Collqoue Epidémiologie Clinique

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Techniques de régression pour mesures répétées : exemple de l'analyse des chutes à l'hôpital

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Background

Some events (hospitalization, stroke, falls,..) occurs repeatedly but too often, only the first occurrence is described in the literature.

The repeated nature of falls provides an opportunity to describe a wide spectrum of statistical analysis techniques used for repeated risk modeling.

Methods

Here we propose to improve probability estimates of conditions characterized by their repeated nature, like stroke or falls by using incidence data.

The selection of the appropriate model will depend on the research question, the study design and the type of the dependent variable.

Epidemiological Measures

Frequency

Outcomes

Association

Strength of the relationship « Risk factor – Outcome »

Impact

Factor contribution to an outcome frequency

Frequency measures

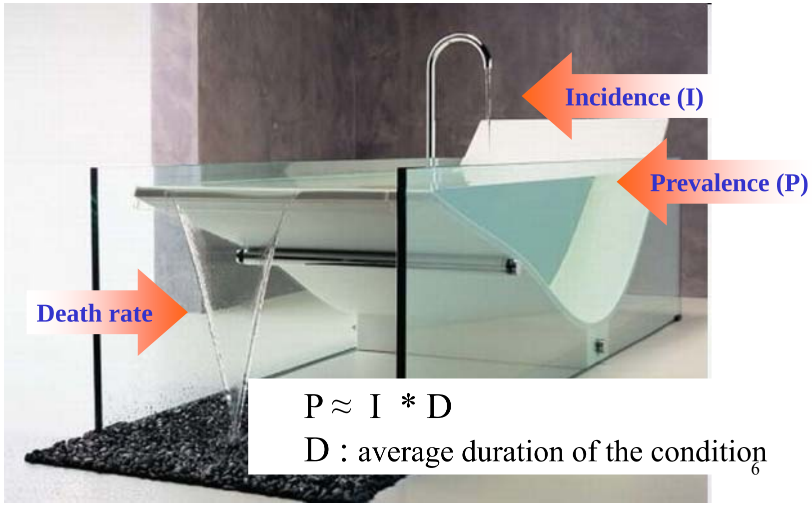
Prevalence (P)

Number of individual with a condition during a time period or at a given time, in a defined population.

Incidence (I)

Number of new cases with a condition

Frequency measures



$P \approx I * D$

D : average duration of the condition

Prevalence / cumulative incidence

	Outcome		
Exposure	**I+**	**I-**	**Total**
E+	A	B	A+B
E -	C	D	C+D
Total	**A+C**	B+D	**N**

Prevalence of exposure = A+B / N
Prevalence of non exposure = C+D / N
Prevalence /cumulative incidence of + outome = A+C / N

Epidemiological Measures

Frequency

Outcomes

Association

Strength of risk factor - outcome relationship

Impact

Factor contribution to an outcome frequency

Risk

	Outcome Condition		
Exposure	**I+**	**I-**	**Total**
E+	A	B	A+B
E -	C	D	C+D
Total	A+C	B+D	**N**

Risk of I+ among the exposed = A / A+B
Risk of I+ among the non-exposed = C / C+D

Relative risk (RR)

	Outcome Condition		
Exposure	**I+**	**I-**	**Total**
E+	A	B	A+B
E -	C	D	C+D
Total	A+C	B+D	**N**

Risk of I+ among the exposed = A / A+B
Risk of I+ among the non-exposed = C / C+D

$$RR = \frac{R(E+)}{R(E-)} = \frac{A / A+B}{C / C+D}$$

Odds ratio (OR)

	Outcome Condition		
Exposure	**I+**	**I-**	**Total**
E+	A	B	A+B
E -	C	D	C+D
Odds	A / C	B / D	**N**

$$OR = \frac{\frac{A}{B}}{\frac{C}{D}} = \frac{A / B}{C / D} = \frac{A / C}{B / D} = \frac{A\ D}{C\ B}$$

Incidence rate ratio (IRR)
Hazard ratio (HR)

	Issue		
Exposure	**I+**	**PT**	**TI**
E+	A	PT_1	A/PT_1
E -	C	PT_2	C/PT_2
Total	A+C	PT_1+PT_2	

$$IRR = \frac{\text{Incidence rate E+}}{\text{Incidence rate E-}} = \frac{TI_1}{TI_2} = \frac{A / PT_1}{C / PT_2}$$

PT = person-time

RR, OR, IRR, HR

Units: none
Range: [0 ; +∞]
Interpretation :

RR, OR, IRR, HR < 1 : Exposure decreases the risk
RR, OR, IRR, HR = 1 : No risk – outcome association
RR, OR, IRR, HR > 1 : Exposure increases the risk

Epidemiological Measures

Frequency
Outcomes

Association
Strength of the Factor - Outcome relationship

Impact
Factor contribution to an outcome frequency

Impact

Risk differences = Attributable risk = %X-%Y

Number needed to treat (NNT)

Number needed-to-harm (NNH)

$$\frac{\mathbf{1}}{\textbf{attributable risk}}$$

Attributable risk (AR)

	Outcome Condition		
Exposure	**I+**	**I-**	**Total**
E+	A	B	A+B
E -	C	D	C+D
Total	A+C	B+D	**N**

$$AR = R(E+) - R(E-) = \frac{A}{A+B} - \frac{C}{C+D}$$

Results

Results are illustrated with a systematic data collection of falls occurring in a 298 beds, acute and rehabilitation geriatric teaching hospital.

Over a 10 y. period 7'795 falls among 13'949 patients.

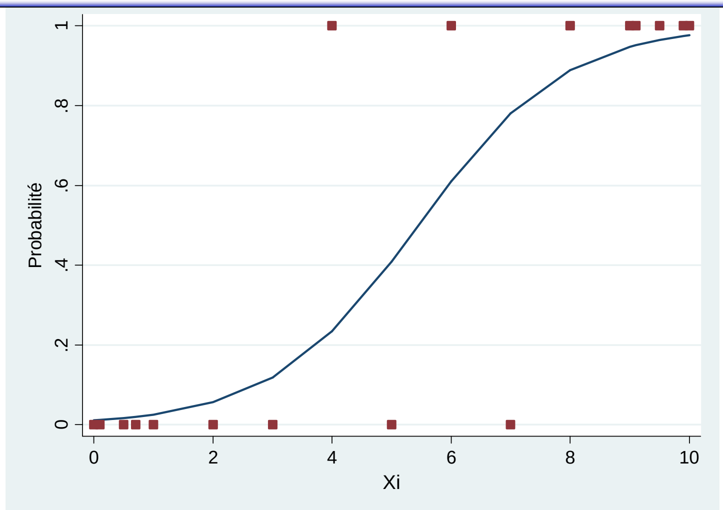
Petitpierre NJ, Trombetti A, Carroll I, Michel JP, Herrmann FR. The FIM(R) instrument to identify patients at risk of falling in geriatric wards: a 10-year retrospective study. *Age Ageing* 2010.

(Mouse Mickey. 1927 -…)

Regression models and falls

Dependent Var.	Statistical Unit	Regression
Binary	Non faller Faller	Logistic General linear model
Polytomous	Non faller One time faller Recurrent faller	Ordered logistic regression
Discrete	Number of falls	Poisson Negative Binomiale
Time dependent binary	Date of each fall	Cox + Andersen-Gill

Logistic regression



Logistic regression

$$y = \operatorname{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon_i$$

$$p = \frac{e^y}{1+e^y} = \frac{e^{\operatorname{logit}(p)}}{1+e^{\operatorname{logit}(p)}} = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k+\varepsilon_i}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k+\varepsilon_i}}$$

$$OR_i = e^{\beta_i}$$

Logistic regression

xi:logistic nbchuteb sex ageentree

```
Logistic regression                               Number of obs   =      24787
                                                  LR chi2(2)      =     159.94
                                                  Prob > chi2     =     0.0000
Log likelihood =  -12103.581                      Pseudo R2       =     0.0066
```

nbchuteb	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.312103	.0456875	7.80	0.000	1.225545	1.404776
ageentree	1.025537	.0024166	10.70	0.000	1.020811	1.030284

xi:logistic nbchuteb sex ageentree, cluster(nopatient)

```
Logistic regression                               Number of obs   =      24787
                                                  Wald chi2(2)    =     135.83
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood =  -12103.581                Pseudo R2       =     0.0066

                          (Std. Err. adjusted for 13949 clusters in nopatient)
```

nbchuteb	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.312103	.0496708	7.18	0.000	1.218274	1.413159
ageentree	1.025537	.0025927	9.97	0.000	1.020468	1.030631

Logistic regression: verification of log linear assumption via quartiles (not recommended)

xtile ageentreeq4 = ageentree , nq(4)
xi:logistic nbchuteb ib1.ageentreeq4

4 quantiles of ageentree	Freq.	Percent	Cum.
1	6,199	25.01	25.01
2	6,195	24.99	50.00
3	6,201	25.02	75.02
4	6,192	24.98	100.00
Total	24,787	100.00	

```
. xi:logistic nbchuteb ib1.ageentreeq

Logistic regression                               Number of obs   =      24787
                                                  LR chi2(3)      =      89.91
                                                  Prob > chi2     =     0.0000
Log likelihood = -12138.593                       Pseudo R2       =     0.0037
```

nbchuteb	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ageentreeq						
2	1.257631	.0598122	4.82	0.000	1.145699	1.380499
3	1.377974	.0647011	6.83	0.000	1.256822	1.510804
4	1.522846	.070626	9.07	0.000	1.390526	1.667756

Logistic regression: Verification of log linear assumption via equally spaced interval

logistic nbchuteb i.age10

. ta age10

age10	Freq.	Percent	Cum.
60	790	3.19	3.19
70	5,717	23.06	26.25
80	12,675	51.14	77.39
90	5,508	22.22	99.61
100	97	0.39	100.00
Total	24,787	100.00	

```
Logistic regression                               Number of obs   =      24787
                                                  LR chi2(4)      =      99.04
                                                  Prob > chi2     =     0.0000
Log likelihood = -12134.029                       Pseudo R2       =     0.0041
```

nbchuteb	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age10						
70	1.426757	.1642071	3.09	0.002	1.138634	1.787787
80	1.820831	.2032454	5.37	0.000	1.463041	2.266119
90	2.081443	.2374854	6.42	0.000	1.664353	2.603057
100	2.821794	.7098811	4.12	0.000	1.723407	4.620222

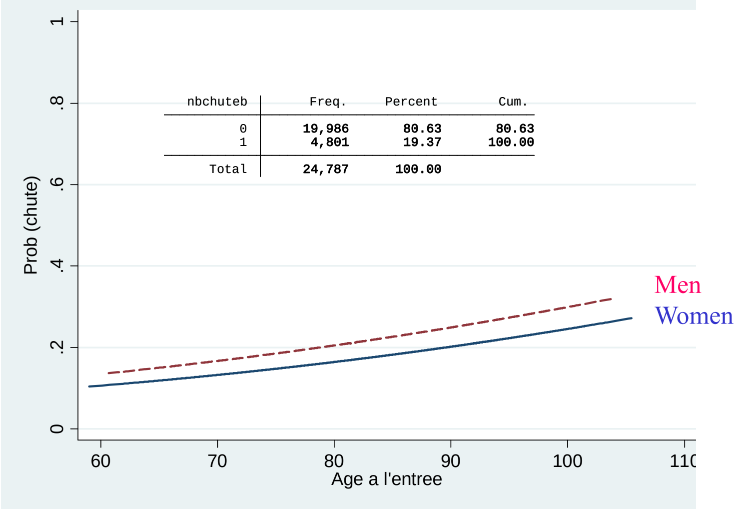
Logistic regression: Verification of log linear assumption via equally spaced interval

logistic nbchuteb i.age5r if age5r > 55

```
Logistic regression                               Number of obs   =      24787
                                                  LR chi2(8)      =     105.37
                                                  Prob > chi2     =     0.0000
Log likelihood = -12130.865                       Pseudo R2       =     0.0043
```

Freq.	nbchuteb	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
124	age5r						
666	65	1.198864	.3788063	0.57	0.566	.6453793	2.227025
1,880	70	1.570002	.4709604	1.50	0.133	.8720906	2.826434
3,837	75	1.712455	.5074279	1.82	0.069	.9580639	3.060863
5,893	80	2.023439	.5969175	2.39	0.017	1.13497	3.607413
6,782	85	2.215025	.6527065	2.70	0.007	1.243235	3.946427
4,482	90	2.458422	.7260282	3.05	0.002	1.378088	4.385667
1,026	95	2.303632	.6977952	2.75	0.006	1.272257	4.171106
97	100	3.293318	1.220098	3.22	0.001	1.593248	6.807444

Logistic regression



Ordered logistic regression

$$P(\text{issue}_j = i) = P\left(k_{i-1} < \beta_0 + \beta_1 x_{1j} + \beta_2 x_{2j} + \ldots + \beta_k x_{kj} + u_i \le k_i\right)$$

u_i	Follows a logistic distribution
k	Number of outcome
K_i	Cutpoint

Ordered logistic regression

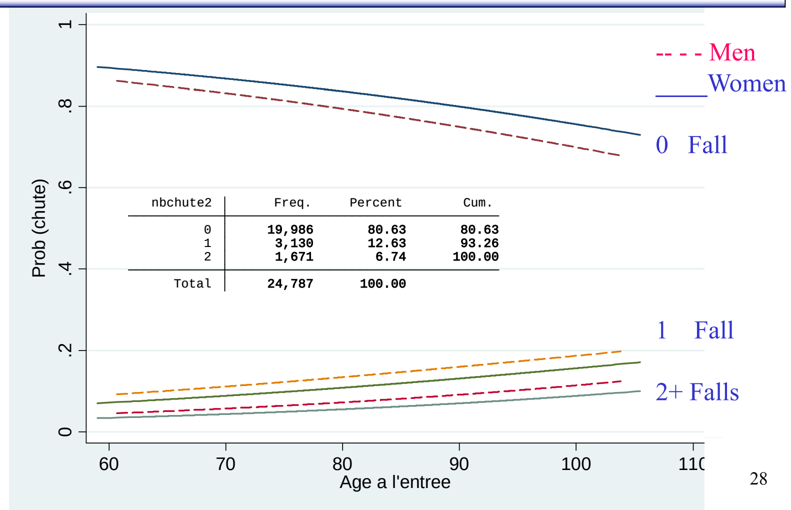
xi:ologit nbchute2 sex ageentree , or cluster(nopatient)

```
Ordered logistic regression                       Number of obs   =      24787
                                                  Wald chi2( 2)    =     141.19
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood =  -15202.904                 Pseudo R2       =     0.0054

                          (Std. Err. adjusted for  13949 clusters in nopatient)
```

nbchute2	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.330441	.0504039	7.54	0.000	1.23523	1.432991
ageentree	1.025463	.0025662	10.05	0.000	1.020446	1.030505
/cut1	3.642564	.2156241			3.219948	4.065179
/cut2	4.848833	.2164997			4.424501	5.273164

Ordered logistic regression



General linear model

glm chute sexe ageentree, family(bin) link(log) eform vce(cluster nopatient)

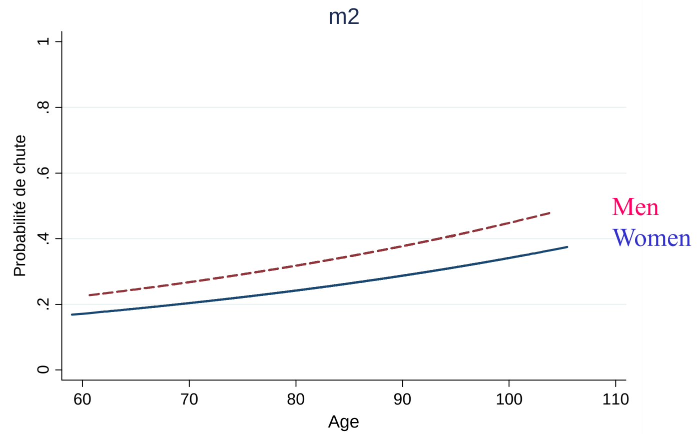
```
Generalized linear models                          No. of obs      =     24787
Optimization     : ML                              Residual df     =     24784
                                                   Scale parameter =         1
Deviance         =  24208.33594                    (1/df) Deviance =  .9767728
Pearson          =  24773.71739                    (1/df) Pearson  =  .9995851

Variance function: V(u) = u*(1-u)                  [Bernoulli]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =  .9768966
Log pseudolikelihood = -12104.16797                BIC             =   -226558

                          (Std. Err. adjusted for 13949 clusters in nopatient)
------------------------------------------------------------------------------
             |               Robust
    nbchuteb | Risk Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        sexe |   1.240248   .0368743     7.24   0.000     1.170042    1.314668
   ageentree |   1.020314   .0020524    10.00   0.000       1.0163    1.024345
------------------------------------------------------------------------------
```


General linear model



Poisson regression

Model a discrete, positive variable

- Rare event (N < 100)
- ie: number of falls
- E(Y) = Var(Y) = λ
- λ parameter allows to modify the shape of the distribution

Poisson regression

$$\Pr[Y_i = y_i] = \frac{e^{\lambda_i}\lambda_i^{y_i}}{y_i!}, y_i = 0,1,2..$$

$$\log \lambda_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik}$$

\# of expected event $$E[y_i \mid x_i] = \lambda_i = e^{x_i^{'}\beta}$$

Poisson regression

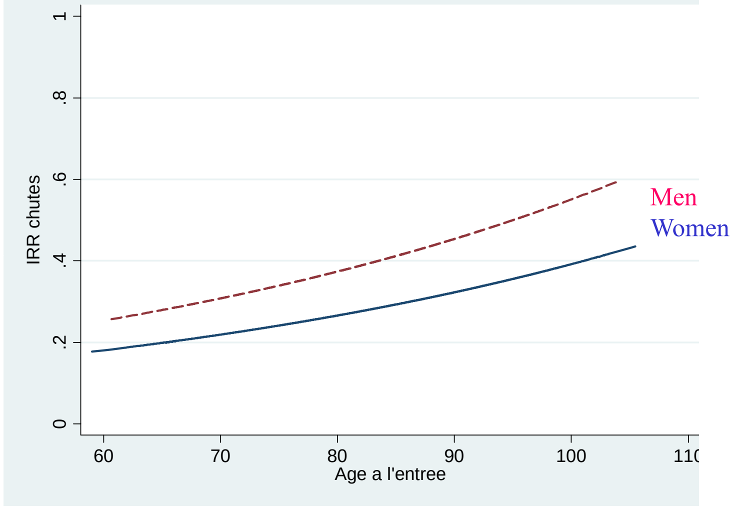
xi:poisson nbchute sexe ageentree , irr cluster(nopatient)

Pseudo R2 = 0.0077

```
Poisson regression                              Number of obs   =      24787
                                                Wald chi2( 2)   =     115.55
Log pseudolikelihood = -20374.312               Prob > chi2     =     0.0000

                          (Std. Err. adjusted for  13949 clusters in nopatient)
------------------------------------------------------------------------------
             |               Robust
     nbchute |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        sexe |    1.40594   .0571526     8.38   0.000      1.29827    1.522541
   ageentree |   1.019584   .0026049     7.59   0.000     1.014492    1.024703
------------------------------------------------------------------------------
```


Poisson regression



Observed and predicted probabilies

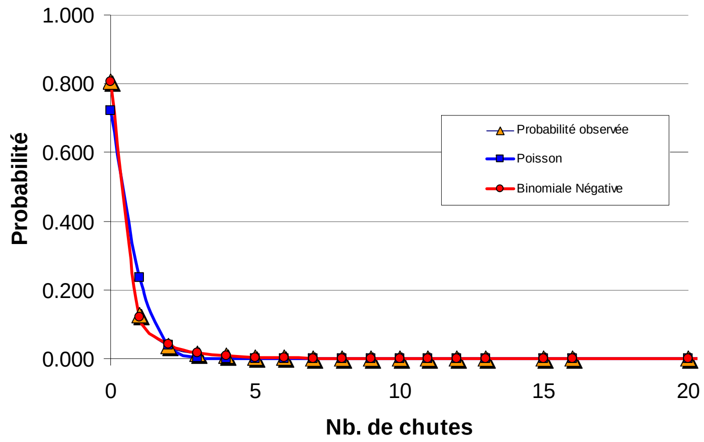
Falls #	Freq	Observed Prob.	Poisson	Negative binomial
0	19986	0.806	0.722	0.807
1	3130	0.126	0.235	0.119
2	930	0.038	0.038	0.041
3	360	0.015	0.004	0.017
4	193	0.008	0.000	0.008
5	97	0.004	0.000	0.004
6	35	0.001	0.000	0.002
7	20	0.001	0.000	0.001
8	11	0.000	0.000	0.000
9	4	0.000	0.000	0.000
10	5	0.000	0.000	0.000
11	5	0.000	0.000	0.000
12	3	0.000	0.000	0.000
13	2	0.000	0.000	0.000
15	3	0.000	0.000	0.000
16	1	0.000	0.000	0.000
20	1	0.000	0.000	0.000
21	1	0.000	0.000	0.000
	24787			

Mean = .3255739
Variance = .8024941

Poisson probability
lambda = .3255739

Negative binomial
With mean = .3255739 &
over dispersion = 3.690428

Observed and predicted probabilies



Binomial negative regression

- Extension of the Poisson model to correct for over dispersion
- Include a noise parameter

$$\log \lambda_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \boxed{+ \sigma \varepsilon_i}$$

Binomial negative regression

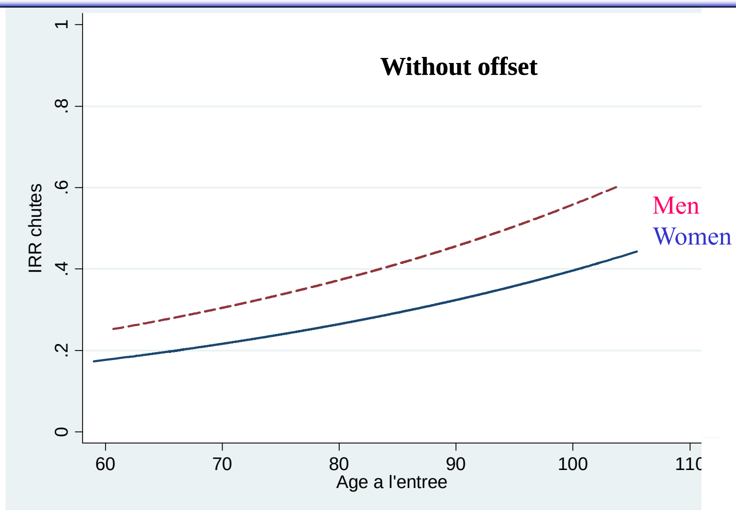
xi:nbreg nbchute sexe ageentree , irr cluster(nopatient)

```
Negative binomial regression                      Number of obs   =      24787
Dispersion           = mean                        Wald chi2(2)    =     111.29
Log pseudolikelihood = -17481.849                  Prob > chi2     =     0.0000

                      (Std. Err. adjusted for  13949 clusters in nopatient)
```

nbchute	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.408448	.0579207	8.33	0.000	1.29938	1.526671
ageentree	1.020393	.0027368	7.53	0.000	1.015043	1.025771
/lnalpha	1.273565	.0352127			1.204549	1.34258
alpha	3.573569	.125835			3.335255	3.828911

Binomial negative regression



Binomial negative regression

$$P(y = r) = \frac{(\lambda_i t_i)^r e^{-\lambda_i t_i}}{r!}$$

$$\log \lambda_i = \boxed{\log(t_i)} + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \boxed{+ \sigma \varepsilon_i}$$

Adjusted for the time of exposure (los)

Binomial negative regression

xi:nbreg nbchute sexe ageentree , irr cluster(nopatient) offset(logdursj)

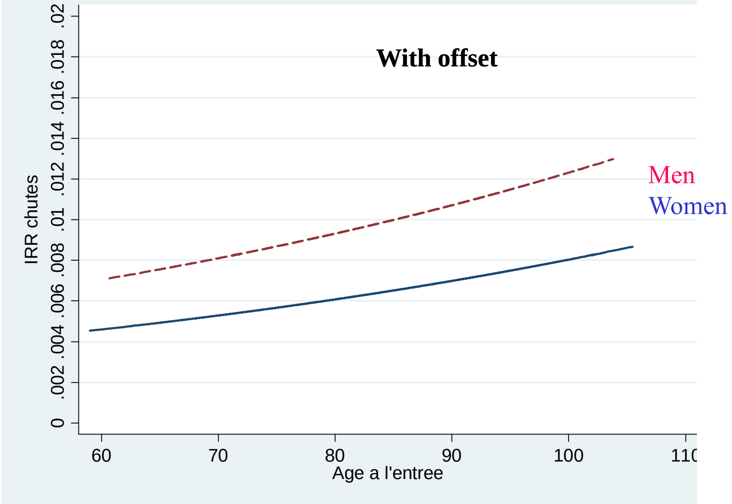
Negative binomial regression
Dispersion = mean
Log pseudolikelihood = -15868.716

Number of obs = 24787
Wald chi2(2) = 139.61
Prob > chi2 = 0.0000

(Std. Err. adjusted for 13949 clusters in nopatient)

nbchute	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.532328	.0585667	11.17	0.000	1.421734	1.651526
ageentree	1.014042	.0026012	5.44	0.000	1.008957	1.019153
logdursj	(offset)					
/lnalpha	.5209404	.0452081			.4323341	.6095467
alpha	1.68361	.0761129			1.54085	1.839597

Binomial negative regression



Cox regression

Hazard function

$$h(t) = \lim_{dt->0} \frac{prob((t \le T < t + dt)/(T \ge t)}{dt}$$

$$h(t) = \frac{f(t)}{S(t)} = -\frac{S'(t)}{S(t)} = -\frac{d}{dt}\ln[S(t)]$$

$$S(t) = \exp\left[-\int_0^t h(u)du\right] = \frac{1}{e^{\int_0^t h(u)du}}$$

Cox regression

stset timep, id(seqadmin) failure(chuteb==1) origin(time 0) exit(time 1)
stcox sexe ageentree, vce(cluster nopatient)

Cox regression -- Breslow method for ties

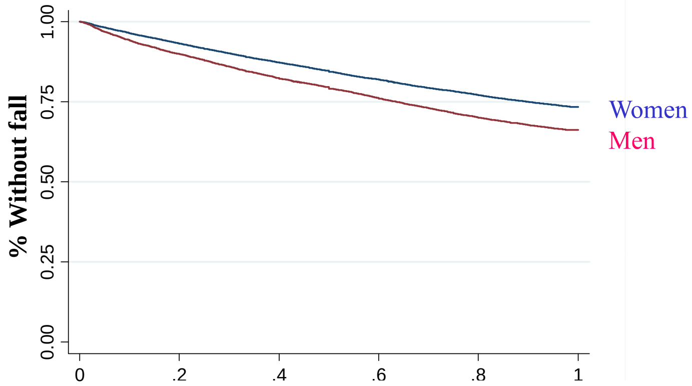
No. of subjects = 13920
No. of failures = 3936
Time at risk = 518931.4166
Log pseudolikelihood = -34812.176

Number of obs = 20119
Wald chi2(2) = 145.77
Prob > chi2 = 0.0000

(Std. Err. adjusted for 13920 clusters in nopatient)

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.358143	.0466334	8.92	0.000	1.269751	1.452688
ageentree	1.021364	.002374	9.09	0.000	1.016722	1.026028

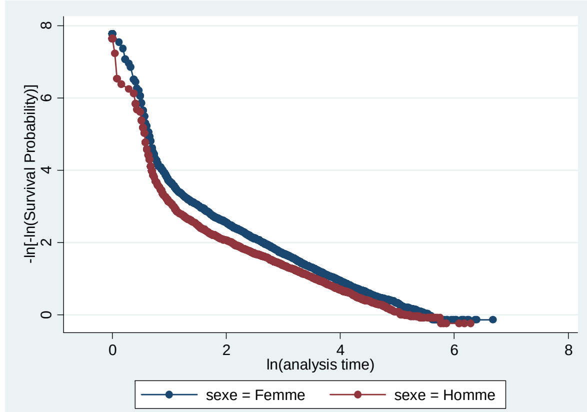
Cox regression



Nb at risk						
Women	17109	16539	15953	15337	14666	14019
Men	6989	6668	6388	6106	5776	5499

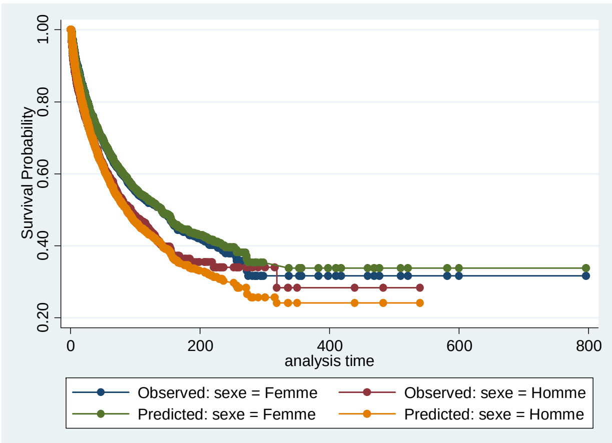
Cox regression: Verification 1 of proportional hazard assumption

stphplot, by(sexe)



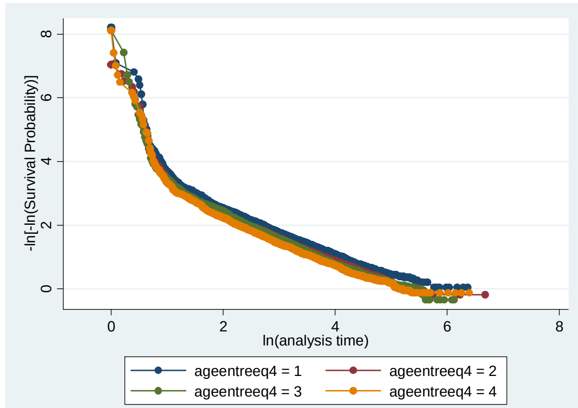
Cox regression: Verification 2 of proportional hazard assumption

stcoxkm, by(sexe)



Cox regression: Verification 3 of proportional hazard assumption

stphplot, by(ageentreeq4)



Cox regression: Verification 4 of proportional hazard assumption

estat phtest, det

```
Test of proportional-hazards assumption

Time:  Time
```

	rho	chi2	df	Prob>chi2
sexe	-0.04118	6.73	1	0.0095
ageentree	-0.00580	0.13	1	0.7208
global test		6.73	2	0.0346

```
note: robust variance-covariance matrix used.
```


Cox regression (modified according to Andersen–Gill)

stset tbf3, fail(nbchuteb==1) exit(time .) id(nopatient) enter(time 0)
stcox sexe ageentree, efron robust nolog

```
Cox regression -- Efron method for ties

No. of subjects      =        13925                 Number of obs   =      26634
No. of failures      =         7780
Time at risk         =  635394.0909
                                                    Wald chi2(2)    =     127.47
Log pseudolikelihood =   -67316.882                 Prob > chi2     =     0.0000

                            (Std. Err. adjusted for 13925 clusters in nopatient)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sexe	1.51168	.0605413	10.32	0.000	1.397559	1.63512
ageentree	1.016567	.0027541	6.06	0.000	1.011183	1.021979

Andersen PK and Gill RD. Cox's Regression Model for Counting Processes: A Large Sample Study- *Ann. Stat.* **1982; 4 (10): 1100-20.**

Summary of regression models

Regression Model	Parameter	Short	Sex Value	Sex 95 % CI		Age Value	Age 95 % CI	
Logistic	Odds ratio	OR	**1.32**	1.23	1.42	**1.03**	1.02	1.03
General linear model	Risk ratio	RR	**1.25**	1.18	1.32	**1.02**	1.02	1.03
Ordered logistic regression	Odds ratio	OR	**1.34**	1.24	1.44	**1.03**	1.02	1.03
Poisson	Incidence rate ratio	IRR	**1.40**	1.30	1.51	**1.02**	1.02	1.03
Negative binomial	Incidence rate ratio	IRR	**1.40**	1.30	1.51	**1.02**	1.02	1.03
Negative binomial + offset	Incidence rate ratio	IRR	**1.53**	1.42	1.65	**1.01**	1.01	1.02
Cox modified according to Andersen–Gill	Hazard ratio	HR	**1.51**	1.40	1.64	**1.02**	1.01	1.02

Herrmann FR, Petitpierre NJ. Techniques de régression pour l'analyse des facteurs de risque de chute. *Annales de Gérontologie* 2009;2(4):225-29.

Discussion

The results produced by the different models are quite equivalent (risk of falls 1.2 to 1.5 times higher in men, and increases significantly by 1.2 to 2.6 % with each year of age) but addresses different research question:

Discussion

Logistic model predict who will fall or not

Poisson model address the number of falls
It assumes that the probability of observing a fall must be the same in each individual, over time and not depending on the previous falls suffered by the individual, (occurrence independence).

Navarro *A. et al., Prev Med **48, 298-302 (2009).***

Discussion

Binomial models address the number of falls
"It assumes that the count of falls follows a Poisson whose λ parameter, in turn, follows a Gamma distribution (i.e. the parameter varies, rather than being fixed)."

Cox model predicts the speed at which falls occur
The term "hazard" is used to describe the concept of risk of occurrence in an infinitesimal interval after time t, conditional on the subject having survived to time t.

Navarro *A. et al., Prev Med **48, 298-302 (2009).***

Discussion

Cox model predicts the speed at which falls occur
"The term "hazard" is used to describe the concept of risk of occurrence in an infinitesimal interval after time t, conditional on the subject having survived to time t."

- Hazard ratio (HR) for two subjects at risk, with fixed covariate vectors, remains constant over time.

- Probability of observing a fall do not need to be constant along the follow-up.

Navarro *A. et al., Prev Med **48, 298-302 (2009).***

Discussion

Cox model
The event can occur only once
a) analyze only the first occurrence
b) treat each observation as independent, not taking into account that there may be more than one per individual.

Navarro A, Ancizu I, *Prev Med **48, 298-302 (2009)***

Discussion

Andersen–Gill model

“ Marginal models incorporate recurrence which involves estimating the coefficients ignoring the dependence between observations and subsequently correcting the naive variance through robust estimators. But the hazard of suffering a fall is independent of previous falls that the same individual may have experienced, (occurrence independence).”

Navarro A, Ancizu I, *Prev Med* ***48, 298-302 (2009)***
Andersen PK, Gill RD, 1982. *Ann. Stat.* ***10, 1100–1120.***

Discussion

Prentice–Williams–Peterson (PWP)

“An individual cannot be at risk of suffering fall s until they have suffered fall s−1. For this reason this model is commonly referred to as a “conditional model”. Hence this is a proportional hazards model with time-dependent strata, where the dependence between times of falls is handled through stratifying by the number of previous occurrences and presenting each strata its own baseline hazard.”

Navarro A, Ancizu I, *Prev Med* ***48, 298-302 (2009)***
Prentice, RL, Williams, BJ, Peterson, AV. *Biometrika* ***68, 373–379(1981)***

Medline Bibliometrics (10.1.2011)

N	%	Key words
554	10.9	Logistic
8	0.2	General linear model
0	0.0	Ordered logistic
45	0.9	Poisson
9	0.2	Binomial negative
81	1.6	Cox
2	0.0	Andersen–Gill
1	0.0	Prentice–Williams–Peterson
5095	**100.0**	**Falls risk factors**

Conclusions

For commodity reasons or lack of the appropriate software many studies with repeated outcomes reports only the occurrence of a first event, but to limit information loss, model dealing with repeated measure design are recommended so that all observed events are considered in risk modeling, thus avoiding data loss.

ORIGINAL INVESTIGATION

ONLINE FIRST

Arch Intern Med (2010)

Effect of Music-Based Multitask Training on Gait, Balance, and Fall Risk in Elderly People

A Randomized Controlled Trial

Andrea Trombetti, MD; Mélany Hars, PhD; François R. Herrmann, MD, MPH; Reto W. Kressig, MD; Serge Ferrari, MD; René Rizzoli, MD

Methods

- 12-month RCT
- 134 community-dwelling individuals > 65y at increased risk of falling.
- Intervention group (n=66) vs delayed intervention control group (n=68).

Intervention : 6-month multitask exercise program performed to the rhythm of piano music. 1-hour weekly class.

Outcomes

- Change in gait variability under dual-task condition from baseline to 6 months was the primary end point.
- Secondary outcomes = changes in:
  - Balance
  - functional performances
  - fall risk

Trombetti A., Hars M. Herrmann FR *et al.*, Effect of Music-Based Multitask Training on Gait, Balance, and Fall Risk in Elderly People: A Randomized Controlled Trial. *Arch Intern Med (2010).*

Results

At 6 months, in the intervention group)

- Reduction in stride length variability (−1.4%; P<.002) under dual-task condition
- Improvement in balance and functional tests
- Fewer falls (IRR, 0.46; 95% CI 0.27-0.79)
- Lower risk of falling (RR, 0.61; 95% CI 0.39-0.96)

In the delayed intervention control

- Similar changes during the second 6-month period with intervention

Trombetti A., Hars M. Herrmann FR *et al.*, Effect of Music-Based Multitask Training on Gait, Balance, and Fall Risk in Elderly People: A Randomized Controlled Trial. *Arch Intern Med (2010).*

Table 4. Falls at the 6-Month Follow-up

Outcomes	Early Intervention (n=66)	Delayed Intervention (n=68)	Unadjusted	Adjusted[a]	Method
Falls, rate[b]	24 (0.7)	54 (1.6)			
IRR (95% CI)			0.46 (0.27-0.79)[d]	0.49 (0.27-0.91)[c]	Negative binomial regression model
Participants with ≥1 fall, No. (%)	19 (28.8)	32 (47.1)			
RR (95% CI)			0.61 (0.39-0.96)[c]	0.69 (0.44-1.07)	Log-binomial regression model
Participants with multiple (≥2) falls, No. (%)	3 (4.6)	16 (23.5)			
RR (95% CI)			0.19 (0.06-0.63)[d]	0.21 (0.06-0.67)[d]	Log-binomial regression model
Survival analysis					
HR (95% CI)			0.53 (0.30-0.94)[c]	0.55 (0.31-0.99)[c]	Cox proportional hazards model
HR (95% CI)			0.46 (0.27-0.78)[d]	0.46 (0.27-0.79)[d]	Andersen-Gill model

Abbreviations: CI, confidence interval; HR, hazard ratio; IRR, incidence rate ratio; RR, relative risk.
[a]Adjusted for age, history of falls over the previous 12 months, simplified Tinetti test performance, and total number of frailty criteria (according to Fried et al[21]) met.
[b]Fall rates per person per year.
[c]$P<.05$.
[d]$P<.01$.

Trombetti A., Hars M. Herrmann FR *et al.*, Effect of Music-Based Multitask Training on Gait, Balance, and Fall Risk in Elderly People: A Randomized Controlled Trial. *Arch Intern Med (2010).*

Conclusion

In community-dwelling older people at increased risk of falling, a 6-month music-based multitask exercise program

- improved gait under dual-task condition,
- improved balance,
- and reduced both the rate of falls and the risk of falling.