Direct and indirect effects in a logit model

Maarten L. Buis

Department of Social Research Methodology Vrije Universiteit Amsterdam http://home.fsw.vu.nl/m.buis/

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Outline

The aim

The problem

The solution

example

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The Total Effect



The Indirect Effect



The Direct Effect



The aim

The aim is to find the size of the indirect effect relative to the direct effect.



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Averaging the proportions transforming the average proportion

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Averaging the proportions transforming the average proportion

Estimation

- When using regress:
 - 1. college = class + performance
 - 2. college = class

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Averaging the proportions transforming the average proportion

Estimation

- When using regress:
 - 1. college = class + performance
 - 2. college = class

The direct effect is the effect of class in model 1.

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Averaging the proportions transforming the average proportion

Estimation

- When using regress:
 - 1. college = class + performance
 - 2. college = class
- The direct effect is the effect of class in model 1.
- The total effect is the effect of class in model 2.

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Averaging the proportions transforming the average proportion

Estimation

- When using regress:
 - 1. college = class + performance
 - 2. college = class
- The direct effect is the effect of class in model 1.
- The total effect is the effect of class in model 2.
- The indirect effect is the total effect direct effect.

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Averaging the proportions transforming the average proportion

Estimation

- When using regress:
 - 1. college = class + performance
 - 2. college = class
- The direct effect is the effect of class in model 1.
- The total effect is the effect of class in model 2.
- The indirect effect is the total effect direct effect.
- This won't work when using logit

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Averaging the proportions transforming the average proportion

Log odds



Averaging the proportions transforming the average proportion

Effect



Averaging the proportions transforming the average proportion



Averaging the proportions transforming the average proportion

Transform log odds to probability



The problem The solution example

Averaging the proportions transforming the average proportion



Averaging the proportions transforming the average proportion

Transform log odds to probability



Averaging the proportions transforming the average proportion

Transform log odds to probability



Averaging the proportions transforming the average proportion



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Averaging the proportions transforming the average proportion

Transform log odds to probability



Averaging the proportions transforming the average proportion



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Transform log odds to probability



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Transform log odds to probability



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Transform log odds to probability



Averaging the proportions transforming the average proportion



The problem The solution example

Averaging the proportions transforming the average proportion

Average probability


Averaging the proportions transforming the average proportion



Averaging the proportions transforming the average proportion



Averaging the proportions transforming the average proportion



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Averaging the proportions transforming the average proportion

Effect of class without controlling for performance



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Direct and indirect effects in logit



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Counterfactual odds

		logit curve	
		low class high class	
distribution of	low class	<i>O</i> _{//}	O _{lh}
performance	high class	O_{hl}	O_{hh}

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Counterfactual odds

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Counterfactual odds

		logit curve	
		low class	high class
distribution of	low class	<i>O</i> _{//}	O _{lh}
performance	high class	O_{hl}	O _{hh}
	$\underbrace{\frac{O_{hl}}{O_{ll}}}_{indirect}$	$\underbrace{\frac{O_{hh}}{O_{hl}}}_{direct}$	

The solution

Counterfactual odds

		logit curve	
		low class	high class
distribution of	low class	<i>O</i> _{//}	O _{lh}
performance	high class	O_{hl}	O_{hh}

$$\underbrace{\frac{O_{hl}}{O_{ll}}}_{indirect} \times \underbrace{\frac{O_{hh}}{O_{hl}}}_{direct} = \underbrace{\frac{O_{hh}}{O_{ll}}}_{total}$$

indirect

total

The solution

Counterfactual odds

		logit curve	
		low class	high class
distribution of	low class	<i>O</i> ₁₁	O _{lh}
performance	high class	O_{hl}	O_{hh}
	$\frac{O_{hl}}{O_{ll}} \times \frac{O_{hh}}{O_{hl}}$	$= \ln \left(\underbrace{\frac{O_{hh}}{O_{ll}}}_{total} \right)$)

Counterfactual odds



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Counterfactual odds

		logit curve	
		low class	high class
distribution of	low class	<i>O</i> _{//}	O _{lh}
performance	high class	O_{hl}	O_{hh}

$$\ln\left(\frac{O_{hl}}{O_{ll}}\right) + \ln\left(\frac{O_{hh}}{O_{hl}}\right) = \ln\left(\frac{O_{hh}}{O_{ll}}\right)$$
$$\underbrace{\ln\left(\frac{O_{hh}}{O_{lh}}\right)}_{indirect} + \underbrace{\ln\left(\frac{O_{lh}}{O_{ll}}\right)}_{direct} = \underbrace{\ln\left(\frac{O_{hh}}{O_{ll}}\right)}_{total}$$

The solution

Estimating counterfactual odds

As proposed by Buis (2008): • The odds is $\frac{\text{probability}}{1-\text{probability}}$

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Estimating counterfactual odds

As proposed by Buis (2008): • The odds is $\frac{\text{probability}}{1-\text{probability}}$ • probability = $\frac{\sum_{i \in c_1} \Lambda(\alpha_{c_2} + \beta_{c_2} x_i)}{N_{c_1}}$

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c₁ is the distribution of performance

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Estimating counterfactual odds

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- c₁ is the distribution of performance
- c₂ is the logit curve

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Estimating counterfactual odds

As proposed by Buis (2008): The odds is $\frac{\text{probability}}{1-\text{probability}}$ probability = $\frac{\sum_{i \in c_1} \Lambda(\alpha_{c_2} + \beta_{c_2} x_i)}{N_{c_1}}$

- c₁ is the distribution of performance
- c₂ is the logit curve

As proposed by Erikson and colleagues (2005):

$$\int_{-\infty}^{\infty} \phi(\mu_{c_1}, \sigma_{c_1}) \Lambda(\alpha_{c_2} + \beta_{c_2} x) dx$$
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example

Descriptives

. table ocf57 if !missing(hsrankq, college) , ///

occupation of r father in 1957	mean(college)	mean(hsrankq)	Freq.
Unskilled	.287	46.4	3,528
Farming	.277	51.9	1,690
Skilled	.38	50.6	868
White collar	.54	54	1,868
Professional or executive	.771	60.5	969

> contents(mean college mean hsrankg freg) format(%9.3g)

The ldecomp package

ldecomp depvar [weight] [if] [in] , direct(varname) indirect(varlist) [obspr predpr predodds rindirect rdirect lor noor normal range(##) nip(#) interactions]

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Counterfactual proportions

. ldecomp college , direct(ocf57) indirect(hsrankq) predpr predodds lor rind predicted and counterfactual proportions

distribution	Unskilled	Farming	association Skilled	White col_r	Professio_e
Unskilled	.287	.251	.356	.492	.702
Farming	.316	.277	.388	.527	.731
Skilled	.309	.271	.38	.518	.723
White collar	.329	.289	.402	.54	.74
Profession_e	.365	.323	.441	.581	.771

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- ► The odds is probability 1-probability
- The odds that a child from a unskilled worker enters college is <u>.287</u> <u>1-.287</u> = .403

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Counterfactual odds

Unskilled	Farming	association Skilled	White col~r	Professio_e
.403	.335	.553	.969	2.35
.462	.383	.635	1.12	2.72
.447	.371	.613	1.07	2.61
.49 .574	.407	.672 .789	1.17 1.38	2.84 3.36
	Unskilled .403 .462 .447 .49 .574	Unskilled Farming .403 .335 .462 .383 .447 .371 .49 .407 .574 .476	association Unskilled Farming Skilled .403 .335 .553 .462 .383 .635 .447 .371 .613 .49 .407 .672 .574 .476 .789	association Unskilled Farming Skilled White col_r .403 .335 .553 .969 .462 .383 .635 1.12 .447 .371 .613 1.07 .49 .407 .672 1.17 .574 .476 .789 1.38

predicted and counterfactual odds

Counterfactual odds

predicted and	counterfactual	odds			
distribution	Unskilled	Farming	association Skilled	White col~r	Professio_e
Unskilled	.403	.335	.553	.969	2.35
Farming	.462	.383	.635	1.12	2.72
Skilled	.447	.371	.613	1.07	2.61
White collar	.49	.407	.672	1.17	2.84
Profession_e	.574	.476	.789	1.38	3.36



Counterfactual odds

predicted and counterfactual odds

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Unskilled	.403	.335	.553	.969	2.35
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White collar	.49	.407	.672	1.17	2.84
Profession_e	.574	.476	.789	1.38	3.36

$\underbrace{\frac{O_{hl}}{O_{ll}}}_{indirect}$	$\times \frac{O_{hh}}{O_{hl}} = $	$= \frac{O_{hh}}{O_{ll}}$
.574	3.36	3.36
.403 ×	574	.403
indirect	direct	total

Counterfactual odds

predicted	and	counterfactual	odds
-----------	-----	----------------	------

distribution	Unskilled	Farming	association Skilled	White col~r	Professio_e
Unskilled	.403	.335	.553	.969	2.35
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Skilled	.447	.371	.613	1.07	2.61
White collar Profession_e	.49	.407 .476	.672 .789	1.17	2.84 3.36

1.43	× <u>5.86</u> =	8.35
indirect	direct	total

Decomposition of odds ratios

decomposition of odds ratios

(indirect	direct	total
	[+,]]/[],]]	[±,±]/[±,]]	[±,±]/[],]]
2/1	1.15	.83	.951
3/1	1.11	1.37	1.52
4/1	1.22	2.4	2.92
5/1	1.43	5.86	8.35
3/2	.97	1.65	1.6
4/2	1.06	2.89	3.07
5/2	1.24	7.06	8.79
4/3	1.1	1.75	1.91
5/3	1.29	4.27	5.49
5/4	1.18	2.43	2.86
(motho)	1 01		
(mechod	1 2)		
(mecnoc	indirect	direct	total
(mecnoc	indirect [i,i]/[j,i]	direct [j,i]/[j,j]	total [i,i]/[j,j]
2/1	indirect [i,i]/[j,i] 1.14	direct [j,i]/[j,j] .831	total [i,i]/[j,j] .951
2/1 3/1	1 2) indirect [i,i]/[j,i] 1.14 1.11	direct [j,i]/[j,j] .831 1.37	total [i,i]/[j,j] .951 1.52
2/1 3/1 4/1	indirect [i,i]/[j,i] 1.14 1.11 1.21	direct [j,i]/[j,j] .831 1.37 2.4	total [i,i]/[j,j] .951 1.52 2.92
2/1 3/1 4/1 5/1	1 2) indirect [i,i]/[j,i] 1.14 1.11 1.21 1.43	direct [j,i]/[j,j] .831 1.37 2.4 5.85	total [i,i]/[j,j] .951 1.52 2.92 8.35
2/1 3/1 4/1 5/1 3/2	indirect [i,i]/[j,i] 1.14 1.11 1.21 1.43 .966	direct [j,i]/[j,j] .831 1.37 2.4 5.85 1.66	total [i,i]/[j,j] .951 1.52 2.92 8.35 1.6
2/1 3/1 4/1 5/1 3/2 4/2	indirect [i,i]/[j,i] 1.14 1.11 1.21 1.43 .966 1.05	direct [j,i]/[j,j] .831 1.37 2.4 5.85 1.66 2.91	total [i,i]/[j,j] .951 1.52 2.92 8.35 1.6 3.07
2/1 3/1 4/1 5/1 3/2 4/2 5/2	indirect [i,i]/[j,i] 1.14 1.11 1.21 1.43 .966 1.05 1.24	direct [j,i]/[j,j] .831 1.37 2.4 5.85 1.66 2.91 7.1	total [i,i]/[j,j] .951 1.52 2.92 8.35 1.6 3.07 8.79
2/1 3/1 4/1 5/1 3/2 4/2 5/2 4/3	indirect [i,i]/[j,i] 1.14 1.11 1.21 1.43 .966 1.05 1.24 1.24	direct [j,i]/[j,j] .831 1.37 2.4 5.85 1.66 2.91 7.1 1.75	total [i,i]/[j,j] 1.52 2.92 8.35 1.6 3.07 8.79 1.91
2/1 3/1 4/1 5/1 3/2 4/2 5/2 4/3 5/3	indirect [i,i]/[j,i] 1.14 1.11 1.33 .966 1.05 1.24 1.09 1.29	direct [j,1]/[j,j] .831 1.37 2.4 5.85 1.66 2.91 7.1 1.75 4.26	total [i,i]/[j,j] .951 1.52 2.92 8.35 1.6 3.07 8.79 1.91 5.49

Column names:

i refers to the first category in the row name j refers to the second category in the row name first number in pair refers to the distribution second number in pair refers to the association value labels
1 Unskilled
2 Farming
3 Skilled
4 White collar
5 Professional or
executive

Decomposition of log odds ratios

decomposition of log odds ratios

(1110 01100)			
	indirect	direct	total	
	[4 4]/[4 4]	[1 1]/[1 1]	[1 1]/[4 4]	
	[-/]]/[]/]]	[=/=]/[=/]]	[+/+]/[]/]]	
2./1	100	107	05.04	
2/1	.130	187	0504	
3/1	.104	.316	.421	
4/1	.196	.874	1.07	
5/1	.354	1.77	2.12	
3/2	0308	. 502	. 471	
4/2	.0611	1.06	1.12	
5/2	.218	1.95	2.17	
4/3	.0911	. 559	. 65	
5/3	251	1 45	1 7	
5/5	.2.51	1.45	1.7	
5/4	.164	.888	1.05	
(method 2)				
(method	12)			
(method	12) I indirect	direct	total	
(method	indirect	direct	total	
(method	i 2) indirect [i,i]/[j,i]	direct [j,i]/[j,j]	total [i,i]/[j,j]	
(method	i 2) indirect [i,i]/[j,i]	direct [j,i]/[j,j]	total [i,i]/[j,j]	
(method	i 2) indirect [i,i]/[j,i] .135	direct [j,i]/[j,j] 186	total [i,i]/[j,j] 0504	
(method 2/1 3/1	i 2) indirect [i,i]/[j,i] .135 .104	direct [j,i]/[j,j] 186 .317	total [i,i]/[j,j] 0504 .421	
(method 2/1 3/1 4/1	i 2) indirect [i,i]/[j,i] .135 .104 .193	direct [j,i]/[j,j] 186 .317 .877	total [i,i]/[j,j] 0504 .421 1.07	
2/1 3/1 4/1 5/1	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357	direct [j,i]/[j,j] 186 .317 .877 1.77	total [i,i]/[j,j] 0504 .421 1.07 2.12	
2/1 3/1 4/1 5/1 3/2	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357 0342	direct [j,i]/[j,j] 186 .317 .877 1.77 .505	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471	
2/1 3/1 4/1 5/1 3/2 4/2	i 2) indirect [i,i]/[j,i] .104 .193 .357 0342 .0516	direct [j,i]/[j,j] 186 .317 .877 1.77 .505 1.07	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471 1.12	
2/1 3/1 4/1 5/1 3/2 4/2 5/2	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357 0342 .0516 .213	direct [j,i]/[j,j] 186 .317 .877 1.77 .505 1.07 1.96	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471 1.12 2.17	
2/1 3/1 4/1 5/1 3/2 4/2 5/2 4/3	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357 0342 .0516 .213 .089	direct [j,i]/[j,j] 186 .317 .877 1.77 .505 1.07 1.96 .561	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471 1.12 2.17 .65	
2/1 3/1 4/1 5/1 3/2 4/2 5/2 4/3 5/3	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357 0342 .0516 .213 .089 .253	direct [j,i]/[j,j] 186 .317 1.77 .505 1.07 1.96 .561 1.45	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471 1.12 2.17 .65 1.7	
2/1 3/1 4/1 5/1 3/2 4/2 5/2 4/3 5/3 5/4	i 2) indirect [i,i]/[j,i] .135 .104 .193 .357 0342 .0516 .213 .089 .253 .169	direct [j,i]/[j,j] 186 .317 1.77 1.77 505 1.07 1.96 .561 1.45 .884	total [i,i]/[j,j] 0504 .421 1.07 2.12 .471 1.12 2.17 .65 1.7 1.05	

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The aim example

Relative importance of indirect effect

relativ	/e importance	importance of indirect effect		
	method 1	method 2	average	
2/1	-2.7	-2.68	-2.69	
3/1	.248	.247	.248	
4/1	.183	.18	.182	
5/1	.167	.168	.168	
3/2	0654	0725	069	
4/2	.0545	.0461	.0503	
5/2	.101	.098	.0993	
4/3	.14	.137	.139	
5/3	.148	.149	.148	
5/4	.156	.16	.158	

value labels 1 Unskilled 2 Farming 3 Skilled 4 White collar 5 Professional or executive

Discussion

This is "an area of active research"

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Discussion

There are unanswered questions:



Discussion

There are unanswered questions:

The need to take the average indirect effect is less than elegant.

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Discussion

There are unanswered questions:

- The need to take the average indirect effect is less than elegant.
- This procedure only provides a point estimate, and no tests or confidence intervals.

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Discussion

There are unanswered questions:

- The need to take the average indirect effect is less than elegant.
- This procedure only provides a point estimate, and no tests or confidence intervals.
- How does it relate to the alternative method proposed by Fairlie (2005) and implemented by Ben Jann as the fairlie package?

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References



Buis, M. L.

Direct and indirect effects in a logit model.

http://home.fsw.vu.nl/m.buis/wp/ldecomp.html



Erikson, R., J. H. Goldthorpe, M. Jackson, M. Yaish, and D. R. Cox. On class differentials in educational attainment.

Proceedings of the National Academy of Science, 102:9730–9733, 2005.



Fairlie, R. W.

An extension of the Blinder-Oaxaca decomposition technique to logit and probit models.

Journal of Economic and Social Measurement, 30:305–316, 2005.

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Intervening variable



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Confounding variable

