Supplementary Material to:

The Relevance Effect and Conditionals – The Influence of the Prior Manipulation & Analysis of Individual Regressions

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The supplementary materials, including all data and analysis scripts, are available at: https://osf.io/j4swp/

The Influence of the Prior Manipulation

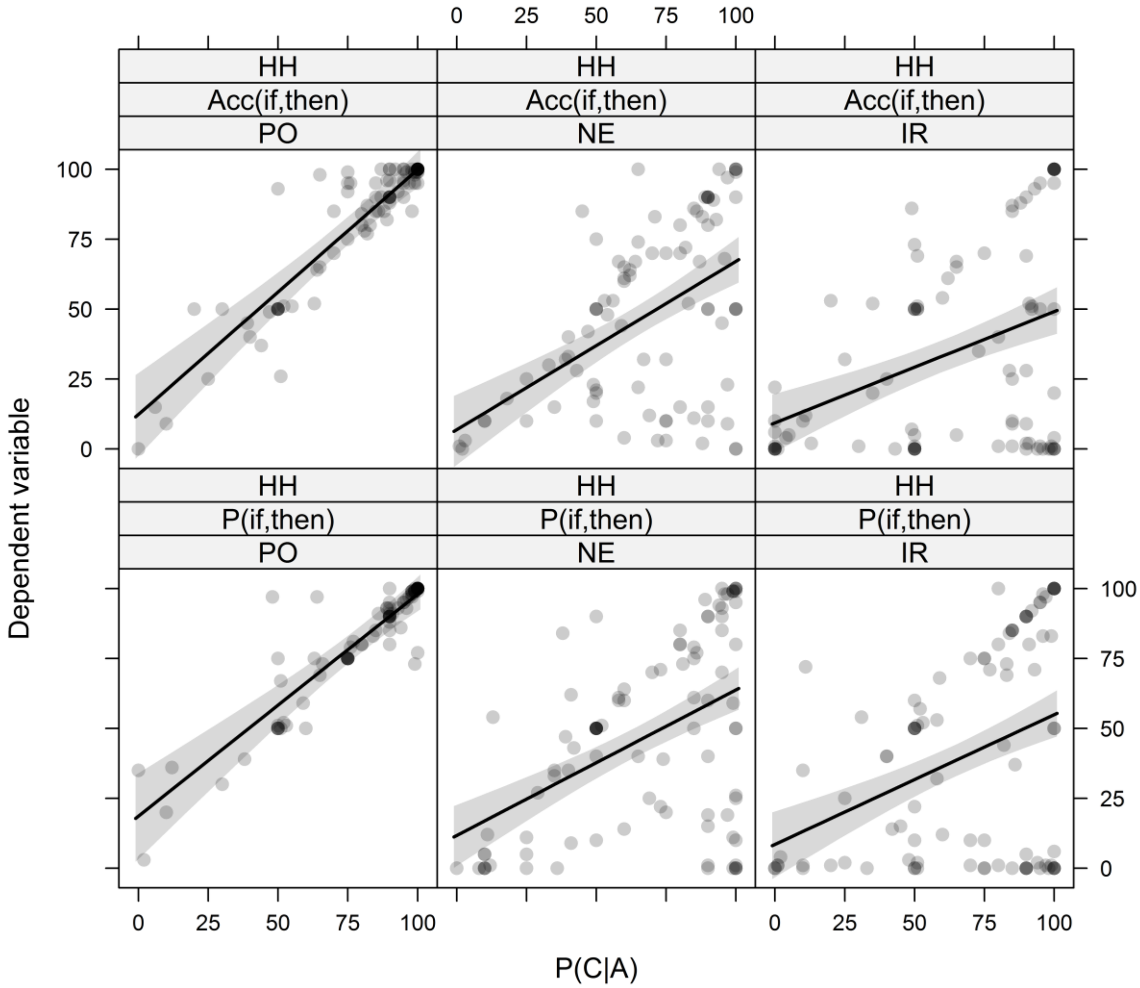
Besides the two between-participants factors (conditionals and mode of evaluation) we had two within-participants factors: relevance (with three levels: PO, NE, IR), and priors (with four levels: HH, HL, LH, LL, meaning, for example, that P(A) = high and P(C) = low for HL). Combining these two within-participants factors lead to the 12 items on which each participant worked.

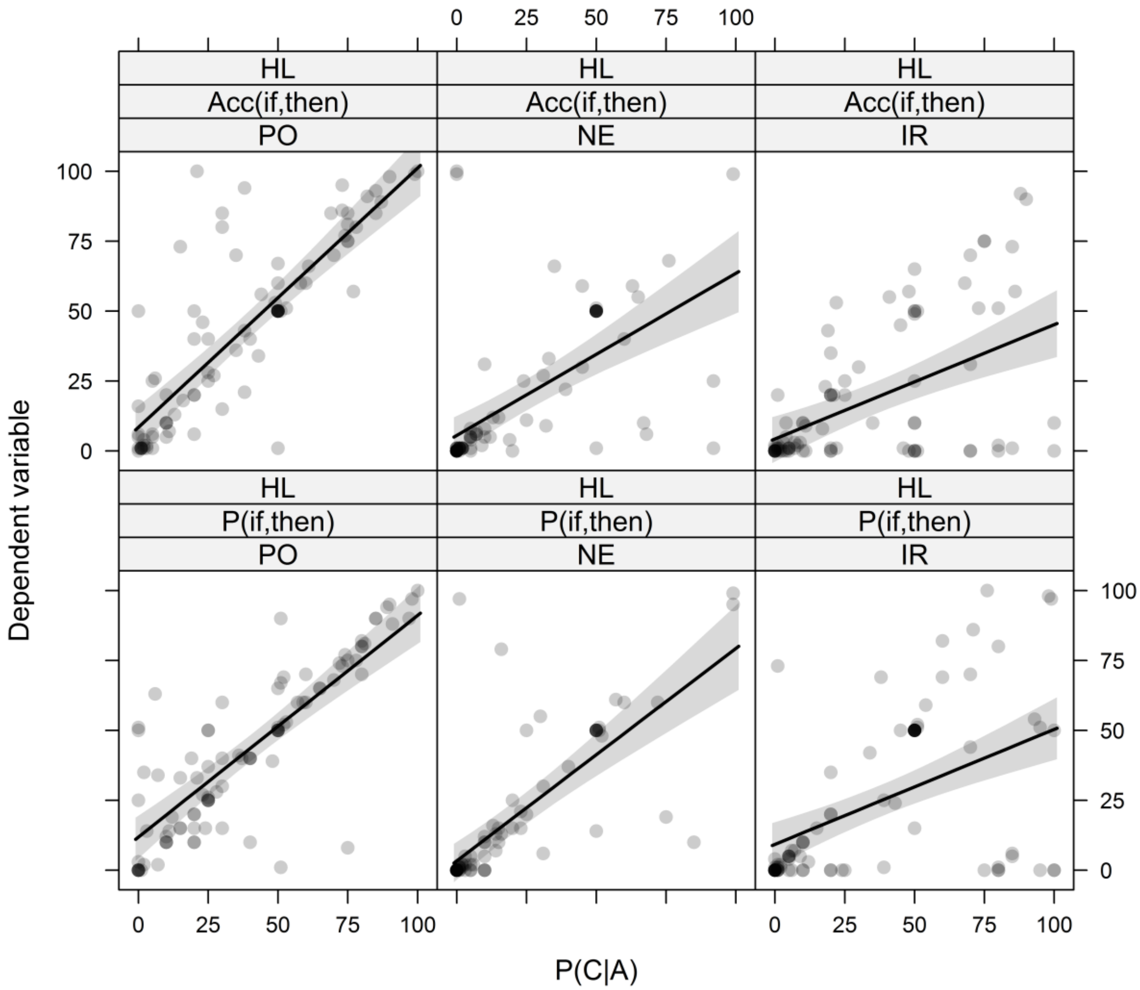
Indicative Conditionals by Prior Manipulation

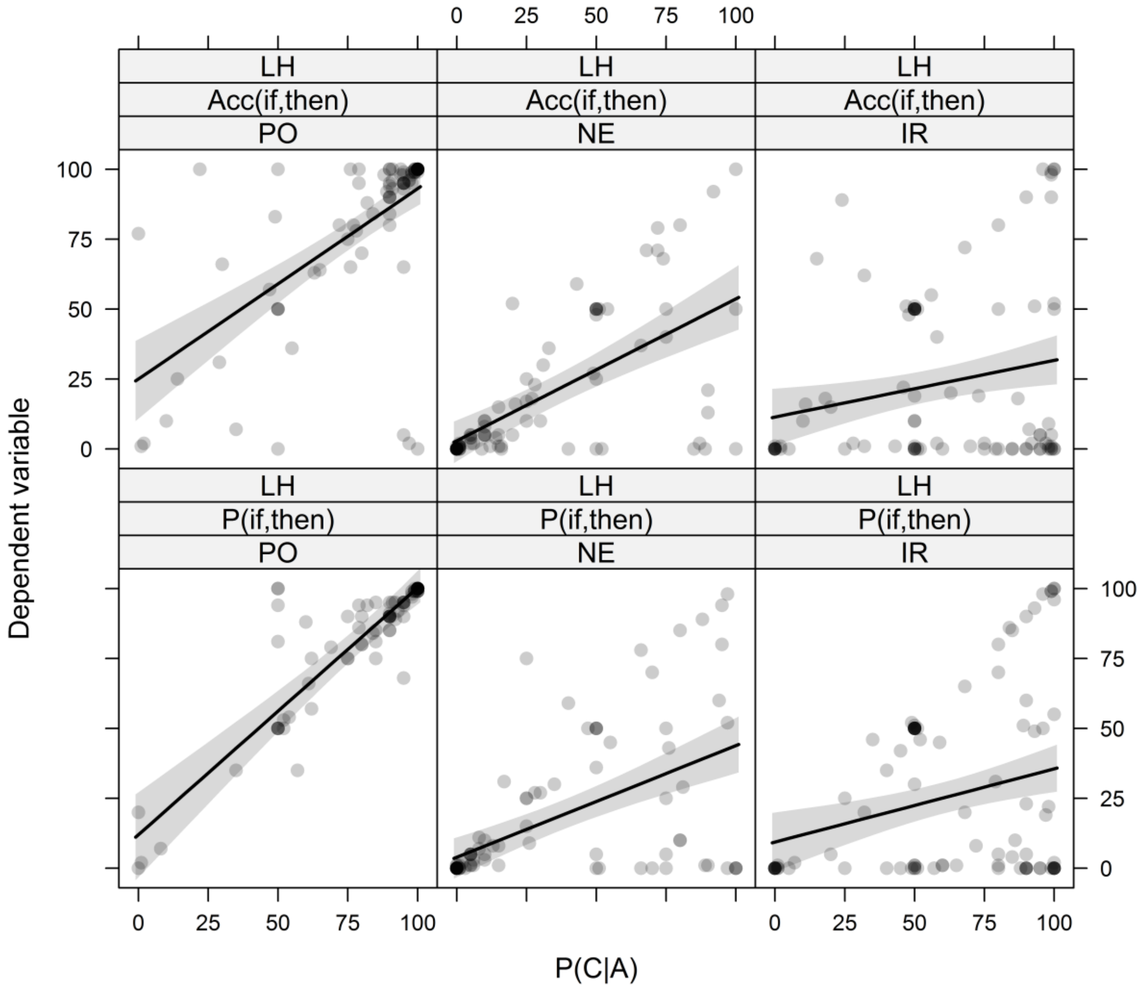
The following plots show the data for the indicative conditionals separated by prior manipulation. The order is HH (P(A) = high and P(C) = high), HL (P(A) = high and P(C) = low), LH (P(A) = low and P(C) = high), and LL (P(A) = low and P(C) = low). As can be seen when comparing HH and LH with HL and LL, manipulating the prior of the consequent achieved the intended goal of producing a spread in the conditional probability. For HH and LH most of the mass is on the right side of the scale (i.e., near 100), whereas for LH and LL most of the mass is near the left end of the scale (i.e. near 0). Interestingly, this pattern does not seem to hold completely consistently. For the LH and the NE relevance condition most of the data points remained on the left side and for the LL conditionals and the PO relevance condition the data still showed a relatively uniform spread. This shows that while in general the prior manipulation worked, participants' estimates of the conditional probabilities were not unaffected by the relevance condition.

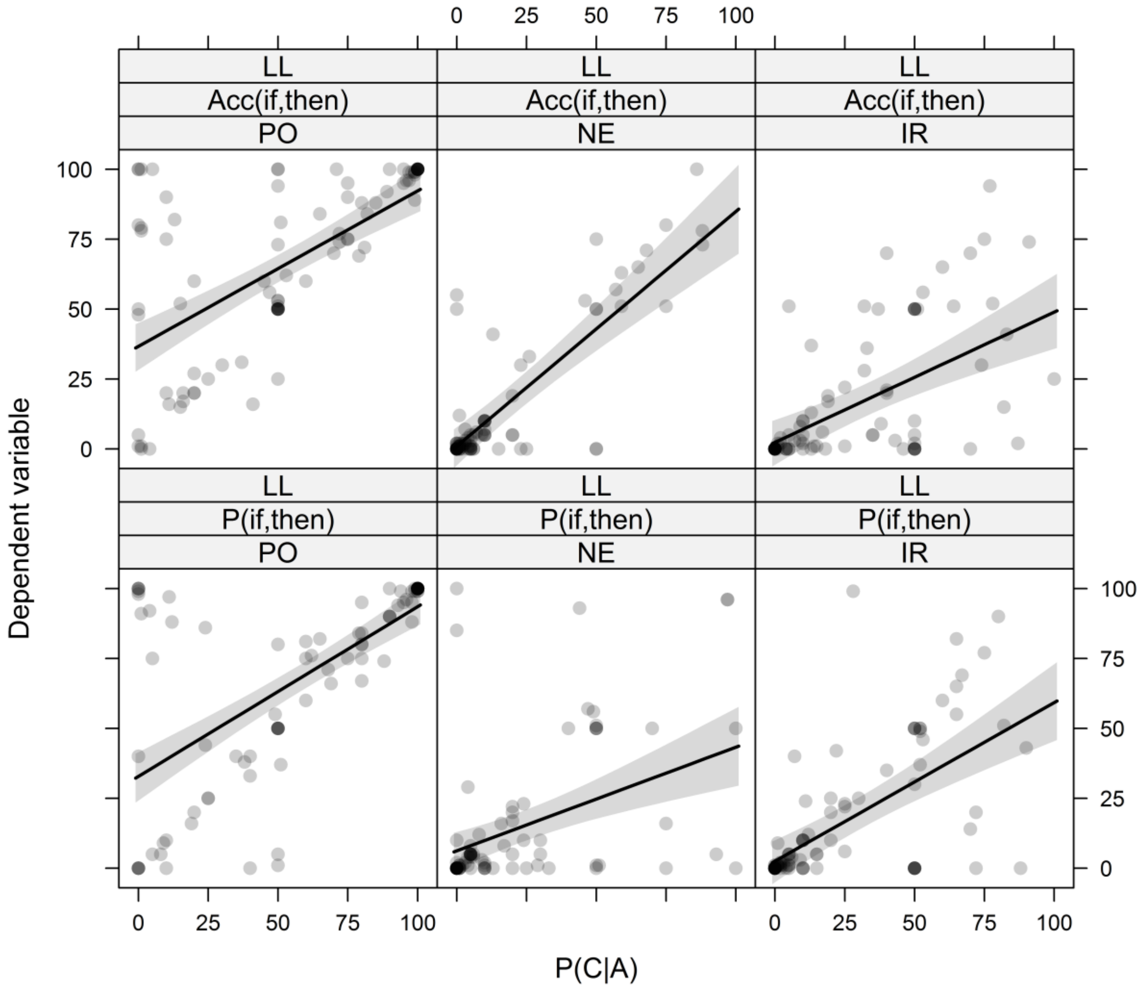
Given the reduced spread in each of the sub-plots the precision with which the individual slopes were estimated was obviously reduced compared to the main analysis. If all data points were on the same value of the independent variable (i.e., the conditional probability), the estimated slope would be 0. Consequently, the few data points that did not have the same value of independent variable as most others have an unusually and unjustifiably high influence on the estimate of the slope (so-called *influential observations*). Nevertheless, the pattern was surprisingly robust. With the exception of the LL prior the estimated slopes always followed the order PO > NE > IR. For the LL prior, the estimates of PO and NE were almost identical. This shows that the main pattern holds across the prior manipulation and they did not systematically affect the results. The following tables gives the estimated slopes by condition aggregated across conditional type:

CONDITION	**HH**	**HL**	**LH**	**LL**
PO	0.83	0.86	0.78	0.58
NE	0.56	0.67	0.45	0.60
IR	0.43	0.41	0.23	0.52


HH
Acc(if,then)
PO
NE
IR
P(if,then)
Dependent variable
P(C|A)
0
25
50
75
100


HL
Acc(if,then)
PO
NE
IR
P(if,then)
Dependent variable
P(C|A)
0
25
50
75
100

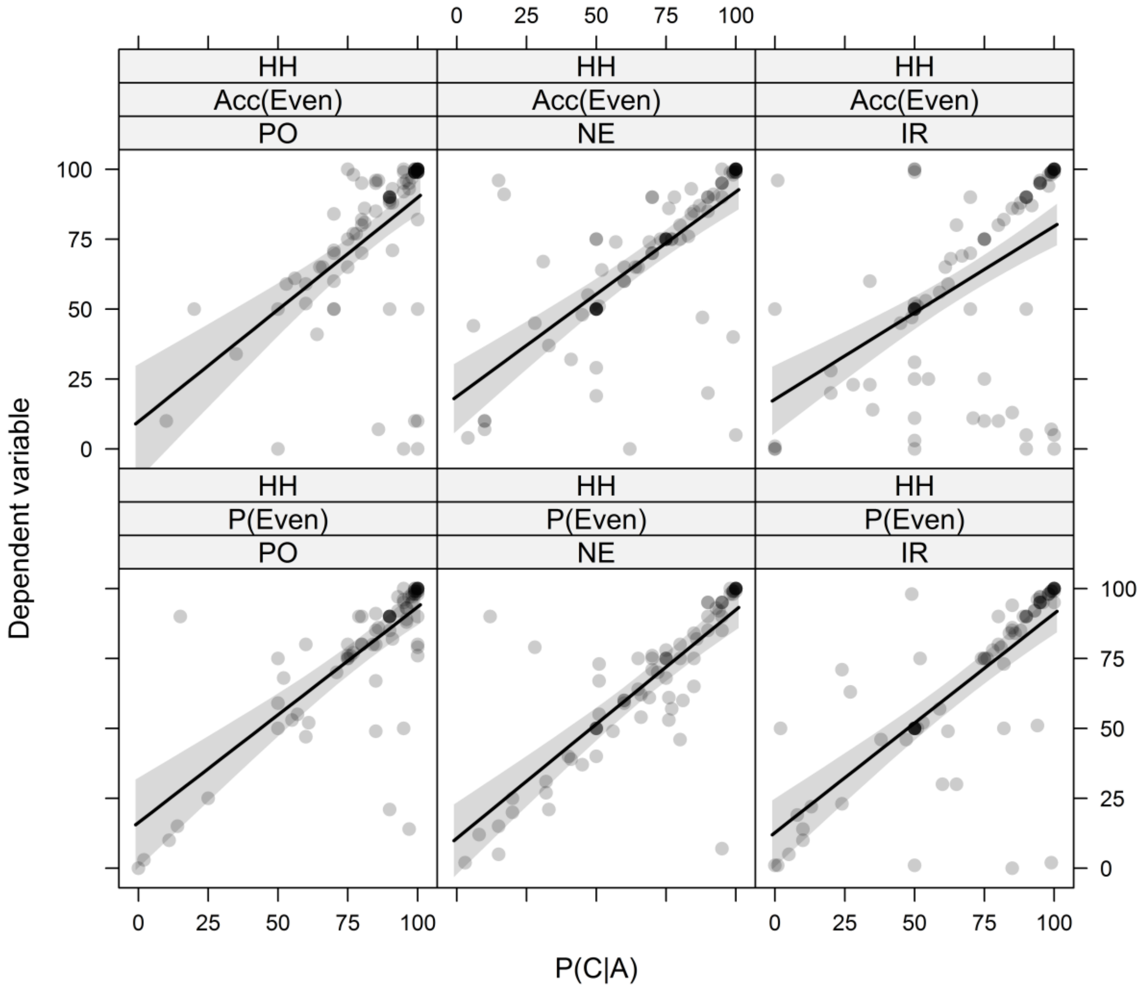

LH
Acc(if,then)
PO
NE
IR
P(if,then)
0
25
50
75
100
Dependent variable
P(C|A)

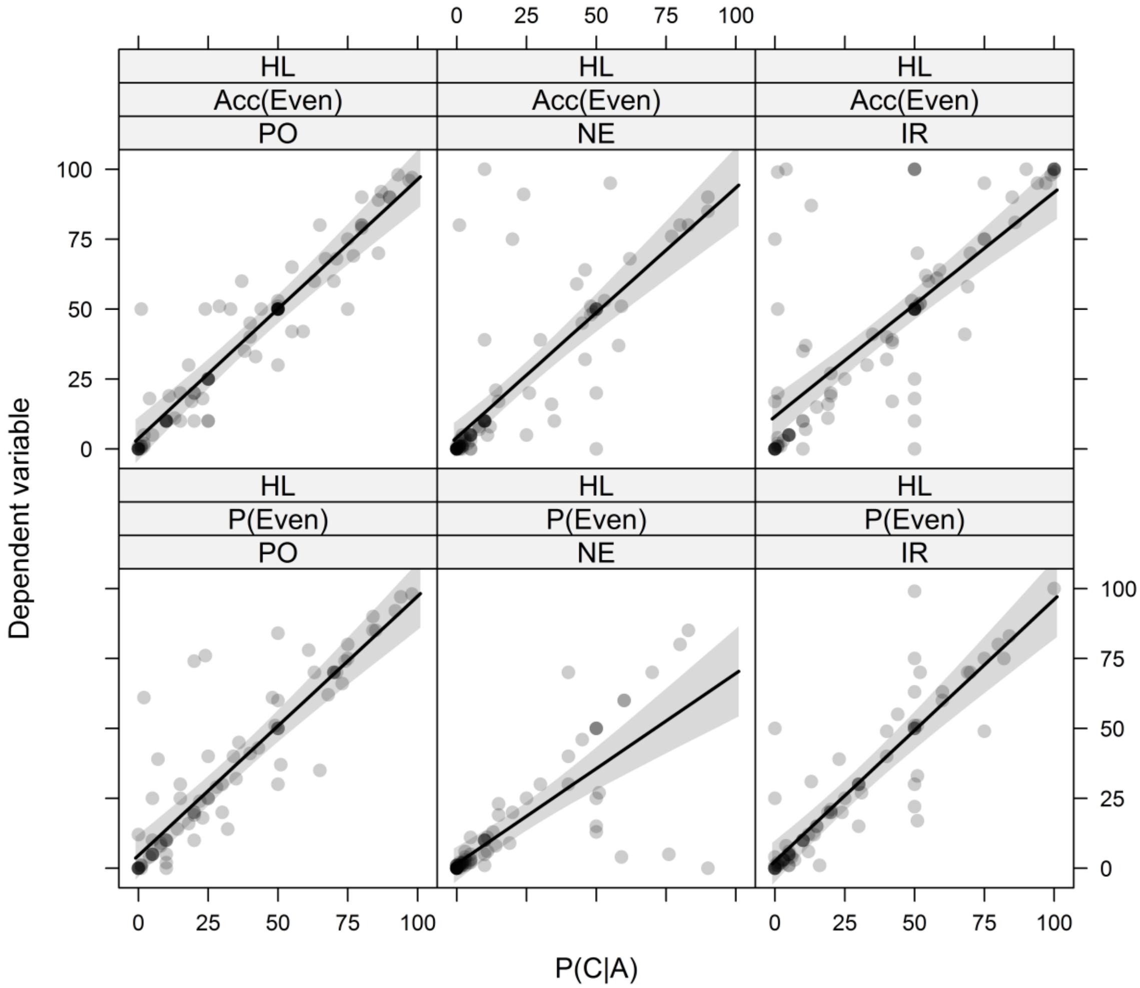

LL
Acc(if,then)
PO
NE
IR
P(if,then)
Dependent variable
P(C|A)
0
25
50
75
100

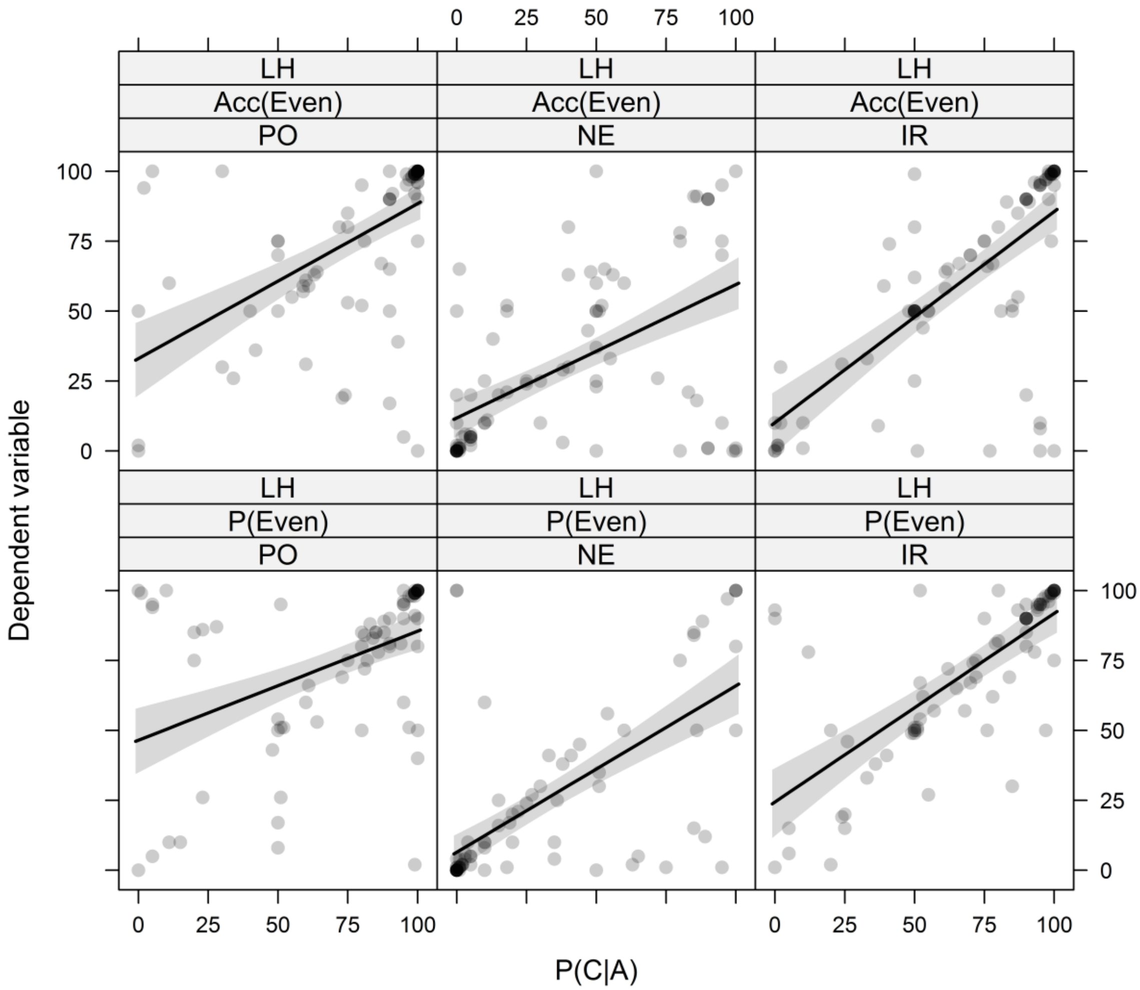
Concessive Conditionals by Prior Manipulation

For the concessive conditionals the following plots show the data by prior manipulation; the order is again HH, HL, LH, and LL. As before, the prior of the consequent (i.e., the second letter) seems to have a strong effect on where on the y-axis most of the data mass was located. For HH and LH, most data points were on the right side of the scale and for LH and LL most of the data points were on the left side of the scale. Also replicating the findings from the indicative conditionals, the only real outliers of this pattern seemed to be LH for NE and LL for PO.

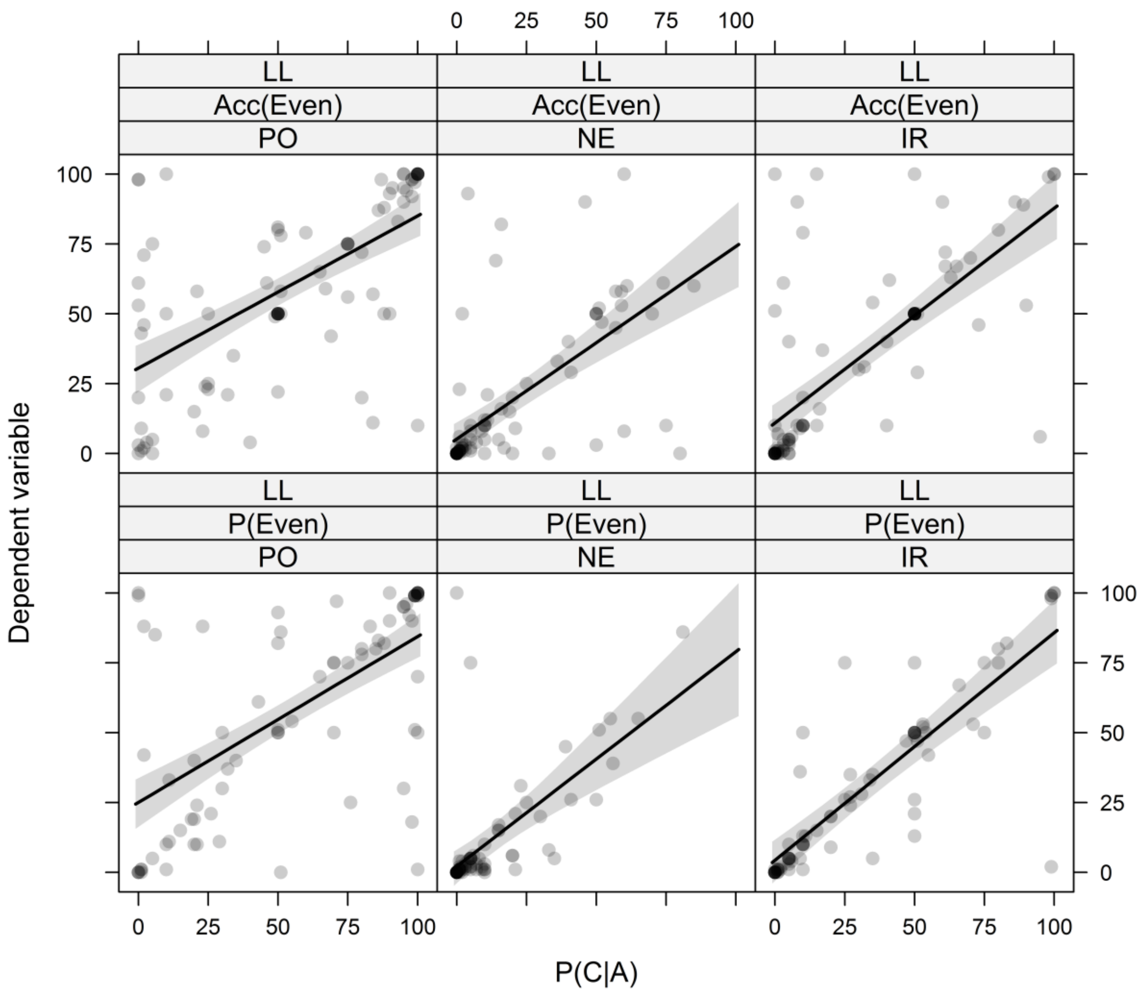
As for the indicative conditionals, the pattern obtained for the full data set was also mostly replicated for each prior manipulation. For HH and HL the pattern was perfectly replicated despite the lowered spread (although there was some imprecision in the estimates at those parts of the scale for which there was little data). For LH and LL there was more variance in the estimated slopes but this was again due to some influential outliers: in the PO and NE conditions most data was so lumped at the ends of the scale that just a few outliers were enough to drag the slope away from 1. There did not seem to be any systematic deviation from the overall pattern.


HH
Acc(Even)
PO
NE
IR
P(Even)
Dependent variable
P(C|A)
0
25
50
75
100


HL
Acc(Even)
PO
HL
Acc(Even)
NE
HL
Acc(Even)
IR
HL
P(Even)
PO
HL
P(Even)
NE
HL
P(Even)
IR
Dependent variable
P(C|A)
0
25
50
75
100



LH
Acc(Even)
PO
LH
Acc(Even)
NE
LH
Acc(Even)
IR
LH
P(Even)
PO
LH
P(Even)
NE
LH
P(Even)
IR
Dependent variable
P(C|A)
0
25
50
75
100


LL
Acc(Even)
PO
NE
IR
P(Even)
0
25
50
75
100
Dependent variable
P(C|A)

Analysis of Individual Regressions

Our hierarchical modeling approach (LMM) ensured that the individual estimates were distributed nicely around the mean slope estimate for each condition via shrinkage of the individual parameters. This allowed us to perform a joint analysis of all participants while simultaneously controlling for random participant and item (i.e., scenario) variability. However, this parameter shrinkage might not be completely desired at this point as it might mask a bimodal distribution of the slopes in the IR condition. Consequently, we also estimated individual regressions for each participant and condition, which are displayed in the following figure. In total we estimated 1044 individual regressions (348 x 3) of which 25 slopes were above 1.5 (max = 6.4), 2 were below -1.5 (min = -2.12), and 13 could not be estimated (as the conditional probabilities were constant).

For the indicative conditionals the figure shows a pattern very similar to the LMM estimates, but also hinted at a bimodal distribution in (at least) the IR condition with one peak around 0 and one peak around 1. The median slope estimate was 0.96 in the PO condition, 0.60 in the NE condition, and 0.29 in the IR condition confirming the pattern of the LMM analysis (the mean estimates were close to the LMM means, as shown when comparing the next figure to Figure 2 in the main text).

For the concessive conditionals, the median estimates from the individual regressions were 0.91 (PO), 0.94 (NE) and 0.93 (IR).

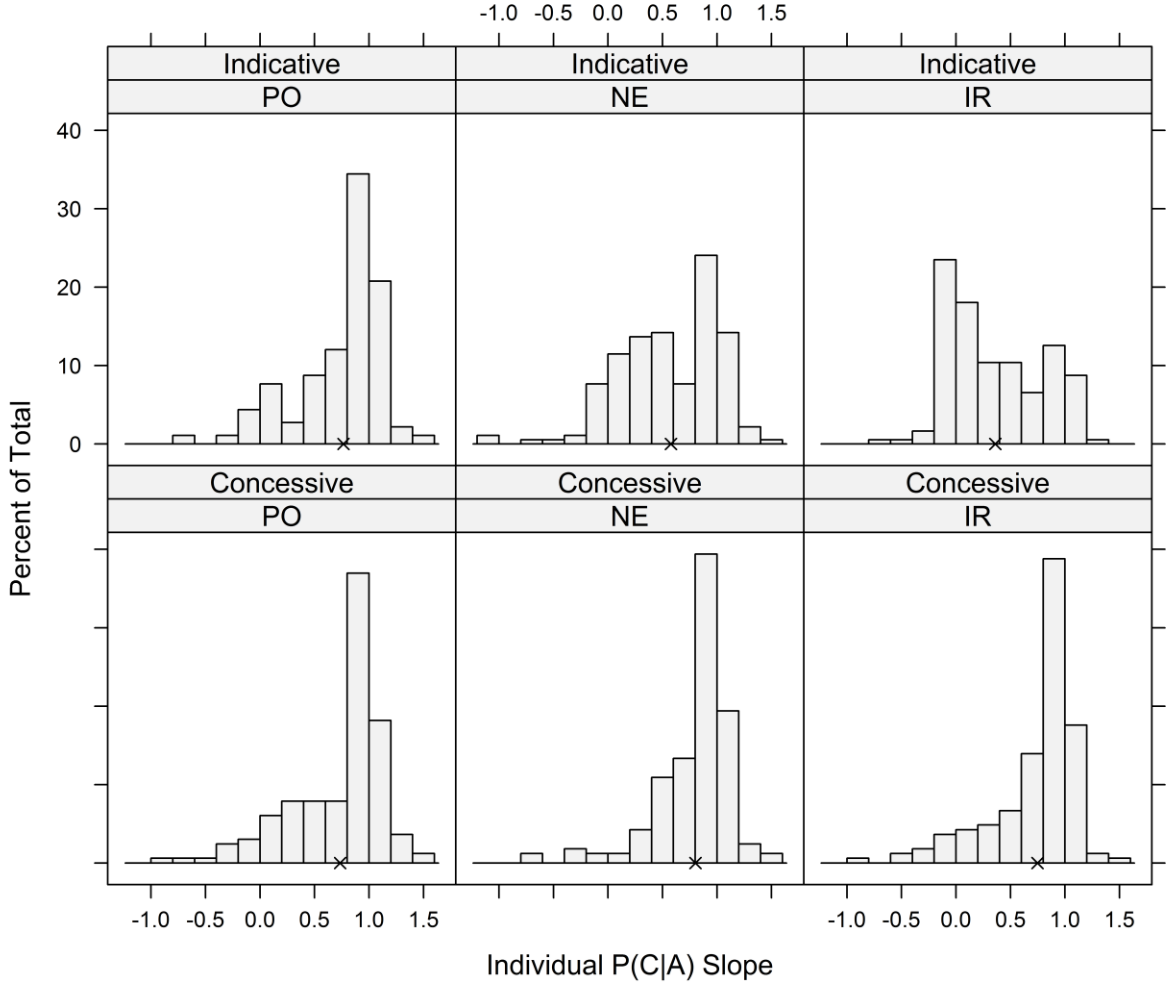


Figure SLOPES. Individual slope estimates for the effect of conditional probability P(C|A) on the dependent variable across conditions. These estimates are derived from individual regressions per relevance condition based on four data points each. In each plot each participant provided one slope estimate. We excluded estimates above 1.5 and below -1.5. The x denotes the mean of the displayed estimates.