 2483, 2484, 2485, 2486, 2487, 2488, 2489, 2490, 2491, 2492, 2493, 2494, 2495, 2496, 2497, 2498, 2499, 2500, 2501, 2502, 2503, 2504, 2505, 2506, 2507, 2508, 2509, 2510, 2511, 2512, 2513, 2514, 2515, 2516, 2517, 2518, 2519, 2520, 2521, 2522, 2523, 2524, 2525, 2526, 2527, 2528, 2529, 2530, 2531, 2532, 2533, 2534, 2535, 2536, 2537, 2538, 2539, 2540, 2541, 2542, 2543, 2544, 2545, 2546, 2547, 2548, 2549, 2550, 2551, 2552, 2553, 2554, 2555, 2556, 2557, 2558, 2559, 2560, 2561, 2562, 2563, 2564, 2565, 2566, 2567, 2568, 2569, 2570, 2571, 2572, 2573, 2574, 2575, 2576, 2577, 2578, 2579, 2580, 2581, 2582, 2583, 2584, 2585, 2586, 2587, 2588, 2589, 2590, 2591, 2592, 2593, 2594, 2595, 2596, 2597, 2598, 2599, 2600, 2601, 2602, 2603, 2604, 2605, 2606, 2607, 2608, 2609, 2610, 2611, 2612, 2613, 2614, 2615, 2616, 2617, 2618, 2619, 2620, 2621, 2622, 2623, 2624, 2625, 2626, 2627, 2628, 2629, 2630, 2631, 2632, 2633, 2634, 2635, 2636, 2637, 2638, 2639, 2640, 2641, 2642, 2643, 2644, 2645, 2646, 2647, 2648, 2649, 2650, 2651, 2652, 2653, 2654, 2655, 2656, 2657, 2658, 2659, 2660, 2661, 2662, 2663, 2664, 2665, 2666, 2667, 2668, 2669, 2670, 2671, 2672, 2673, 2674, 2675, 2676, 2677, 26

```
. hausman FE RE
```

	---- Coefficients ----			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	EF	EA	Difference	S.E.
age	-.0112009	.0019159	-.0131168	.0037402
lfam	.0877134	-.1351786	.2228919	.0489874
child	.1059867	.1082678	-.0022812	.0273886

b = consistent under  $H_0$  and  $H_a$ ; obtained from xtpoisson  
 B = inconsistent under  $H_a$ , efficient under  $H_0$ ; obtained from xtpoisson

Test:  $H_0$ : difference in coefficients not systematic

```
chi2(3) = (b-B)' [(V_b-V_B)^(-1)] (b-B)
        = 29.73
Prob>chi2 = 0.0000
```

→ The hypothesis of random effects is rejected

# Illustration 10 – Question 1

```
. drop if LE==1  
(1922 observations deleted)
```

```
. summarize LEV_LT1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
LEV_LT1	30304	.0734047	.1668595	0	.9982489

```
. count if LEV_LT1==0  
23027
```

```
. display 23027/30304  
.75986668
```

# Illustration 10 – Question 2.1

```
. glm LEV_LT1 SIZE2 COLLAT2 PROF1 GROWTH2 AGE, family(binomial) link(logit)
vce(cluster id)
(...)
```

```
Log pseudolikelihood = -6448.71996      AIC      = .4259979
                                      BIC      = -304709.7
```

(Std. Err. adjusted for 4995 clusters in id)

-----						
		Robust				
LEV_LT1		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
SIZE2		.3160809	.0150444	21.01	0.000	.2865946 .3455673
COLLAT2		.453255	.1394787	3.25	0.001	.1798818 .7266282
PROF1		-3.629699	.2667238	-13.61	0.000	-4.152469 -3.10693
GROWTH2		.0004846	.0002476	1.96	0.050	-6.89e-07 .0009699
AGE		-.0045993	.0017012	-2.70	0.007	-.0079335 -.0012651
_cons		-6.823869	.2264392	-30.14	0.000	-7.267681 -6.380056
-----						

```
. estimates store LOGIT
```

# Illustration 10 – Question 2.2

```
. gen DEBT=LEV_LT1>0
```

```
. probit DEBT SIZE2 COLLAT2 PROF1 GROWTH2 AGE, vce(cluster id)
(...)
```

Probit regression	Number of obs	=	30304
	Wald chi2(5)	=	1125.30
	Prob > chi2	=	0.0000
Log pseudolikelihood = -14363.976	Pseudo R2	=	0.1401

(Std. Err. adjusted for 4995 clusters in id)

-----							
		Robust					
DEBT		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
SIZE2		.3309445	.011001	30.08	0.000	.309383	.3525061
COLLAT2		.754961	.07028	10.74	0.000	.6172147	.8927074
PROF1		-2.114841	.176704	-11.97	0.000	-2.461175	-1.768508
GROWTH2		.000226	.0001309	1.73	0.084	-.0000307	.0004826
AGE		.0011396	.0011065	1.03	0.303	-.001029	.0033082
_cons		-5.510938	.1548431	-35.59	0.000	-5.814425	-5.207451
-----							

```
. estimates store TP1
```

# Illustration 10 – Question 2.2 (cont.)

```
. glm LEV_LT1 SIZE2 COLLAT2 PROF1 GROWTH2 AGE if LEV_LT>0, family(binomial)
link(logit) vce(cluster id)
(...)
```

```

                                     AIC          =   .8776548
Log pseudolikelihood = -3187.347033      BIC          = -63243.49
```

(Std. Err. adjusted for 2064 clusters in id)

-----							
		Robust					
LEV_LT1		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
SIZE2		-.185588	.0140524	-13.21	0.000	-.2131301	-.1580459
COLLAT2		-.7261906	.0998168	-7.28	0.000	-.9218279	-.5305533
PROF1		-1.523694	.2894609	-5.26	0.000	-2.091027	-.9563615
GROWTH2		.0030029	.0004916	6.11	0.000	.0020395	.0039663
AGE		-.0071666	.0013872	-5.17	0.000	-.0098856	-.0044477
_cons		2.389845	.2057352	11.62	0.000	1.986611	2.793078
-----							

```
. estimates store TP2
```

# Illustration 10 – Question 2.3

```
. tobit LEV_LT1 SIZE2 COLLAT2 PROF1 GROWTH2 AGE, ll(0) vce(cluster id)
(...)
```

(Std. Err. adjusted for 4995 clusters in id)

		Robust					
LEV_LT1		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
SIZE2		.1228862	.0040377	30.43	0.000	.1149721	.1308004
COLLAT2		.2341081	.0318943	7.34	0.000	.1715941	.2966222
PROF1		-.9789402	.0758649	-12.90	0.000	-1.127639	-.8302418
GROWTH2		.0001581	.0000812	1.95	0.052	-1.14e-06	.0003174
AGE		-.0003276	.0004359	-0.75	0.452	-.001182	.0005268
_cons		-2.064098	.0565277	-36.51	0.000	-2.174894	-1.953301
var(e.LEV_LT1)		.2180737	.0075559				

```
. estimates store TOBIT
```

# Illustration 10 – Question 3.1

Fractional logit model:

$$E(LEV\_LT_i|x_i) = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

```
. estimates restore LOGIT  
(results LOGIT are active now)
```

```
. scalar xb = _b[_cons] + _b[SIZE2]*13.54 + _b[COLLAT2]*0.41 + _b[PROF1]*0.07 +  
_b[GROWTH2]*15.03 + _b[AGE]*19
```

```
. display exp(xb)/(1+exp(xb))  
.06341858
```

# Illustration 10 – Question 3.1 (cont.)

Two-part model:

$$E(LEV\_LT_i|x_i) = \Phi(x_i'\theta) \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

```
. estimates restore TP1  
(results DP1 are active now)
```

```
. scalar xb1 = _b[_cons] + _b[SIZE2]*13.54 + _b[COLLAT2]*0.41 + _b[PROF1]*0.07  
+ _b[GROWTH2]*15.03 + _b[AGE]*19
```

```
. estimates restore TP2  
(results DP2 are active now)
```

```
. scalar xb2 = _b[_cons] + _b[SIZE2]*13.54 + _b[COLLAT2]*0.41 + _b[PROF1]*0.07  
+ _b[GROWTH2]*15.03 + _b[AGE]*19
```

```
. display normal(xb1)*exp(xb2)/(1+exp(xb2))  
.06985232
```



# Illustration 10 – Question 3.1 (cont.)

Tobit model:

$$E(LEV\_LT_i|x_i) = \Phi\left(\frac{x_i'\beta}{\sigma}\right) x_i'\beta + \sigma\phi\left(\frac{x_i'\beta}{\sigma}\right)$$

```
. estimates restore TOBIT
(results TOBIT are active now)

. scalar xbt = _b[_cons] + _b[SIZE2]*13.54 + _b[COLLAT2]*0.41 + _b[PROF1]*0.07
+ _b[GROWTH2]*15.03 + _b[AGE]*19

. display normal(xbt/sqrt(_b[/var(e.LEV_LT1)]))*xbt+sqrt(_b[/var(e.LEV_LT1)])*
normalden(xbt/sqrt(_b[/var(e.LEV_LT1)]))
.05549759
```

# Illustration 10 – Question 3.2

## Fractional logit model:

- By definition, it is approximately equal to one

## Two-part model:

$$Pr(LEV\_LT_i > 0|x_i) = \Phi(x_i'\theta)$$

```
. display normal(xb1)  
.19950111
```

## Tobit model:

$$Pr(LEV\_LT_i > 0|x_i) = \Phi\left(\frac{x_i'\beta}{\sigma}\right)$$

```
. estimates restore TOBIT  
(results TOBIT are active now)  
  
. display normal(xbt/sqrt(_b[/var(e.LEV_LT1)]))  
.20998609
```

# Illustration 10 – Question 3.3

## Fractional logit model:

- By definition,  $E(LEV\_LT_i | x_i, Y_i > 0) \approx E(LEV\_LT_i | x_i)$

## Two-part model:

$$E(LEV\_LT_i | x_i, Y_i > 0) = \frac{e^{x_i' \beta}}{1 + e^{x_i' \beta}}$$

```
. display exp(xb2)/(1+exp(xb2))  
.35013498
```

## Tobit model:

$$E(Y_i | x_i, Y_i > 0) = x_i' \beta + \sigma \lambda \left( \frac{x_i' \beta}{\sigma} \right)$$

```
. estimates restore TOBIT  
(results TOBIT are active now)
```

```
. display xbt+sqrt(_b[/var(e.LEV_LT1)])*normalden(xbt/sqrt(_b[/var(e.LEV_LT1)]))  
)/normal(xbt/sqrt(_b[/var(e.LEV_LT1)]))  
.26429175
```

# Illustration 10 – Question 4

```
. xtset id YEAR
      panel variable:  id (unbalanced)
      time variable:  YEAR, 1995 to 2001, but with gaps
                  delta:  1 unit

. gen LEVt= LEV_LT1/(1-LEV_LT1)

. xtpoisson LEVt SIZE2 COLLAT2 PROF1 GROWTH2 AGE, fe vce(robust)
(...)
```

(Std. Err. adjusted for clustering on id)

-----							
		Robust					
LEVt		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
SIZE2		-.2563746	.1914515	-1.34	0.181	-.6316126	.1188634
COLLAT2		.7169194	.5366941	1.34	0.182	-.3349818	1.768821
PROF1		-1.205703	2.620676	-0.46	0.645	-6.342134	3.930727
GROWTH2		.0024675	.00165	1.50	0.135	-.0007665	.0057014
AGE		.0402399	.0259754	1.55	0.121	-.010671	.0911508
-----							