university of groningen

faculty of arts

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Historical changes in long-distance movement constructions

A Multinomial Logistic Regression Analysis

Ankelien Schippers

Outline

1. Multinomial logistic regression
2. Long-distance movement
3. The data
4. Analysis
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Multinomial logistic regression

Basically the same as binary logistic regression. It tells you whether an independent variable has an effect on the outcome of the dependent variable, and what the size of that effect is.

Binary logistic regression is used when the dependent (‘output’) variable has two categories (i.e. yes or no, dead or alive, etc.).

If the dependent variable can be divided in more than two categories, multinomial logistic regression is used.

Often used when the dependent variable has several categories of possible outcomes, which can be influenced differently by variations in the independent variable. (e.g. what is the effect of different drug doses on survival rates?)

Assumptions

The independent variable may either be numerical or categorical

The dependent variable has to be categorical, i.e. it must be possible to divide the responses into different categories.

The data do not need to have a normal distribution, no linear relationship and no equality of variances.

Example:

You want to know whether the amount of exposure to a radioactive substance predicts the physical state someone is in. The independent variable is ‘exposure rate’. The dependent variable is ‘physical well-being’, with three categories: healthy, sick, deceased.

	Healthy	**Sick**	**Deceased**	**Total**
Low	10	4	3	17
Middle	8	8	9	25
High	6	16	27	49
Total	24	28	39	91

-2 log likelihood

The test value used to determine whether the independent variable has an effect on the dependent variable is the -2 log likelihood.

Likelihood = probability $-2LL_{i,j} = -2 \ln (Pr_{i,j})$

First, the -2 log likelihood for the model without taking the independent variable into account is computed

Next, the independent variable is taken into account and -2 log likelihood is computed again.

Then this latter -2 log likelihood is subtracted from the former, which gives you your final test value.

Step 1: compute -2 log likelihood without taking the independent variable into account

	Healthy	Sick	Deceased	Total
Low	10	4	3	17
High	8	8	9	25
Middle	6	16	27	49
Total	24	28	39	91

Simplifying: compute probabilities without taking the independent variable into account

Step 2: compute -2 log likelihood with taking the independent variable into account

	Healthy	**Sick**	**Deceased**	**Total**
Low	10	4	3	17
Middle	8	8	9	25
High	6	16	27	49
Total	24	28	39	91

Simplifying: compute probabilities with taking the independent variable into account

Interpretation

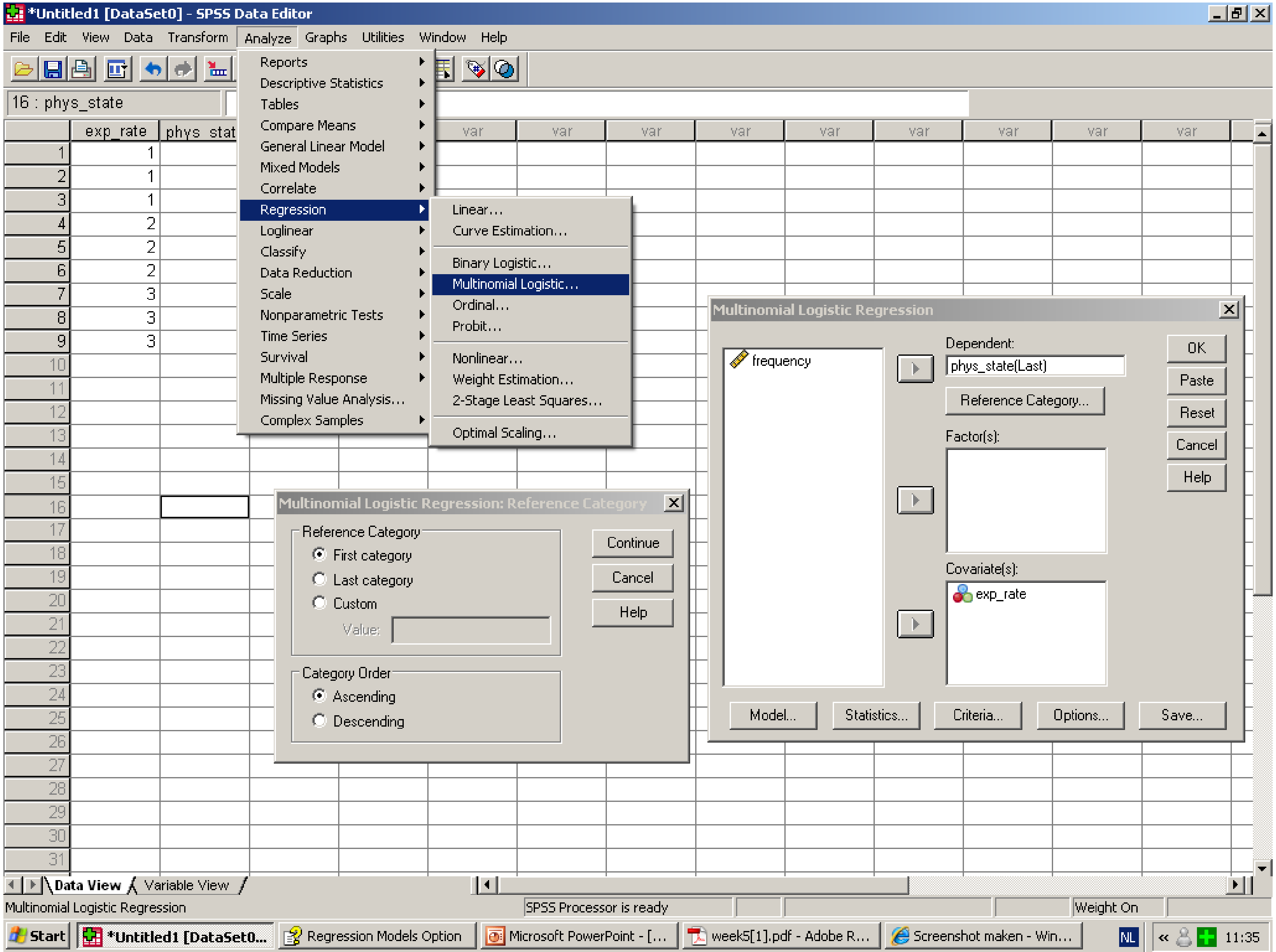
The -2 log likelihood has a chi-square distribution, which can be used to determine whether the outcome of the test is significant.

If the two -2 log likelihoods are the same, subtracting them amounts to 0 and the result is not significant

Hence, if the -2 log likelihood (“probabilities”) for the model that takes de independent variable into account is the same as the one in which that variable wasn’t taking into account, the independent variable had no effect on the outcome of the dependent variable.

If the two -2 log likelihoods are different, subtractions them gives you a value < 0 >

SPSS procedure



16 : phys_state

	exp_rate	phys_stat
1	1	
2	1	
3	1	
4	2	
5	2	
6	2	
7	3	
8	3	
9	3	

Multinomial Logistic Regression

frequency

Dependent: phys_state(Last)

Covariate(s): exp_rate

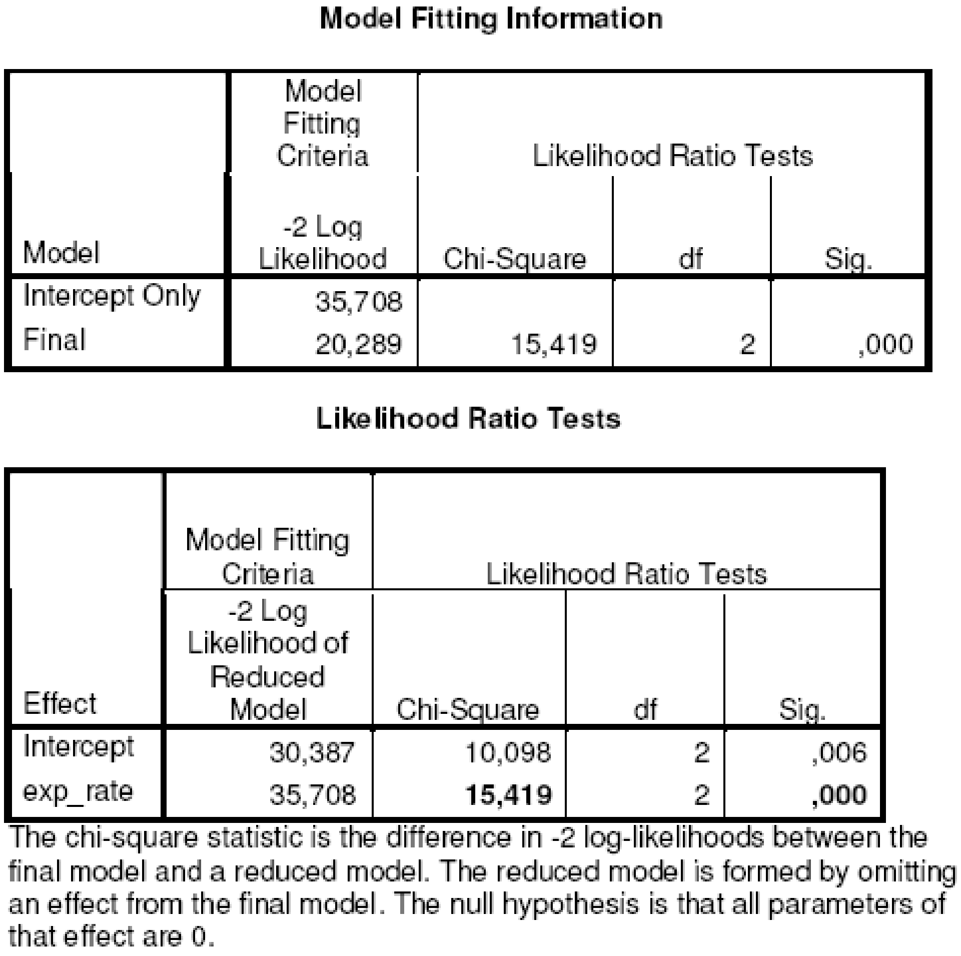
Multinomial Logistic Regression: Reference Category

Reference Category
- ● First category
- ○ Last category
- ○ Custom

Value:

Category Order
- ● Ascending
- ○ Descending

Output



Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	35,708			
Final	20,289	15,419	2	,000

Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	30,387	10,098	2	,006
exp_rate	35,708	**15,419**	2	**,000**

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Post-hoc

The -2 LL showed that the independent variable has an effect on the dependent variable. Now we want to know whether that effect is the same or not for each of the categories of the dependent variable. That is: does exposure rate have the same effect of being healthy/sick/alive?

In order to determine that, we make a series of comparisons between two categories of the dependent variable (e.g. healthy vs. sick, healthy vs. dead, etc).

SPSS gives the option of choosing a reference category for these comparisons. I chose category 1 (= healthy).

To compare two categories, the ODDS ratio's are computed, which SPSS gives in terms of a β1 value.

ODDS ratio

	Healthy	**Sick**	**Total**
Low	10	4	14
High	6	16	22
Total	16	20	

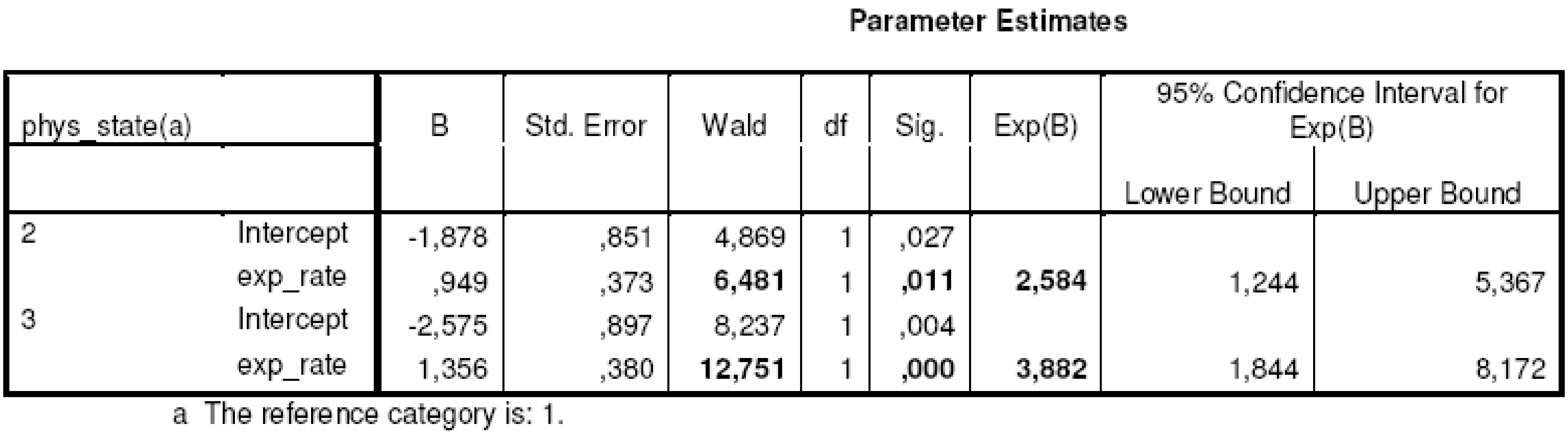
Odds healthy/sick for low exposure: $\frac{10/14}{4/14} = 2.5 \quad \ln 2.5 = 0.916$

Odds healthy/sick for high exposure: $\frac{6/22}{16/22} = 0.375 \ \ln 0.375 = -0.981$

$$\frac{\ln OR_{low}}{\ln OR_{high}} = \frac{0.916}{-0.981} = -0.934$$

β1

Because the log ODDS ratio's are kind of hard to interpret, SPSS gives them as β1, i.e. the slope of the regression line.



Parameter Estimates

phys_state(a)		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
2	Intercept	-1,878	,851	4,869	1	,027			
	exp_rate	,949	,373	**6,481**	1	**,011**	**2,584**	1,244	5,367
3	Intercept	-2,575	,897	8,237	1	,004			
	exp_rate	1,356	,380	**12,751**	1	**,000**	**3,882**	1,844	8,172

a The reference category is: 1.

Interpretation of β1

β1 represent the probability of a change in the reference group versus a change in the comparison group as the independent variable changes.

category 1(healthy) vs 2(sick) β1 = 2.584.

‘the chance of being healthy versus the chance of being sick increases with 1:2.584 as the independent variable increases’.

So if the exposure rate increases, the probability of getting sick is greater than the probability of staying healthy.

Why use logistic regression instead of normal regression?

Most important reason: if your dependent variable has two or more categories, the probability of falling in one of these categories should be >0 and <1. Transforming your data into odds ratio’s expresses this fact naturally, while the untransformed data does not.

Another reasons to use logistic regression may be that your data violates certain requirements to do normal regression: for example, if the data do not form a linear pattern.

Long-distance movement

Generative grammar: dependency relations are analyzed as involving movement

Canonical example: wh-movement

Declarative:
John kissed Mary

Wh-question:
Who did Mary kiss t_{who}? Who = John

We speak of long-distance movement if the dependency relation spans more than one clause: e.g. a wh-word moves from a suborindate clause into a matrix clause:

$[_{CP}$ Who do you think $[_{CP}$ t_{who} kissed Mary]] (CP = clause)

4 types of long-distance wh-movement

Chomsky (1977): the type of dependency relation found in questions can also be found in other constructions:

- Relatives

[CP That is the girl [CP who Nina thinks [CP John kissed t_{who}]]]

- Topicalization constructions

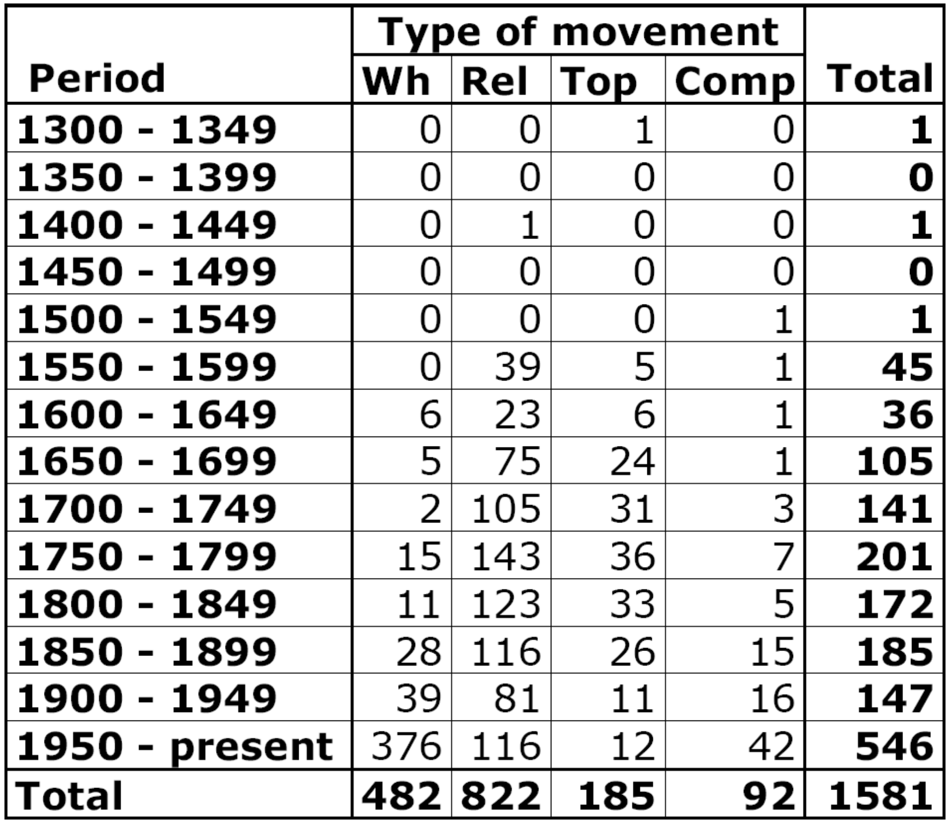
[CP The girl Nina thinks [CP that John kissed $t_{the\ girl}$]]

- Comparatives

[CP John kissed more girls [CP than OP Nina thinks [CP he did t_{OP}]]]

The data

- Dutch historical corpus data, collected by Jack Hoeksema
- Data ranges from the 14th century up to contemporary Dutch

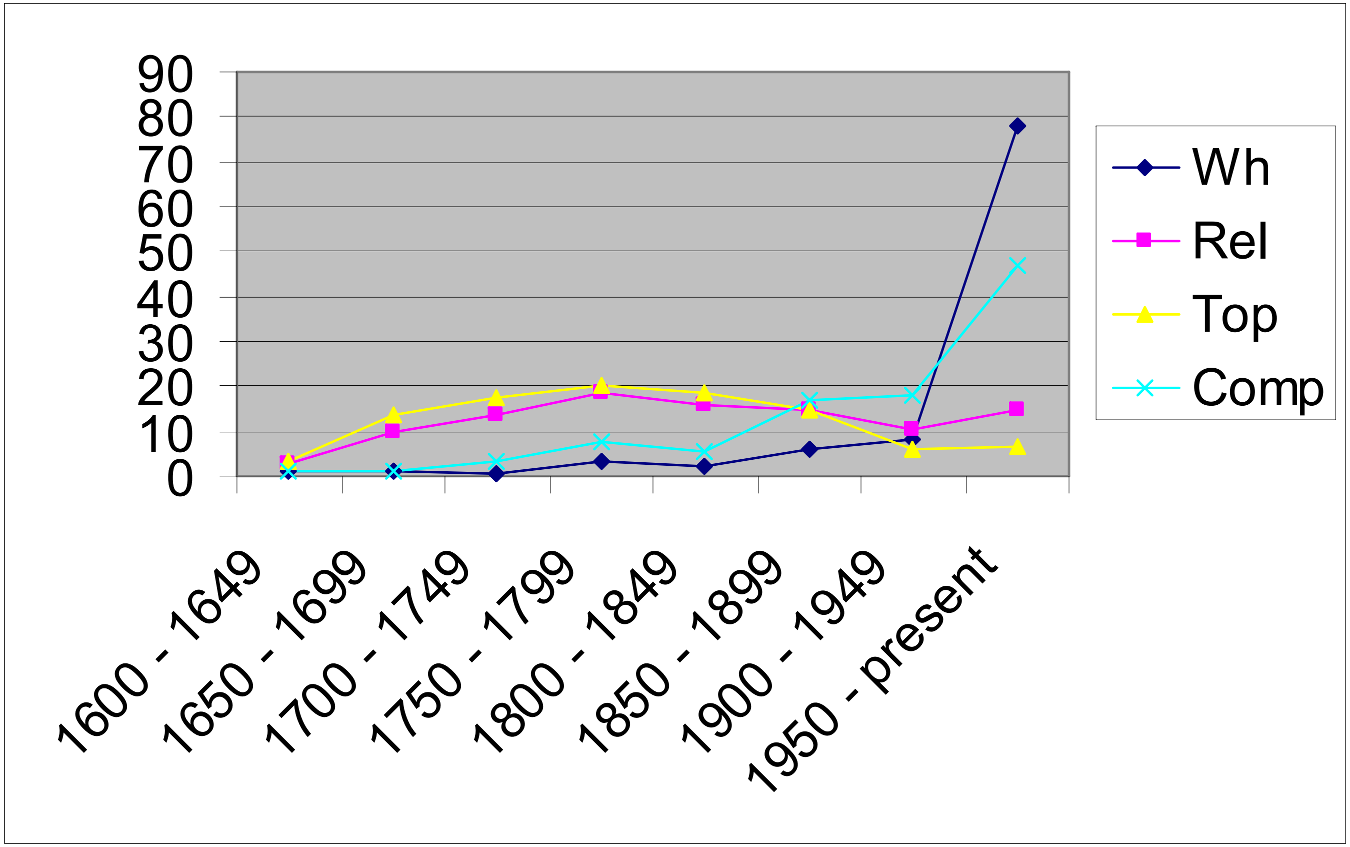


Period	Type of movement				Total
	Wh	Rel	Top	Comp	
1300 - 1349	0	0	1	0	**1**
1350 - 1399	0	0	0	0	**0**
1400 - 1449	0	1	0	0	**1**
1450 - 1499	0	0	0	0	**0**
1500 - 1549	0	0	0	1	**1**
1550 - 1599	0	39	5	1	**45**
1600 - 1649	6	23	6	1	**36**
1650 - 1699	5	75	24	1	**105**
1700 - 1749	2	105	31	3	**141**
1750 - 1799	15	143	36	7	**201**
1800 - 1849	11	123	33	5	**172**
1850 - 1899	28	116	26	15	**185**
1900 - 1949	39	81	11	16	**147**
1950 - present	376	116	12	42	**546**
Total	**482**	**822**	**185**	**92**	**1581**

Table 1: Frequencies per movement type per period

Graph 1

Relative frequencies per movement type over time



Research question

Do the four types of long-distance movement constructions develop the same over type?

Rephrasing it: does the independent variable [PERIOD] have the same effect on the frequencies of the four types of LD movement?

Points of caution

>Very little data before 1600, so these were omitted.

>type of text genre that was investigated is not the same for each period.

>data were collected manually, which means the data might be distorted due to human error.

>some types of long-distance movement simply occur more frequently, e.g. questions are normally used more often than comparatives.

the last issue can be overcome by performing a regression analysis, which compares changes in two or more variables, and not absolute values

why use logistic regression in this case?

the data did not comply with the requirements to perform a normal regression analysis (residuals showed a pattern)

chi-square only tells you whether one variable has an effect on the other, but not what the strength or the direction of that effect is.

Logistic regression does.

SPSS multinomial logistic regression procedure:
LD movement type = dependent variable
Period = the independent variable, entered as a covariate.

Results

-2 log likelihood = 623.94, df 3, $p < 0.000$

meaning: the frequencies of the four types of movement changed significantly different over time relatively to each other.

wh vs. rel: $\beta1 = 0.408$ (95% CI 0.368 – 0.452)
Wald = 296.54, $p < 0.000$

wh vs top: $\beta1 = 0.356$ (95% CI 0.315 – 0.403)
Wald = 268.45, $p < 0.000$

wh vs comp: $\beta1 = 0.662$ (95% CI 0.567 – 0.772)
Wald = 27.45, $p = 0.024$

conclusion: wh-movement increases more than the other three types of movement as the dependent variable ‘period’ increases.

Results (continued)

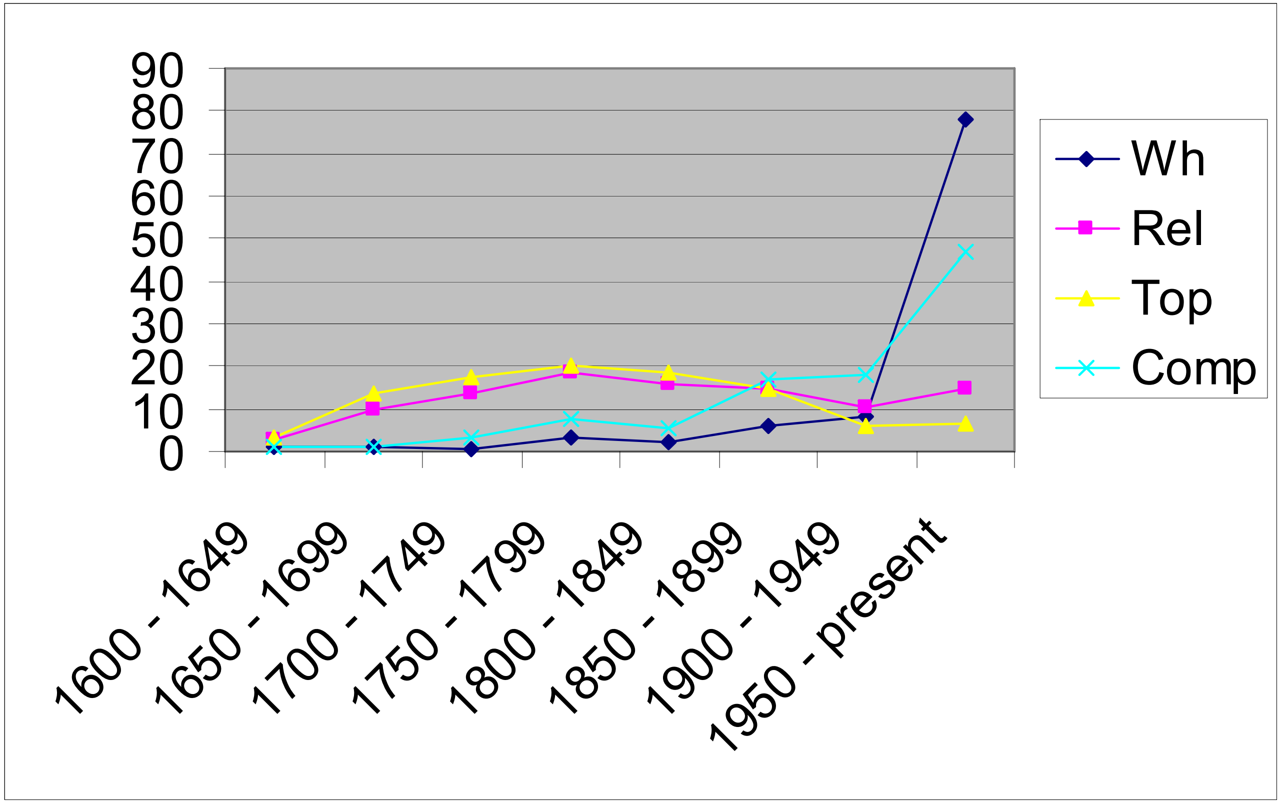
rel vs. top β1 = 0.874 (95% CI 0.805 – 0.947)
Wald = 10.65, $p < 0.000$

rel vs. comp β1 = 1.622 (95% CI 1.419 – 1.855)
Wald = 50.07, $p < 0.000$

top vs comp β1 = 1.857 (95% CI 1.598 – 2.159)
Wald = 65.17, $p < 0.000$

conclusions: relatives increase less than topicalization constructions and comparatives as time increases, and topicalization construction increase less than comparatives as time increases.

Back to graph 1



the results may be interpreted as following:

wh-movement and comparatives increase whereas relatives and topicalization constructions decrease over time

wh-movement constructions increase faster than comparatives

topicalization constructions decrease faster than relatives

Further reading

Field, A. (2009). Discovering statistics using SPSS. (third edition has a section on multinomial logistic regression)