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The probability of causal conditionals

David E. Over^{a,*}, Constantinos Hadjichristidis^b,
Jonathan St. B.T. Evans^c, Simon J. Handley^c, Steven A. Sloman^d

^a Psychology Department, University of Sunderland, Sunderland SR6 0DD, UK

^b University of Leeds, UK

^c University of Plymouth, UK

^d Brown University, USA

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Abstract

Conditionals in natural language are central to reasoning and decision making. A theoretical proposal called the Ramsey test implies the conditional probability hypothesis: that the subjective probability of a natural language conditional, $P(\text{if } p \text{ then } q)$, is the conditional subjective probability, $P(q|p)$. We report three experiments on causal indicative conditionals and related counterfactuals that support this hypothesis. We measured the probabilities people assigned to truth table cases, $P(pq)$, $P(p\neg q)$, $P(\neg pq)$ and $P(\neg p\neg q)$. From these ratings, we computed three independent predictors, $P(p)$, $P(q|p)$ and $P(q|\neg p)$, that we then entered into a regression equation with judged $P(\text{if } p \text{ then } q)$ as the dependent variable. In line with the conditional probability hypothesis, $P(q|p)$ was by far the strongest predictor in our experiments. This result is inconsistent with the claim that causal conditionals are the material conditionals of elementary logic. Instead, it supports the Ramsey test hypothesis, implying that common processes underlie the use of conditionals in reasoning and judgments of conditional probability in decision making.

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* Corresponding author. Fax: +44 0191 515 2308.

E-mail address: david.over@sunderland.ac.uk (D.E. Over).

28 1. Introduction

29 Conditional statements are ubiquitous in both ordinary and scientific discourse. They
30 are used for many purposes, from laying down rules for guiding behaviour to expressing
31 scientific hypotheses (Evans & Over, 2004). One basic use of conditionals is to express
32 uncertainty. We are unsure about the weather, and so we say that we will have an alfresco
33 lunch *if* it is sunny. We are unconvinced by our colleagues' arguments, but conclude that
34 their theory will be confirmed *if* there is a significant result in an experiment. Uncertainty
35 is always with us in human affairs, and indicative conditionals are of great importance for
36 this reason alone. It is unsurprising that so much research has been done on them since the
37 ancient Greeks (Sanford, 1989).

38 Though people often use a conditional to express uncertainty, they can of course be
39 uncertain about the conditional itself. They can have high or low confidence in it, judging
40 it to have high or low probability. For a Saturday in the summer, our friends can be fairly
41 confident that, if it is sunny, we will have an alfresco lunch. Our colleagues would be less
42 confident that, if we are given a deadline for finishing our marking, then we will meet it.

43 1.1. The subjective probability of a conditional

44 Consider an ordinary indicative conditional, of the form 'if p then q,' in natural
45 language:

46 (1) If the cost of petrol increases (p), then traffic congestion will improve (q).

47 Suppose (1) is asserted about a possible increase in the cost of petrol (or gasoline) at a par-
48 ticular time in the UK (or the USA). People make subjective probability judgments about
49 conditionals like (1) all the time in ordinary affairs. The question is how they do it. Ramsey
50 (1931/1990, p. 247) hypothesized that people could judge 'if p then q' by '...adding p
51 hypothetically to their stock of knowledge and arguing on that basis about q...' By these
52 means, they would then fix '...their degrees of belief in q given p...' which would be their
53 degrees of conditional subjective probability, $P(q|p)$. This suggested procedure for making
54 a probability judgment about a conditional came to be known as the *Ramsey test*. It
55 implies that common processes underlie judgments about conditionals and conditional
56 probability. At one extreme, people can deduce q from p with valid inferences in a Ramsey
57 test, and then $P(\text{if } p \text{ then } q)$ and $P(q|p)$ will be 1. At the other extreme, people will judge p
58 and q to be inconsistent, and then $P(\text{if } p \text{ then } q)$ and $P(q|p)$ will be 0. In many more cases,
59 people will use inductive inferences, heuristics, or causal models in a Ramsey test, and then
60 $P(\text{if } p \text{ then } q)$ and $P(q|p)$ will be between 0 and 1. Explaining how the Ramsey test is actu-
61 ally implemented—by means of deduction, induction, heuristics, causal models, and other
62 processes—is a major challenge, in our view, in the psychology of reasoning.

63 The consequence of the Ramsey test, that $P(\text{if } p \text{ then } q)$ is $P(q|p)$, has been very influ-
64 ential in philosophical logic. Leading philosophical logicians (Adams, 1975, 1998; Bennett,
65 2003; Edgington, 1995, 2003; Ramsey, 1931; Stalnaker, 1968) have long argued for this
66 consequence. A famous proof in philosophical logic by Lewis (1976) established that
67 $P(\text{if } p \text{ then } q)$ cannot be identical with $P(q|p)$ if we accept some prominent analyses of con-
68 ditionals, e.g., that of Stalnaker (1968), though it can if we accept others, e.g., that of
69 Adams (1975, 1998). Whether or not $P(\text{if } p \text{ then } q)$ should be $P(q|p)$ has implications in

70 philosophical logic about whether conditionals always express propositions that are objec-
71 tively true or false (Bennett, 2003, has an account of Lewis's proof and what it implies).

72 In this paper, we will be concerned with experimental tests of the consequence of a
73 Ramsey test: the *conditional probability hypothesis* that the subjective probability of a condi-
74 tional, $P(\text{if } p \text{ then } q)$, is the conditional subjective probability of q given p , $P(q|p)$. Rips
75 and Marcus (1977) were the first psychologists to state a theory that implied the condition-
76 al probability hypothesis. They were influenced by Stalnaker (1968) and described a kind
77 of Ramsey test for making judgments about conditionals. However, they did not support
78 their theory with experimental studies of the relation between the probability of condition-
79 als and conditional probability (see Evans & Over, 2004, Ch. 4, for an extended account
80 and evaluation of Rips & Marcus's theory). Much more recently, other psychologists and
81 some linguists have become interested in the conditional probability hypothesis
82 (Kaufmann, 2004, 2005; Liu, Lo, & Wu, 1996; Oaksford & Chater, 1998, 2003; Oaksford,
83 Chater, & Larkin, 2000; Politzer & Bourmand, 2002; Stevenson & Over, 1995, 2001). The
84 hypothesis has been supported in a number of psychological experiments (Evans, Handley,
85 & Over, 2003; Evans, Over, & Handley, 2005; Hadjichristidis et al., 2001; Oberauer, Gei-
86 ger, Fischer, & Weidenfeld, in press; Oberauer & Wilhelm, 2003; Ohm & Thompson, in
87 press; Over & Evans, 2003). On the other hand, Girotto and Johnson-Laird (2004, p.
88 224) argued that a result in Oberauer and Wilhelm (2003) does not support the conditional
89 probability hypothesis. Girotto and Johnson-Laird also found that a minority of partici-
90 pants conformed to the hypothesis. They concluded (p. 224), '...not that the conditional
91 probability hypothesis is false, but rather that its use is only *one* of the strategies that naive
92 individuals use in estimating the probability of conditional extensionally' (emphasis in the
93 original).

94 One limitation of the above experiments (with the exception to some extent of Hadji-
95 christidis et al., 2001 & Over & Evans, 2003) is that they only concern conditionals about
96 frequency distributions that are assumed to be understood by the participants. An exam-
97 ple is a conditional about a specific card randomly drawn from a pack of cards of different
98 colours and shapes:

99 (2) If the card is yellow, then it has a circle on it.

100 Conditionals like (2) are sometimes called *basic conditionals*. They have a '...neutral con-
101 tent that is as independent as possible from context and background knowledge...' (John-
102 son-Laird & Byrne, 2002, p. 648). In most early experiments, minimal background
103 information was given on the relevant frequency distribution, e.g., on the number of cards
104 in the pack of different colours and shapes. People do sometimes make judgments about
105 cases like these in ordinary affairs, a simple gamble being an obvious example. Studying
106 these examples might also reveal how people try to use relevant frequency distributions
107 in more complex or difficult cases.

108 However, people use many conditionals in ordinary reasoning and decision making
109 when there is no known relevant frequency distribution. The conditional probability
110 hypothesis is about *subjective* probability. It is the claim that people's subjective judgment
111 about $P(\text{if } p \text{ then } q)$ will be the same as their subjective judgment about $P(q|p)$. People can
112 base their subjective confidence in a conditional on relevant frequency information. But in
113 the absence of this, they can use inductive or categorical inferences (Hadjichristidis et al.,
114 2001), heuristics (Evans & Over, 2004), or causal models (Sloman, 2005). The Ramsey test

115 can be seen as a special case of the simulation heuristic of Kahneman and Tversky (1982)
116 applied to conditionals. When running a simulation from p , people can apply other heu-
117 ristics, such as availability, and inductive inferences and causal models to try to find a rela-
118 tion between p and q (Keren & Teigen, 2004; Lagnado & Sloman, 2004).

119 Almost all conditionals that are central to reasoning and decision making, from ordin-
120 ary affairs to scientific research, are non-basic. The assertion of these conditionals depends
121 very much on their ‘non-neutral’ content and on context and background knowledge. Pre-
122 vious experiments on basic conditionals about simple frequency distributions yield no
123 results about people’s probability judgments under the influence of content, context,
124 and background knowledge. Our aim here is to change the emphasis of previous experi-
125 mental research, by concentrating on non-basic conditionals of a sort that are ubiquitous
126 in real-world reasoning and decision making. We will focus on indicative conditionals like
127 (1) and closely related counterfactuals. Such conditionals can be called *causal conditionals*
128 in the weak sense that they can be justified by evidence about a possible causal relation or
129 mechanism. One question we will ask about these conditionals is whether they are properly
130 called ‘causal’ in the strong sense that they actually express a causal relation.

131 We can easily ask people to rate their confidence in (1). However, Girotto and Johnson-
132 Laird (2004) have argued that some care is necessary in how this question is formulated.
133 They contend (p. 208) that a question

134 (Q1) What is the probability that if p then q ?

135 can be easily re-interpreted as the question

136 (Q2) If p , what is the probability of q ?

137 They assume that the probability operator in (Q2) is applied only to what they call (p. 208)
138 the main clause, i.e., to the consequent q , rather than to the whole conditional, as it clearly
139 seems to be, to us, in (Q1). They claim that a question of the form (Q2) is ‘...a direct
140 request for the conditional probability’ (p. 223). It is, however, a logical fallacy to claim
141 that (Q2), with the probability operator applied to the main clause, is a request for the
142 conditional probability. This *modal fallacy*, as it is called, implies the absurd consequence
143 that all subjective probabilities collapse to 1 or 0 (Edgington, 1995, p. 269). Another
144 instance of the fallacy is to hold that in ordinary conditionals of the form, ‘if p then nec-
145 essarily q ,’ the necessity attaches to the main clause. This implies the absurd consequence
146 that all propositions are either necessarily true or necessarily false (see Swartz, 1999, for a
147 general introduction to the modal fallacy that covers its probabilistic instance).

148 The general view in philosophical logic is that the ambiguity is in (Q2) and not in (Q1).
149 The probability operator in (Q1) is clearly applied to the conditional as a whole, but in
150 (Q2) it might be applied to the whole conditional or only to its main clause. According
151 to Kaufmann (personal communication), the general view among linguists is that people
152 will interpret questions like (Q2) as (Q1), at least where the operator is epistemic. People
153 who responded to (Q2) in an experiment with the conditional probability could be inter-
154 preting (Q2) as (Q1). By the conditional probability hypothesis, it is the answer to (Q1),
155 with the probability operator applied to *the whole conditional*, that is $P(q|p)$, the condition-
156 al probability judgment. (See again Edgington, 1995, on why the conditional probability
157 hypothesis takes this form.)

158 When evaluating a causal conditional, ‘if p then q,’ we can ask whether the antecedent
159 event p causes the consequent event q, in order to justify a conditional probability judge-
160 ment, $P(q|p)$. But if we attached subjective probability to the main clause q, then our ques-
161 tion would become whether the p event caused in us a mental state of confidence in q, and
162 *this* question is not about $P(q|p)$. Consider running a Ramsey test on the conditional, ‘if
163 the salesman is a brilliant con man then he is deceiving us.’ In the test for this example,
164 we subjectively see a causal relation between his being a brilliant con man and his deceiv-
165 ing us. That is why we have high confidence in the conditional *as a whole* and the condi-
166 tional probability, $P(\text{deceiving us}|\text{brilliant con man})$, is high. If the confidence attached to
167 the main clause, then the question would be whether his being a brilliant con man causes
168 us to have high confidence that he is deceiving us. But of course his being a brilliant con
169 man does not cause us to have high confidence that he is deceiving us, but rather high con-
170 fidence that he is *not* deceiving us. That illustrates why we should not commit the modal
171 fallacy of imagining that the subjective probability is attached to the main clause: that the
172 con man is deceiving us.

173 Logicians and linguists call the type of ambiguity that we are illustrating in (Q2) a *scope*
174 *ambiguity*, as it concerns the scope of application of the probability operator. Questions
175 like (Q2) should not be asked in experiments because of the ambiguity. In fact, to forestall
176 all questions about ambiguity, we have avoided both (Q1) and (Q2) in all our work on
177 conditionals. We have followed a suggestion of Johnson-Laird (personal communication)
178 of asking participants how likely a *claim* or *sentence* like (1) or (2) is to be *true*. In
179 Hadjichristidis et al. (2001) we attributed the claim to a person (called ‘Peter’), as suggest-
180 ed later by Girotto and Johnson-Laird (2004). But in other work, we have got similar
181 results just by using phrases like ‘the following statement’ (Evans et al., 2003; Over &
182 Evans, 2003). We adopted this practice in the experiments reported here, using the follow-
183 ing general form.

184 For each of the following, could you please rate the probability that the statement is
185 TRUE:
186 If the cost of petrol increases, then traffic congestion will improve.
187 ...
188 ...
189 ...

190 As shown above, we placed the probability operator before the truth operator, and fol-
191 lowed that with a list of the conditionals to be rated on separate lines. The purpose of this
192 procedure was to make it as unlikely as possible that the participants would ‘jump’ the
193 probability operator over the truth operator and then all the way down to the consequent,
194 or the main clause, of each conditional in the list. We note that Girotto and Johnson-Laird
195 (2004, p. 223) report that they ‘...tried to block the re-interpretation of the question about
196 the probability of a conditional as the conditional probability’ but ‘...individuals still have
197 a tendency to re-interpret the question as a question about a conditional probability.’ For
198 some reason that we do not understand, they do not see their difficulty in blocking the con-
199 ditional probability interpretation as evidence for the conditional probability hypothesis.
200 We do.

201 We could also directly ask people for their judgments about the conditional probability
202 of q given p. The problem with such a direct question is that ordinary people might not
203 interpret it in the way the experimenters intend. The ‘given that’ construction is common

204 in technical language. But according to the conditional probability hypothesis itself, the
 205 natural way to express a conditional probability judgment in natural language is to express
 206 a degree of confidence in a conditional. To use the ‘given that’ construction in natural lan-
 207 guage could be confusing and hard for the participants to interpret. In this paper, we will
 208 use a new technique (introduced briefly in Over & Evans, 2003) to obtain *implicit* condi-
 209 tional probability judgments. (Manktelow & Over, 1995; Over, Manktelow, & Hadjichris-
 210 tidis, 2004, proposed and used a version of this technique to study deontic conditionals,
 211 and Oaksford & Moussakowski, 2004; Oaksford & Wakefield, 2003, used another version
 212 of it to study the selection task.)

213 Using our technique, we ask the participants for their probability judgments about four
 214 natural language conjunctions that would often be expressed in ordinary contexts. These
 215 conjunctions correspond to the four possible states of affairs that might be relevant to the
 216 probability of a conditional of the form ‘if p then q’ like (1). First, it could true (T) that the
 217 cost of petrol will increase and true (T) that traffic congestion will improve. This is a ‘p &
 218 q,’ or TT, possibility. Second, it could be true (T) that the cost of petrol will increase but
 219 false (F) that traffic congestion will improve. This is ‘p & not-q,’ or TF, possibility. Third,
 220 it could be false (F) that the cost of petrol will increase but true (T) that traffic congestion
 221 will improve. This is a ‘not-p & q,’ or FT, possibility. And fourth, it could be false (F) that
 222 the cost of petrol will increase and false (F) that traffic congestion will improve. This is a
 223 ‘not-p & not-q,’ or FF, possibility.

224 The participants do not have to understand what ‘conditional probability’ and the ‘giv-
 225 en that’ construction mean in the technical sense. They only have to give us their degrees of
 226 confidence in the four natural language conjunctions: ‘p & q’ (TT), ‘p & not-q’ (TF), ‘not-
 227 p & q’ (FT), and ‘not-p & not-q’ (FF). We can use these probabilities to derive an implicit
 228 conditional probability judgment, $P(q|p)$, that is,

$$230 \quad \frac{P(p \ \& \ q)}{P(p \ \& \ q) + P(p \ \& \ \text{not-}q)},$$

231 for each participant. Finally, we can compare this implicit conditional probability judg-
 232 ment with each participant’s explicit probability judgment about (1), ‘if p then q’. Notice
 233 how strong a test this is of the conditional probability hypothesis. Any computational lim-
 234 itations or biases that people possess that apply differentially to the different kinds of prob-
 235 ability judgment work against the prediction that people’s explicit judgments about $P(\text{if } p$
 236 $\text{then } q)$ will equal their implicit $P(q|p)$.

237 1.2. The material conditional

238 There is another point of view that makes a different prediction about how the partic-
 239 ipants’ explicit judgments will be related to their implicit judgments. If conditionals like (1)
 240 were the material, truth functional conditional of elementary extensional logic, then ‘if p
 241 then q’ would be logically equivalent to ‘not-p or q’ and be true in TT, FT, and FF, but
 242 false in TF. That would mean that $P(\text{if } p \text{ then } q)$ would be $P(\text{not-}p \text{ or } q)$, which is $P(p \ \& \ q) + P(\text{not-}p \ \& \ q) + P(\text{not-}p \ \& \ \text{not-}q)$. Some philosophers (see Bennett, 2003, for a review)
 244 would predict this equality, as they have held that conditionals like (1) are simply material
 245 conditionals.

246 In psychology, Johnson-Laird and Byrne (1991) originally claimed that conditionals
 247 like (1) are material conditionals. According to their account, people would represent

248 (1) with an initial mental model of the conjunction, ‘p & q,’ plus some indication that there
249 are other, implicit models. People would also, in some circumstances, make the implicit
250 mental models fully explicit. These explicit mental models would reveal the conditional
251 to be a material conditional, with models corresponding to those for ‘p & q,’ ‘not-p &
252 q,’ and ‘not-p & not-q.’ Thus two competing predictions can be derived from the mental
253 model theory of Johnson-Laird and Byrne (1991; see also Johnson-Laird, Legrenzi,
254 Girotto, Legrenzi and Caverni, 1999). Many people, with only an initial model for ‘if p
255 then q,’ would judge $P(\text{if } p \text{ then } q)$ to be $P(p \ \& \ q)$. We will call this claim the *conjunctive*
256 *probability hypothesis*. Other people, with fully explicit models, would judge $P(\text{if } p \text{ then } q)$
257 to be $P(p \ \& \ q) + P(\text{not-}p \ \& \ q) + P(\text{not-}p \ \& \ \text{not-}q)$. We will call this claim the *material con-*
258 *ditional hypothesis*.

259 Johnson-Laird and Byrne (2002), in the most recent version of mental model theory for
260 conditionals, continue to argue that basic conditionals have a ‘core meaning’ that corre-
261 sponds to the material conditional. They do not, however, make a precise prediction about
262 people’s probability judgments for non-basic conditionals like (1). They do continue to
263 imply the conjunctive probability hypothesis: that the initial mental model of a condition-
264 al, whether basic or non-basic, is ‘p & q,’ with an indication that there are other, implicit
265 models. But they also hold that the specific meaning of a non-basic conditional can some-
266 times ‘modulate’ its core meaning, in a process they term ‘semantic modulation,’ and make
267 it about a relation of some kind, such as a temporal or spatial relation (Johnson-Laird &
268 Byrne, 2002, p. 673). They do not say what the subjective probability of a non-basic con-
269 ditional will be when it is about a temporal, spatial, or other relation (Evans et al., 2005).
270 Of course, such a conditional would be stronger than the mere disjunction ‘not-p or q.’ It
271 would be about a relation between p and q, and its probability would not be $P(\text{not-}p \ \text{or} \ q)$.

272 Johnson-Laird and Byrne (2002, p.655) do discuss an example of a causal conditional,
273 ‘if a patient has malaria then she has a fever.’ But the fully explicit models that they
274 present for it make it equivalent to the disjunction, ‘the patient does not have malaria
275 or she has fever,’ which is the material conditional. Since people have the ability, accord-
276 ing to Johnson-Laird and Byrne (2002), to make mental models fully explicit, their posi-
277 tion seems to be that people’s probability judgments about some causal conditionals will
278 conform to the material conditional hypothesis. In other cases, semantic modulation
279 would make the conditional about a relation and so stronger than the material condi-
280 tional. Our experimental technique can be used to test whether some causal conditionals
281 are treated as material conditionals. In general, it enables us to test the conditional prob-
282 ability, conjunctive probability, and material conditional hypotheses for non-basic
283 conditionals.

284 1.3. Correlation, causation, and the delta-p rule

285 There are two additional proposals that could make more definite predictions about the
286 results of our experiments. These are suggested by some philosophical analyses (Bennett,
287 2003), and by what Johnson-Laird and Byrne (2002) say about semantic modulation. The
288 first is that conditionals like (1) are stronger than an expression that $P(q|p)$ is high: what is
289 additionally expressed is the belief that p *raises* the probability of q. To illustrate, consider:

290 (3) A petrol price increase will raise the probability of an improvement in traffic
291 congestion.

292

293 The first proposal is that (1) has the same meaning as (3). The probability of (1)
294 would then be determined by more than the conditional probability. For (1) would state
295 outright that p will raise the probability of q. The extent to which p raises the probabili-
296 ty of q, or the degree of covariation between p and q, can be measured by the *delta-p*
297 *rule* (Allan, 1980). In our terminology, the delta-p rule states that this degree is given by
298 $P(q|p) - P(q|\text{not-}p)$. Of course, when $P(q|p) - P(q|\text{not-}p)$ is positive, $P(q|p)$ is greater
299 than $P(q)$. Just as we can derive an implicit $P(q|p)$ for each participant from judgments
300 about $P(p \ \& \ q)$ and $P(p \ \& \ \text{not-}q)$, we can derive an implicit $P(q|\text{not-}p)$ from judgments
301 about $P(\text{not-}p \ \& \ q)$ and $P(\text{not-}p \ \& \ \text{not-}q)$. From the implicit $P(q|p)$ and $P(q|\text{not-}p)$, we
302 get an implicit $P(q|p) - P(q|\text{not-}p)$ and can see whether this relates to an explicit judg-
303 ment about $P(\text{if } p \text{ then } q)$. A relation to the delta-p rule would be predicted if a condi-
304 tional like (1) had the same meaning as (3). It could also be predicted on the basis of
305 Johnson-Laird and Byrne (2002) if the relation introduced by semantic modulation
306 was one that implied a correlation between p and q. We will call this prediction the
307 *covariation proposal*.

308 The second possible proposal is stronger still, and we will call it the *causal proposal*.
309 According to it, conditionals like (1) state outright that p causes q. As we have already
310 noted, the conditionals studied in this paper could be called ‘causal conditionals.’ We
311 use this label for conditionals that are at least justified by evidence of a causal relation
312 between p and q. These conditionals could be justified in this way even if they were
313 only material conditionals or just expressed conditional probability judgments. It is
314 an open question, to be tested experimentally, whether they should be called ‘causal’
315 in a stronger sense. One stronger sense would be that they express a correlation judg-
316 ment, as in the covariation proposal. But our causal proposal is stronger still: that
317 these conditionals are semantically equivalent to the statement that p causes q.
318 Consider:

319 (4) A petrol price increase will cause traffic congestion to improve.

320

321 Under the causal proposal, (1) is not only justified by evidence for (4), but (1) has
322 the same meaning as (4). This proposal could also be made on the basis of Johnson-
323 Laird and Byrne (2002) if the relation introduced by semantic modulation was one
324 of causation between p and q. Another possibility is that semantic modulation intro-
325 duces a model of a causal mechanism connecting p and q (Johnson-Laird, personal
326 communication). Under the causal proposal, (1) is stronger than an expression that
327 $P(q|p)$ is high *and* stronger than the statement that p raises the probability of q. For
328 (4) can be false when both $P(q|p)$ is high and $P(q|p) - P(q|\text{not-}p)$ is high. There
329 could, for example, be a spurious correlation between p and q. Nevertheless, there
330 cannot be a causal relation between p and q if $P(q|p) = P(q|\text{not-}p)$, for p and q
331 would then be statistically independent. In recent analyses of causal strength (Cheng,
332 1997; Pearl, 2000), $P(q|p) - P(q|\text{not-}p) > 0$ is a necessary condition for p to be a
333 cause of q.

334 Both the covariation proposal and the causal proposal imply that the probability of a
335 conditional like (1) will be related to the delta-p rule. Both proposals imply that $P(\text{if } p \text{ then } q)$
336 will be positively influenced by $P(q|p)$ but negatively influenced by $P(q|\text{not-}p)$. We will
337 call this prediction the *delta-p rule hypothesis*.

338 1.4. The experiments

339 The antecedents and consequents of the conditionals in Experiments 1 and 2 could be
340 used to make predictions about current events. Participants were instructed to estimate the
341 probability that the events named would occur in the UK in the next 10 years. For exper-
342 imental completeness within our type of conditional, ‘if p then q,’ we sought to cover all
343 four cases in which the antecedent probabilities, $P(p)$, and the consequent probabilities,
344 $P(q)$, were either high or low. We will refer to these four permutations using HH, HL,
345 LH, and LL, which are, respectively, cases in which $P(p)$ is high and $P(q)$ is high, $P(p)$
346 is high and $P(q)$ is low, $P(p)$ is low and $P(q)$ is high, and $P(p)$ is low and $P(q)$ is low.
347 (See Oaksford, Chater, & Grainger, 1999; Oaksford et al., 2000, on the first use of the
348 method of getting prior ratings of $P(p)$ and $P(q)$, and on why these four cases are also
349 of theoretical interest.) Conditionals were selected in each of the cases on the basis of
350 pre-test ratings from an initially larger set. The participants who did the pre-test ratings
351 ($N = 21$) were different from those used in the experiment proper, but were drawn from
352 the same population. They were never shown conditional statements as such, but rated
353 42 antecedent probabilities, $P(p)$, and 42 consequent probabilities, $P(q)$, drawn from 42
354 conditional statements devised by the authors. These were randomly ordered with the pro-
355 viso that an antecedent and a consequent from the same conditional were presented at dif-
356 ferent points in the list. On the basis of this pre-test, 32 conditionals were selected for use
357 in the experiment proper (see Table 1). The experiments were conducted before May 2002
358 at which time none of the specified antecedent events had occurred.

359 In Experiment 3, we evaluate our hypotheses using a type of counterfactual conditional
360 that is closely related to the causal indicative conditionals we study in Experiments 1 and
361 2, differing perhaps only in time orientation. The counterfactuals referred to events that
362 could have, but did not in fact, occur in the last 5 years. There is an extensive literature
363 on counterfactuals in judgment and decision making and social psychology (Byrne,
364 2005; Mandel, Catellani, & Hilton, 2005; Roese, 2005). But this does not include analyses
365 of people’s subjective probability judgments about conditionals. To our knowledge, our
366 experiments are the first on people’s probability judgments about counterfactuals.

367 2. Experiment 1

368 The object of Experiment 1 was to investigate four hypotheses about the probability of
369 a causal conditional: as conjunctive probability, as the material conditional, as conditional
370 probability, and as conforming to the delta-p rule. As explained above, Johnson-Laird and
371 Byrne (1991, 2002) imply the conjunctive probability hypothesis. Johnson-Laird and
372 Byrne (1991), and some parts of Johnson-Laird and Byrne (2002), as well as some philo-
373 sopher, imply the material conditional hypothesis. Rips and Marcus (1977) and a number
374 of recent psychologists, along with some other philosophers, imply the conditional prob-
375 ability hypothesis. The covariation and causal proposals imply conforming to the delta-p
376 rule. To simplify our symbolism, let pq be ‘p & q,’ $p\text{---}q$ be ‘p & not-q,’ and so on. Then the
377 four hypotheses make different predictions about what will affect the probability of a con-
378 ditional like (1) in natural language:

379 Conjunctive probability: $P(pq)$

380 Material conditional: $P(MC) = 1 - P(p\text{---}q)$

Table 1

Indicative conditionals used in Experiments 1 and 2, together with pre-test ratings

	P(p)	P(q)
<i>HH conditionals</i>		
If Adidas get more superstars to wear their new football boots then the sales of these boots will increase	0.72	0.59
If the government takes a stricter approach towards individuals refusing employment then unemployment in this country will increase	0.66	0.49
≠If the American economy continues to grow then the European economy will continue to grow	0.71	0.50
If Labour wins the next election then proportional representation will be introduced for parliamentary elections	0.61	0.49
If nurses' salaries are improved then the recruitment of nurses will increase	0.68	0.64
If fertility treatment improves then the world population will rise	0.71	0.83
If car ownership increases then traffic congestion will get worse	0.66	0.84
If computers become more powerful then economic forecasting will improve	0.91	0.56
<i>HL conditionals</i>		
If the cost of petrol increases then traffic congestion will improve	0.89	0.20
If more doctors are trained then NHS waiting lists will increase	0.57	0.38
If immigration laws are made stricter then the number of immigrants in the UK will increase	0.64	0.40
If computer technology continues to develop then unemployment will increase	0.92	0.42
If more people use protective sun creams when sunbathing then the number of deaths due to skin cancer will be reduced	0.67	0.46
If student fees are increased then applications for university places will drop	0.58	0.27
If global warming continues then London will be flooded	0.75	0.18
If the Conservatives change their leader then they will win the next election	0.68	0.35
<i>LH conditionals</i>		
If NHS waiting lists increase then Labour will win the next election	0.38	0.61
If student grants are brought back then university entries will increase	0.24	0.63
If divorce is made more difficult then the number of marriages will increase	0.29	0.63
If European countries maintain current quotas of fish from the North Sea then many species of fish will be endangered	0.45	0.63
If primary school class sizes are reduced then national literacy will improve	0.46	0.58
If unemployment drops then Labour will win the next election	0.49	0.61
If more people take up smoking then tax on cigarettes will be increased	0.42	0.84
If trial by jury is abandoned then convictions of criminals will increase	0.21	0.58
<i>LL conditionals</i>		
If capital punishment is brought back then the murder rate in the UK will increase	0.08	0.32
If governments across the world prosecute tobacco companies then smoking related diseases will increase	0.39	0.38
If less violence is shown on television then the amount of violent crime will be reduced	0.23	0.38

(continued on next page)

Table 1 (continued)

	P(p)	P(q)
If nationalism in the world declines then the number of conflicts in the world will be reduced	0.33	0.27
If the Conservatives win the next election then Britain will leave the European Community	0.35	0.24
If a cure for AIDS is found then sales of condoms will drop	0.45	0.22
If Saddam Hussein is assassinated then Iraq will become a democracy	0.36	0.32
If Tim Henman wins Wimbledon then he will receive a knighthood	0.41	0.21

Note. \neq In Experiment 2 this statement was substituted by ‘If the American economy recovers then the European economy will recover.’

381 Conditional probability: $P(q|p)$

382 Delta-p rule: $P(q|p) - P(q|\neg p)$

383

384 In order to derive the above probabilities, we determined each participant’s judged
385 probability of the four truth table cases, TT, TF, FT, and FF, for each conditional.
386 The participants in Experiment 1 were required to fill out three booklets with proba-
387 bility ratings for the 32 conditionals shown in Table 1. One booklet required judgments
388 of probability for the four truth table cases, one to judge the probability that the whole
389 conditional was true, and one to judge the probability that the whole conditional was
390 false. Experiment 1 consequently provides the opportunity to examine whether judg-
391 ments of the probability of truth and the probability of falsity are complementary
392 (sum to 1).

393 2.1. Method

394 2.1.1. Participants

395 Forty students of the University of Plymouth volunteered to take part in return for a
396 small fee. Participants were tested in small groups.

397 2.1.2. Materials and procedure

398 A repeated measures design was employed with each participant completing the
399 three booklets. Each of these booklets contained items derived from the same 32 con-
400 ditionals (see Table 1). Direct estimations of probabilities as percentages were used
401 throughout. In the truth table task, participants were asked to judge the probability
402 that the specified events would occur in the UK within the next 10 years. The cases
403 were grouped together and a further instruction was that the scores given must total
404 100. For example, corresponding to conditional (1) above, participants were asked to
405 rate four conjunctions corresponding to the four rows of a truth table, TT, TF, FT,
406 and FF:

407 The cost of petrol increases and traffic congestion improves. _____

411 The cost of petrol increases and traffic congestion does not improve. _____

413 The cost of petrol does not increase and traffic congestion improves. _____

416 The cost of petrol does not increase and traffic congestion does not improve. _____

418 _____ 100%

419

420 The other two booklets asked participants to rate between 0 and 100% the probability that
421 the conditional statements given were true or false. Across the booklets, different random
422 presentation orders of items were employed. Order of presentation of the three booklets
423 was randomized.

424 *2.2. Results and discussion*425 *2.2.1. Truth table task*

426 The mean probability estimates for truth table cases are shown in Table 2 and are bro-
427 ken down by the prior classification of conditionals in terms of component probabilities:
428 HH, HL, LH, and LL. The purpose of this task was to provide relevant probability calcula-
429 tions to test our contrasting theories about the perceived probability of conditional
430 statements, reported below. However, as a manipulation check, we first performed analy-
431 ses of variance to see whether the effect of our prior probability judgments of the anteced-
432 ents and consequents was reflected in the judged probability of the four truth table cases.
433 For example, when assessing the probability of a ‘p & not-q’ conjunction, a TF case, we
434 would expect a higher estimate when the antecedent of the associated conditional had been
435 given a high prior probability, P(p), and when the consequent of the associated conditional
436 had been given a low prior probability, P(q). Here and throughout, ANOVAs were com-
437 puted both across participants (reported as F_1) and across sentences (reported as F_2). Note

Table 2
Mean (*SD*) ratings of the four truth table cases in Experiment 1

TT	Consequent probability	
	High	Low
Antecedent probability		
High	45.3 (13.3)	39.2 (15.5)
Low	33.3 (11.6)	24.4 (12.3)
TF	Consequent probability	
	High	Low
Antecedent probability		
High	18.3 (8.7)	24.8 (10.2)
Low	14.6 (5.3)	20.4 (6.3)
FT	Consequent probability	
	High	Low
Antecedent probability		
High	13.5 (7.2)	10.4 (5.4)
Low	23.8 (8.2)	16.0 (7.2)
FF	Consequent probability	
	High	Low
Antecedent probability		
High	20.7 (9.2)	23.0 (10.2)
Low	27.7 (10.7)	38.7 (12.8)

438 that the analyses of the four cases are not independent, as participants were required to
439 make estimates sum to 100%.

440 All ANOVAs found the expected main effects, confirming our prior classification of
441 sentences. TT ratings were higher when antecedent probability was high
442 ($F_1(1, 39) = 46.5$, $MSE = 154$, $p < .001$; $F_2(1, 28) = 20.92$, $MSE = 75.90$, $p < .001$) and
443 when the consequent probability was high ($F_1(1, 39) = 22.2$, $MSE = 100$, $p < .001$;
444 $F_2(1, 28) = 6.63$, $MSE = 75.90$, $p < .05$). TF ratings were higher when antecedent proba-
445 bility was high ($F_1(1, 39) = 10.1$, $MSE = 65.1$, $p < .005$; $F_2(1, 28) = 4.03$, $MSE = 45.21$,
446 $p = .054$) and when consequent probability was low ($F_1(1, 39) = 43.1$, $MSE = 34.7$,
447 $p < .001$; $F_2(1, 28) = 7.13$, $MSE = 45.21$, $p < .05$). FT ratings were higher when antecedent
448 probability was low ($F_1(1, 39) = 79.3$, $MSE = 32.1$, $p < .001$; $F_2(1, 28) = 22.81$,
449 $MSE = 21.20$, $p < .001$) and when consequent probability was high ($F_1(1, 39) = 25.1$,
450 $MSE = 47.1$, $p < .001$; $F_2(1, 28) = 12.63$, $MSE = 21.20$, $p < .001$). Finally, FF ratings were
451 higher when antecedent probability was low ($F_1(1, 39) = 39.9$, $MSE = 129$, $p < .001$;
452 $F_2(1, 28) = 34.52$, $MSE = 29.01$, $p < .001$) and when consequent probability was low
453 ($F_1(1, 39) = 29.3$, $MSE = 60.1$, $p < .001$; $F_2(1, 28) = 12.03$, $MSE = 29.01$, $p < .005$).

454 Significant interactions between the two factors were observed for FF ratings
455 ($F_1(1, 39) = 12.8$, $MSE = 58.6$, $p < .001$; $F_2(1, 28) = 5.54$, $MSE = 29.01$, $p < .05$) and for
456 FT ratings but only across participants ($F_1(1, 39) = 7.6$, $MSE = 28.8$, $p < .01$;
457 $F_2(1, 28) = 2.17$, $MSE = 21.20$, $p = .15$). In both cases, the effect of consequent probability
458 was more marked when the antecedent probability was low.

459 2.2.2. Probability of conditional task

460 The mean probability estimates for each of the probability of conditional tasks are
461 shown in Table 3 and are broken down by the prior classification of conditionals in terms
462 of component probabilities: HH, HL, LH, and LL. For each case, we performed two 2
463 (Antecedent probability) by 2 (Consequent probability) analyses of variance, one across
464 participants and one across items, to examine the effect of antecedent and consequent
465 probabilities. Participants rated conditionals as more probably true when the antecedent
466 probability was high ($F_1(1, 39) = 13.9$, $MSE = 103$, $p < .001$; $F_2(1, 28) = 2.21$,
467 $MSE = 58.96$, $p = .148$) and when the consequent probability was high
468 ($F_1(1, 39) = 35.5$, $MSE = 103$, $p < .001$; $F_2(1, 28) = 5.09$, $MSE = 58.96$, $p < .05$). Similarly,
469 they rated conditionals as more probably false when the antecedent probability was low
470 ($F_1(1, 39) = 9.3$, $MSE = 103$, $p < .005$; $F_2(1, 28) = 1.99$, $MSE = 105.75$, $p = .17$) and when

Table 3

Mean (*SD*) TRUE and FALSE probability of conditional ratings in Experiment 1

TRUE	Consequent probability	
	High	Low
Antecedent probability		
High	60.7 (16.4)	52.2 (16.4)
Low	55.7 (15.5)	45.2 (15.2)
FALSE	Consequent probability	
	High	Low
Antecedent probability		
High	34.1 (17.0)	37.7 (15.2)
Low	36.0 (13.4)	45.5 (13.0)

471 the consequent probability was low ($F_1(1, 39) = 14.1$, $MSE = 122$, $p < .001$;
472 $F_2(1, 28) = 3.75$, $MSE = 105.75$, $p = .063$). The interaction between these two factors
473 was not significant for true ratings and only marginally significant for false ratings across
474 participants ($F_1(1, 39) = 4.0$, $MSE = 85.2$, $p = .053$; $F_2(1, 28) < 1$). The trend is for condi-
475 tionals low in both antecedent and consequent probability to be rated as less probable
476 than other kinds of conditionals. We defer interpretation of these analyses in Section 5.

477 2.2.3. Correlation and regression analyses

478 The analyses of most theoretical interest concern the relation between probabilities
479 computed from the truth table task and the perceived probability of the whole conditional
480 statement. We considered four alternative hypotheses: the material conditional, condition-
481 al probability, conjunctive probability, and the delta-p rule. We computed their predic-
482 tions from the truth table case estimates, as follows.

483 Conjunctive probability: $P(pq) = P(TT)$

484 Material conditional: $P(MC) = P(TT) + P(FT) + P(FF)$

485 Conditional probability: $P(q|p) = P(TT)/[P(TT) + P(TF)]$

486 Delta-p rule: $P(q|p) - P(q|\neg p) = P(q|p) - [P(FT)/[P(FT) + P(FF)]]$

487

488 We analyzed the relation between these probabilities and the probability of conditionals
489 as measured across problem materials (conditional sentences). We first did this by comput-
490 ing the mean of all participants for each sentence and then calculating correlations and
491 regressions on these mean scores (see Table 4). Looking first at the correlations for the
492 four predictions in Table 4(a), we see that all are statistically significant, but the highest
493 correlations are with conditional probability and the lowest with the probability of the
494 material conditional. (In general, judgments of probable falsity reflect those of probable
495 truth.) We then tested for differences among these critical correlations by using the proce-
496 dure outlined in Meng, Rosenthal, and Rubin (1992). The correlation with conditional
497 probability was significantly higher than those with any of the other three predictors

Table 4

Correlations and regressions computed across sentences using mean ratings of all participants in Experiment 1

	TRUE	FALSE
<i>(a) Correlations between judged probability of conditionals as true or false and various probabilities computed from the truth table task</i>		
Hypotheses		
Conjunctive probability	.74*	-.71*
Material conditional	.65*	-.68*
Conditional probability	.89*	-.89*
Delta-p rule	.72*	-.74*
Other		
P(p)	.29	-.25
P(q)	.73*	-.71*
P(q/¬p)	.10	-.08
<i>(b) Multiple regressions using three statistically independent predictors (β weights)</i>		
P(p)	.05	.00
P(q p)	.90*	-.93*
P(q/¬p)	-.11	.14

498 (for all comparisons $p < .05$). That is, the conditional probability hypothesis captured the
499 data significantly better than any of the other three hypotheses.

500 A problem with our four hypotheses is that they are themselves highly correlated (there
501 is a high degree of multicollinearity) making it hard to detect whether their contribution is
502 significant. To get a better idea about the relevant merits of each hypothesis we performed
503 a multiple linear regression analysis with judged probability of the conditional as the
504 dependent measure and three *statistically independently measured* predictors: $P(p)$, $P(q|p)$
505 and $P(q|\neg p)$.¹ The observed multicollinearity between these predictors was minimal.
506 Across our three experiments tolerance values always exceeded .78, which means that
507 the multiple R^2 of a predictor regressed on the other two never exceeded .22. The four
508 hypotheses make different predictions for the probable truth of the conditional:

509 Conjunctive probability: Both $P(p)$ and $P(q|p)$ should be positive predictors since their
510 product equals $P(pq)$.

511 Material conditional: $P(p)$ should be a negative predictor since the material conditional
512 is true when we have not- p .

513 Conditional probability: $P(q|p)$ should be the only predictor of judgments.

514 Delta- p rule: $P(q|p)$ should be a positive predictor and $P(q|\neg p)$ an equally large negative
515 predictor as their difference measures the degree of correlation between p and q .

516
517 The results of this analysis are presented in Table 4(b) and provide further strong sup-
518 port for the conditional probability hypothesis, since $P(q|p)$ have β weights approaching 1
519 (minus 1 for false judgments) and neither of the other predictors differs significantly from
520 0. However, we are aware that averaging across participants might conceal important indi-
521 vidual differences. Hence we repeated these regression analyses for each individual partic-
522 ipant. The results are summarized in Table 5 where we show the mean regression weights
523 across individual participants together with a one-sample t -test to decide whether these
524 differ from zero (test suggested by Lorch & Myers, 1990). These findings confirm strong
525 support for the conditional probability hypothesis since the mean β weights for $P(q|p)$
526 are very substantial (.42 true, $-.38$ false) compared with those for the other predictors.
527 However, a small effect of $P(q|\neg p)$ emerged ($-.08$ true, $.07$ false) in the direction expected
528 by the delta- p rule hypothesis. This is significant for both true and false cases if a one-
529 tailed probability is computed.

¹ An anonymous reviewer asked whether the data in our studies meet the assumptions of linear regression—*linearity* of the relationship between dependent and independent variables, *homoscedasticity* (constant variance) of the error terms, *normality* of the error terms and *independence* (no serial correlation) of the error terms (see, e.g., Hair, Black, Babin, Anderson, & Tatham, 2006). They do. Visual inspection of studentized residual versus standardized predicted value plots for each study showed symmetrical distribution along the horizontal line. Visual inspection of related partial regression plots showed either a linear relation or no relation. Both of these observations support linearity. Visual inspection of studentized residual versus standardized predicted value plots showed homoscedasticity of the error terms (nice cloudy shapes). Levene's tests for homogeneity of variance were not significant (for all $p > .10$), further supporting homoscedasticity. We tested for normality by inspecting normal probability plots. In each case the residuals fell close to the diagonal line. For each study, we also carried out tests to examine whether the kurtosis and skewness were significantly different than 0 – they were not. As for the independence assumption, this was not a concern in the present studies because participants received the various items in different random orders. Moreover, in each study the *Durbin-Watson statistic* was close to 2, which means no serial correlation in the residuals.

Table 5

Multiple regression analyses carried out on individual participants across sentences for three predictors in Experiments 1 and 2

	TRUE			FALSE		
	Mean (SD) β weights	$t(38)$	p	Mean (SD) β weights	$t(38)$	p
<i>(a) Experiment 1</i>						
P(p)	.02 (.19)	.59	ns	.02 (.20)	.61	ns
P(q p)	.42 (.23)	11.30	<.001	-.38 (.28)	-8.29	<.001
P(q -p)	-.08(.18)	-2.84	.007	.07(.23)	1.95	.059
	Probability of conditional			Causal strength		
	Mean (SD) β weights	$t(40)$	p	Mean (SD) β weights	$t(40)$	p
<i>(b) Experiment 2</i>						
P(p)	.16 (.18)	5.51	<.001	.14 (.17)	5.11	<.001
P(q p)	.51 (.21)	15.77	<.001	.50 (.24)	13.24	<.001
P(q -p)	-.015 (.20)	-.51	ns	-.03 (.25)	-.83	ns
	Probability of conditional			Causal strength		
	Mean (SD) β weights	$t(25)$	p	Mean (SD) β weights	$t(25)$	p
<i>(c) Experiment 3</i>						
P(p)	-.04 (.20)	-1.07	ns	.05 (.25)	.94	ns
P(q p)	.42 (.23)	9.33	<.001	.39 (.26)	7.79	<.001
P(q -p)	-.04 (.18)	-1.21	ns	-.11 (.21)	-2.65	<.05

530 2.2.4. Conditionals always true or false?

531 Some philosophical logicians have argued that indicative conditionals are neither true
 532 nor false when their antecedents are false (Adams, 1975, 1998; Bennett, 2003; Edgington,
 533 1995). The claim is that a conditional ‘if p then q’ with a false antecedent p creates a ‘truth
 534 value gap.’ The antecedent p and consequent q can be ‘factual’ statements that are objec-
 535 tively true or objectively false, but the conditional itself is not ‘factual’ (Adams, 1998).
 536 When the antecedent is false, the conditional is held to be neither true nor false objectively,
 537 but people have a subjective confidence in it that equals P(q|p). A conditional of this type
 538 can be called an Adams conditional (Evans & Over, 2004).

539 Fig. 1 displays stacked bar charts of true and false ratings of conditionals. Judgments
 540 summed to around 93% overall. This was shown to be significantly less than 100%, using a

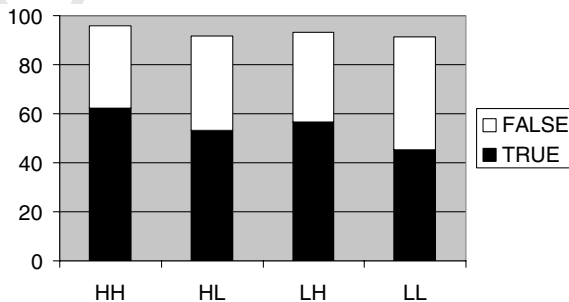


Fig. 1. Stacked TRUE and FALSE ratings of conditionals in Experiment 1.

541 one-sample t -test to compare mean true plus false judgments for each participant with the
542 null hypothesis ($t(39) = 2.50, p < .01$). An analysis of variance carried out on total true
543 plus false ratings produced a significant main effect for consequent probability
544 ($F(1, 39) = 4.28, \text{MSE} = 85.2, p < .05$). High consequent probability items (HH and LH)
545 received higher estimates than low consequent probability items (HL and LL). This vio-
546 lates the prediction of binary complementarity in support theory (Tversky & Koehler,
547 1994) for judgments of event probability (for further violations of this prediction see Mac-
548 chi, Osherson, & Krantz, 1999). The failure of complementarity is driven by a weak trend
549 for scores to be lower when the consequent probabilities were low (HL and LL cases; see
550 Fig. 1). Supposing there are truth value gaps for conditionals, why is there not a more gen-
551 eral failure of complementarity?

552 The question is difficult to answer if one holds *both* that there is a truth value gap when
553 a conditional has false antecedent, *and* that ‘true’ and ‘false’ always have the same strict
554 meanings in natural language. In that case, there should be a significant ‘gap’ between 1
555 and the sum of the probability that a conditional with false antecedent is true and of
556 the probability that it is false. This would have the effect of generally reducing true plus
557 false ratings. However, supporters of the view that conditionals in natural language are
558 Adams conditionals could simply take the result as empirical evidence that ‘true’ and
559 ‘false’ are ambiguous in natural language. They could argue that ‘true’ and ‘false’ do
560 not have the same meaning when applied to a conditional and to its antecedent or conse-
561 quent in our examples. In their view, to say that the antecedent or consequent is ‘probably
562 true’ is to say that it probably corresponds to an objective fact, but to say that the condi-
563 tional itself is ‘probably true’ is just to say it is subjectively probable. The latter is a ‘ple-
564 onastic’ use of ‘true,’ and there does not have to be a truth value gap for that (Edgington,
565 2003). Followers of Adams could argue that this ambiguity in the ordinary use of ‘true’
566 makes truth value gaps for conditionals hard to discover in experiments. We will return
567 to the Adams conditional below, in Section 5.

568 2.2.5. Conclusions

569 Experiment 1 has provided powerful evidence for the conditional probability hypothe-
570 sis. In previously published studies by Evans et al. (2003), Oberauer and Wilhelm (2003),
571 and Over and Evans (2003), it was shown that the judged probability of conditionals was
572 determined by $P(q|p)$ for many participants when abstract, basic conditionals were used
573 with specified probability distributions. The findings of Experiment 1 are stronger than
574 these, in that the conditional probabilities were derived from prior beliefs about relevant
575 possibilities without presenting frequencies, and predict very closely the judged probability
576 of non-basic indicative conditionals. As in earlier studies, there was no evidence at all for
577 the material conditional hypothesis. Moreover, unlike the earlier studies, the conditional
578 probability is the overwhelming factor in these judgments. There was no evidence of a sub-
579 group of people who base their judgments on the conjunctive probability. We will consider
580 what our results imply about the delta- p rule in Section 5.

581 3. Experiment 2

582 One objective of Experiment 2 was to replicate the findings of Experiment 1 with respect
583 to the conditional probability hypothesis. To that end, we again used the truth table task
584 and the true conditional task (the task that asked participants to judge the probability that

585 a conditional is true). Items in Experiment 2 were derived from the same conditionals as
586 items in Experiment 1 (see Table 1), with one exception. The conditional, 'If the American
587 economy continues to grow then the European economy will improve,' was replaced by the
588 conditional, 'If the American economy recovers then the European economy will recover.'
589 At the time we conducted Experiment 2, the American economy was in a recession.

590 A second objective of Experiment 2 was to compare people's judgments of the prob-
591 ability of a conditional with their judgments of the strength of a causal relation
592 between p and q . To that end, Experiment 2 included a causal strength task. Partici-
593 pants were presented with each one of the 32 conditionals and were asked to rate the
594 causal strength of the relation between p and q in each case using a 5-point scale.
595 Higher ratings indicated higher causal strength estimates. The negative effects of
596 $P(q|\neg p)$ were very limited in Experiment 1. It could be argued that this is because par-
597 ticipants were asked to judge the probability that the conditionals were true rather
598 than the strength of the causal relation. The delta- p rule for measuring the degree
599 of correlation between p and q takes the difference between $P(q|p)$ and $P(q|\neg p)$,
600 $P(q|p) - P(q|\neg p)$. A positive difference here is necessary if p is a cause of q (Cheng,
601 1997; Pearl, 2000). It might be that a stronger link would be found with the delta- p
602 rule if participants were asked to rate the causal strength between p and q . Experiment
603 2 provides a test of this hypothesis.

604 3.1. Method

605 3.1.1. Participants

606 Forty-two students of the University of Plymouth volunteered to take part in return for
607 a small fee. Participants were tested in small groups.

608 3.1.2. Materials and procedure

609 The materials and procedure were similar to those of Experiment 1, with the excep-
610 tion that the probability that a conditional is false task was substituted by the causal
611 strength task. A repeated measures design was employed with each participant com-
612 pleting the three similar booklets. The presentation order of the statements within each
613 booklet was randomized. The presentation order of the three booklets was counterbal-
614 anced, such that seven participants were assigned to each of the six possible presenta-
615 tion orders.

616 3.2. Results and discussion

617 3.2.1. Truth table task

618 The mean probability estimates for truth table cases are shown in Table 6 and are
619 broken down by the prior classification of conditionals in terms of component proba-
620 bilities, HH, HL, LH, and LL. For each case, we performed two 2 (Antecedent proba-
621 bility) by 2 (Consequent probability) analyses of variance, one across participants and
622 one across items, to examine the effect of antecedent and consequent probabilities.
623 Table 7 shows that, as in Experiment 1, in each case the trends essentially confirm
624 the prior rating of the pre-test. TT ratings were higher when antecedent probability
625 was high ($F_1(1,41) = 62.11$, $p < .001$, $MSE = 41$; $F_2(1,28) = 15.12$, $p < .01$,
626 $MSE = 93.98$) and when the consequent probability was high ($F_1(1,41) = 43.88$,

Table 6

Mean (*SD*) ratings of the four truth table cases in Experiment 2

TT	Consequent probability	
	High	Low
Antecedent probability		
High	47.87 (12.26)	43.64 (10.86)
Low	38.01 (14.23)	26.85 (12.45)
TF	Consequent probability	
	High	Low
Antecedent probability		
High	17.30 (6.91)	24.90 (9.05)
Low	14.90 (5.97)	24.56 (10.97)
FT	Consequent probability	
	High	Low
Antecedent probability		
High	14.52 (5.24)	9.93 (5.38)
Low	22.36 (10.94)	12.29 (6.88)
FF	Consequent probability	
	High	Low
Antecedent probability		
High	20.31 (8.65)	21.57 (8.72)
Low	24.74 (10.36)	36.30 (15.55)

Table 7

(a) Mean (*SD*) probability of conditional ratings in Experiment 2

	Consequent probability	
	High	Low
Antecedent probability		
High	61.81 (11.31)	55.75 (14.00)
Low	58.16 (13.95)	45.06 (13.60)

(b) Mean (*SD*) causal strength ratings in Experiment 2

	Consequent probability	
	High	Low
Antecedent probability		
High	3.54 (.46)	3.43 (.45)
Low	3.43 (.40)	2.82 (.54)

627 $p < .001$, $MSE = 56.59$; $F_2(1,28) = 5.03$, $p < .05$, $MSE = 93.98$). TF ratings were higher
628 when the consequent probability was low ($F_1(1,41) = 60.41$, $p < .001$, $MSE = 51.79$;
629 $F_2(1,28) = 10.97$, $p < .005$, $MSE = 54.31$), but they were unaffected by antecedent prob-
630 ability (both $F_s < 1$). FT ratings were higher when antecedent probability was low
631 ($F_1(1,41) = 24.95$, $p < .001$, $MSE = 43.69$; $F_2(1,28) = 9.56$, $p < .005$, $MSE = 21.73$)
632 and when the consequent probability was high ($F_1(1,41) = 54.12$, $p < .001$,

633 MSE = 41.71; $F_2(1,28) = 19.79$, $p < .001$, MSE = 21.73). FF ratings were higher when
634 the antecedent probability was low ($F_1(1,41) = 30.14$, $p < .001$, MSE = 127.83;
635 $F_2(1,28) = 24.53$, $p < .001$, MSE = 29.86) and when the consequent probability was
636 low ($F_1(1,41) = 28.42$, $p < .001$, MSE = 60.77; $F_2(1,28) = 11.05$, $p < .005$,
637 MSE = 29.86).

638 Significant interactions between these two factors were observed for TT, FT, and FF
639 ratings across participants (TT: $F_1(1,41) = 11.68$, MSE = 43.09, $p < .001$; FT:
640 $F_1(1,41) = 5.14$, MSE = 61.39, $p < .05$; FF: $F_1(1,41) = 16.61$, MSE = 67.03, $p < .001$).
641 Across items, however, the interaction was significant only for FF ratings (TT:
642 $F_2(1,28) = 1.02$; FT: $F_2(1,28) = 2.76$, MSE = 93.98, $p > .10$; FF: $F_2(1,28) = 7.08$,
643 MSE = 29.86, $p < .05$). In all cases, the effect of consequent probability was more marked
644 when antecedent probability was low.

645 3.2.2. Probability of conditional task

646 Order did not influence judgments ($F_1(5,36) = 1.02$, ns) and therefore was dropped
647 from subsequent analyses. The mean probability estimates for the conditionals are
648 shown in Table 7(a) and are broken down by the classification of conditionals in
649 terms of component probabilities. Probability ratings were higher when the antecedent
650 probability was high ($F_1(1,41) = 68.93$, MSE = 31.30, $p < .001$; $F_2(1,28) = 2.31$,
651 $p = .14$) and when the consequent probability was high ($F_1(1,41) = 49.56$,
652 MSE = 41.00, $p < .001$; $F_2(1,28) = 4.13$, MSE = 177, $p < .06$). An interaction was
653 shown such that consequent probability affected more judgments for low antecedent
654 probability conditionals but only for participants ($F_1(1,41) = 5.92$, $p < .05$,
655 MSE = 67.03; $F_2 < 1$).

656 3.2.3. Causal strength task

657 Order did not influence causal strength judgments ($F_s < 1$) and was dropped from
658 subsequent analyses. The mean causal strength estimates for the relations suggested
659 by the conditional statements are shown in Table 7(b) and are broken down by the
660 classification of conditionals in terms of component probabilities. Causal strength
661 ratings were higher when the antecedent probability was high ($F_1(1,41) = 52.62$,
662 MSE = .10, $p < .001$; $F_2(1,28) = 3.20$, MSE = .32, $p < .10$) and when the consequent
663 probability was high ($F_1(1,41) = 48.20$, MSE = .11, $p < .001$; $F_2(1,28) = 3.31$,
664 MSE = .32, $p < .10$). An interaction was shown such that consequent probability
665 affected more judgments for low antecedent probability conditionals but only for
666 participants ($F_1(1,41) = 15.49$, $p < .001$, MSE = .17; but $F_2(1,28) = 1.56$, ns). An
667 inspection of Table 7(b) suggests that these effects are due to that LL conditionals
668 were judged to involve weaker causal links than the other types of conditionals.
669 These findings are very similar to those for the probability judgments reported
670 above.

671 3.2.4. Correlation and regression analyses

672 As in Experiment 1, we considered four alternative hypotheses: the material condition-
673 al, conditional probability, conjunctive probability, and the delta-p rule. Scores for each of
674 these predictions were derived in the same way as in Experiment 1. These scores when then
675 correlated across sentences with mean probability ratings of the whole conditional and
676 with mean causal strength ratings (Table 8(a)). As in Experiment 1, all the correlations

Table 8

Correlations and regressions computed across sentences using mean ratings of all participants in Experiment 2

	Probability of conditional	Causal strength
<i>(a) Correlations between judged probability of conditionals and judged causal strength with various probabilities computed from the truth table task</i>		
Hypotheses		
Conjunctive probability	.88*	.86*
Material conditional	.77*	.71*
Conditional probability	.91*	.87*
Delta-p rule	.72*	.73*
Other		
P(p)	.46*	.49*
P(q)	.77*	.73*
P(q/¬p)	.11	.07
<i>(b) Multiple regressions using three statistically independent predictors (β weights)</i>		
P(p)	.14*	.19*
P(q p)	.93*	.88*
P(q ¬p)	-.20*	-.23*

677 are statistically significant, but the highest correlations are with conditional probability.
 678 The correlations with conditional probability were significantly higher than those with
 679 the material conditional or with the delta-p rule but no different than those with the con-
 680 junctive probability. We also obtained a near perfect correlation between probability of
 681 the whole conditional and causal strength ($r = .98, p < .001$)² We will consider what this
 682 result implies in Section 5.

683 We again performed a multiple linear regression with three independent predictors as
 684 shown in Table 8(b). For both probability and causal strength judgments there was a large
 685 and significant effect of conditional probability P(q|p). In contrast to Experiment 1, there
 686 was also a significant negative influence of P(q|¬p), as predicted by the delta-p rule
 687 hypothesis. However, the size of the β weights was a lot smaller than for P(q|p).

688 We ran regression analyses, as in Experiment 1, on the data of individual participants
 689 and this is summarized in Table 5(b). As in Experiment 1, we obtained strong support for
 690 the conditional probability hypothesis but, in contrast to that experiment, the secondary
 691 effect that shows up is of P(p) rather than P(q|¬p). This finding provides only weak sup-
 692 port for the conjunctive probability hypothesis since it was not supported in the corre-
 693 sponding regression analysis on item means in Experiment 2 nor in any regression
 694 analysis in Experiment 1. There was yet again no support at all for the material condition-
 695 al hypothesis.

² An anonymous reviewer suggested that this high correlation could be due to carry-over effects because of the close proximity of the two judgments. The design of Experiment 2 allowed us to test this possibility. In that study we counterbalanced the order of presentation of the three tasks (truth table; probability of conditional; causal strength). There were seven participants assigned in each of the six possible orders of these tasks. In two of these orders the probability of conditional task came first, and in another two the causal strength task came first. In the former case probability of conditional estimates are 'clean'; in the latter case causal strength estimates are 'clean.' Therefore, we calculated the correlation (on item means) between 'clean' probability of conditional judgments and 'clean' causal strength judgments. The resulting correlation was highly significant; $r = .87, p < .0001$, a finding that rules out the carry-over effect hypothesis.

696 3.2.5. Conclusions

697 Experiment 2 has replicated the major finding of Experiment 1 in support of the con-
698 ditional probability hypothesis. Judgments of the probability of non-basic indicative con-
699 ditionals were most strongly related to the conditional probability $P(q|p)$, derived from
700 participants' beliefs about relevant possibilities. It is striking that in all our analyses judg-
701 ments of causal strength are affected by the same factors that affect probability judgment.
702 But the evidence shows only weak support for the delta- p rule (significant if small effect of
703 $P(q|\neg p)$) in regressions on mean ratings (see Table 8(b)). We will consider this point in Sec-
704 tion 5 as well as the strong correlation between judgments of the probability of condition-
705 als and of causal strength.

706 4. Experiment 3

707 A strong theoretical case can be made that the causal indicative conditionals we studied
708 in Experiments 1 and 2 differ from certain counterfactuals primarily in their time perspec-
709 tive (Bennett, 2003; Dudman, 1984; Edgington, 1995; Evans & Over, 2004). Suppose that
710 we asserted the indicative (1) last year, about the coming year, but that over the course of
711 that time the cost of petrol did not increase and traffic congestion did not improve. We
712 now know that the cost of petrol did not increase, but our beliefs about the effect of
713 the cost of petrol on traffic congestion are unchanged. Consider the counterfactual:

714 (5) If the cost of petrol had increased, then traffic congestion would have improved.

715
716 How do we make a probability judgment about (5)? Stalnaker (1968) extended the
717 Ramsey test to cases in which the antecedent p of the conditional is strongly disbelieved,
718 as it is in (5) in our example. This extended test has been much discussed in the philosophi-
719 cal literature (Bennett, 2003). In the extended test, we make the smallest possible change
720 to our current belief state in order to accommodate the supposition of p . We then make
721 the conditional probability judgment about q given p . Using this procedure, we can make
722 a probability judgment about (5). We start out, a year ago, not knowing whether the cost
723 of petrol will increase, but we suppose that it will and confidently infer, under that suppo-
724 sition and using the original Ramsey test, that traffic congestion will improve. That gave us
725 confidence in (1), as a statement about the coming year. The year passes, and we notice
726 that the cost of petrol does not increase and traffic congestion does not improve. But
727 we can now use the Ramsey test as extended by Stalnaker. We make the smallest change
728 to our belief state to be consistent in supposing that the cost of petrol did increase during
729 the year, and infer confidently that an improvement in traffic congestion follows. This
730 Ramsey test gives us the same confidence in (5) today as we had in (1) one year ago.

731 Our justification for (5) today is the same as the justification we had for (1) last year. All
732 that has changed is that the antecedent and consequent of (1) turned out to be false. We
733 expressed a belief last year with (1), and express the same belief this year with (5). This
734 close relation between conditionals like (1) and (5) suggests that people will make similar
735 probability judgments about these indicative and counterfactual conditionals, on the basis
736 of similar psychological processes. The prediction that these similar judgments will be
737 made has never before been empirically tested.

738 There is much debate on the general relation between indicative conditionals, whether
739 causal, epistemic, or other type, and counterfactuals (Bennett, 2003; Edgington, 1995;

740 Evans & Over, 2004; Sloman, 2005). Here we consider only the possibility that causal
741 indicative conditionals like (1) and counterfactuals like (5) make common reference in
742 the way just described. We can test this possibility by applying the four hypotheses to
743 counterfactuals like (5). However, note that no one has ever held, as far as we know,
744 the conjunctive probability hypothesis about counterfactuals, and almost no one has held
745 the material conditional hypothesis about them (Bennett, 2003).

746 We can extend the conditional probability hypothesis to counterfactuals of the form, 'if
747 p had been the case, then q would have been the case,' in the following way. We can pro-
748 pose that the subjective probability of the counterfactual at the present time is the same as
749 the conditional probability $P(q|p)$ at an earlier time (as given by the context). In our exam-
750 ple, our confidence in (5) today is predicted to equal the conditional subjective probability
751 judgment we made last year, i.e., our confidence at that time that traffic congestion was
752 going to improve given that the cost of petrol increased.

753 There is a long literature in philosophy that relates counterfactuals to causation
754 (Woodward, 2003). There has been a great deal of interest in this relationship recently
755 in the cognitive sciences (Pearl, 2000; Sloman, 2005). There is also much work in judgment
756 and decision making and social psychology on counterfactuals and causation (Byrne,
757 2005; Mandel et al., 2005; Roese, 2005). In light of this long tradition, and of the close
758 relationship between (1) and (5), counterfactuals can also be called 'causal conditionals'
759 in some sense. We ask in what sense this is true. Are counterfactuals 'causal' because they
760 express conditional probability judgments that can be supported by evidence about a causal
761 relation? Or are they 'causal' in the stronger sense of having the same meaning as a
762 statement that a correlation exists, or the still stronger sense of having the same meaning
763 as a statement that a causal relation exists? A proposal that they are 'causal' in one of the
764 stronger senses implies the delta-p rule hypothesis for the reasons we gave above. As we
765 have explained, a correlation between p and q, or a causal relation between p and q,
766 implies that $P(q|p) - P(q|\neg p)$ is positive.

767 In Experiment 3, we used a similar methodology to that of Experiment 2. However, we
768 did not manipulate antecedent and consequent probability, but instead varied the polarity
769 of these components. We constructed 32 counterfactual conditionals (Table 9) broken
770 down into four groups designated as AA (affirmative antecedent, affirmative consequent),
771 AN (affirmative antecedent, negated consequent), NA and NN. We suspect that people
772 can easily process simple negation in real world conditionals. We can just as easily imagine
773 actions taken or not taken, events that occur or do not occur and so on (see Evans & Over,
774 2004, Chapter 1). Hence, Experiment 3 tests the four hypotheses across conditionals that
775 may contain negated components.

776 We used statements referring to real world events with plausible causal links similar to
777 those used in Experiments 1 and 2 (see Table 9). However, these statements now referred
778 to events that might have occurred within the last 5 years. In all cases, the event had not
779 actually occurred at the time of the study (or in the case of negated components, it had
780 occurred).

781 4.1. Method

782 4.1.1. Participants

783 Twenty-six undergraduate students of the University of Plymouth volunteered to take
784 part in return for a small fee.

Table 9

Counterfactual conditionals used in Experiment 3

AA

If Queen Elizabeth had died last year, then Prince Charles would have become king.

If Michael Owen had played for Arsenal last season, then Arsenal would have won the 2002/03 Premiership.

If a vaccine for AIDS had been available two years ago, then a major health crisis in Africa would have been avoided.

If Turkey had improved its human right practices in 2000, then Turkey would have been awarded membership in the European Union.

If Robbie Williams had advertized Nike last year, then Nike sales would have increased.

If an economist had come up with a theory that correctly predicted stock market fluctuations two years ago, then that economist would have been awarded the Nobel Prize.

If the Conservatives had been elected to government in the 2001 elections, then taxes would have been increased.

If car theft had been penalized with life-sentence in 2001, then companies that sell car theft systems would have gone bankrupt.

AN

If the Conservatives had won the 2001 elections, then UK would not have sent troops to Iraq.

If university admission had been easier two years ago, then secondary school students would not have studied hard for A-levels.

If more people had practiced safe sex in 2000, then there would not have been an increase in AIDS fatalities.

If David Beckham had been involved in a tax scandal two years ago, then he would not have received an OBE.

If a method to successfully predict earthquakes had been found two years ago, then there would not have been victims due to earthquakes.

If alternative fuels had become widely available five years ago, then the price of petrol would not have remained high.

If the UK had joined euro in 1999, then the UK's relations with France would not have been difficult.

If Sylvester Stallone had run for Mayor of California in 2000, then he would not have continued his career as an actor.

NA

If David Beckham had not played for Manchester United last season, then Manchester United would have been relegated.

If Michael Schumacher had not won the GP title last year, then Ferrari would have fired him.

If the British climate had not become warmer in the last two years, then British energy consumption would have increased.

If Space Shuttle Columbia had not crashed in 2003, then NASA would have sent more manned missions to the moon.

If Cherie Blair had not been married to Tony Blair, then she would have been appointed as a judge.

If England had not played against Brazil in the 2002 FIFA World Cup quarterfinals, then they would have gone through to the next round.

If Geri Hallowell had not left the Spice Girls, then the Spice Girls would still be together.

If Michael Jackson had not given an interview to Martin Bashir, then he would have produced the best-selling album in 2003.

NN

If New York had not been attacked by terrorists in 2001, then the US would not have attacked Iraq.

If the UK had not invaded Iraq in 2003, then Robin Cook would not have resigned.

If railways had not become privatized, then there would not have been an increase in train delays.

If SARS had not been deadly, then the World Health Organization would not have introduced travel sanctions in infected areas.

If London had not introduced congestion charging, then traffic congestion in central London would not have decreased.

If France continued not to support US foreign policy last year, then US companies would not have renewed contracts with France.

If unemployment had not been reduced in 1997–2001, then Labour would not have won the last elections.

If Saddam Hussein had not been Iraq's President in 2003, then the US would not have attacked Iraq.

785 4.1.2. *Design*

786 The experimental design was identical to that of Experiment 2.

787 4.1.3. *Materials and procedure*

788 The materials were constructed and presented in a similar manner to that of Experi-
789 ment 2. In the probability of counterfactuals task, we asked, as before, people to judge
790 the probability of truth of such statements. An example from our actual materials is:

791 If New York had not been attacked by terrorists in 2001, then the US would not have
792 attacked Iraq.

793
794 The other tasks needed some modification. In the causal strength and truth table tasks,
795 we asked people to make judgments about a point in time 5 years in the past. In the causal
796 strength task, instead of presenting the conditional sentences, we asked people to rate the
797 causal strength of the relation between antecedent and consequent events. For example,
798 we asked for the causal strength between the statement that New York will not be attacked
799 by terrorists and the statement that the US will not attack Iraq.

800 In the truth table task, we again used the perspective of a point 5 years previous to the
801 current time with future tense from that point. So, for example, participants were asked to
802 judge the probability of the following cases using future tense from a past point in time:

803 New York will not be attacked by terrorists and the US will not attack Iraq.

804 New York will not be attacked by terrorists and the US will attack Iraq.

805 New York will be attacked by terrorists and the US will not attack Iraq.

806 New York will be attacked by terrorists and the US will attack Iraq.

807 These judgments were used to predict the probability of the conditional and the causal
808 strength judgments.

809 4.2. *Results and discussion*810 4.2.1. *Probability of conditional and causal strength tasks*

811 The mean judged probability of conditionals and mean causal strength ratings are
812 shown in Table 10, broken down by the polarity of components. For the probability rat-
813 ings, there was no significant effect of antecedent polarity (F_1 and $F_2 < 1$) but an effect of
814 consequent polarity ($F_1(1,25) = 36.76$, $p < .001$, $MSE = 1921$; $F_2(1,25) = 4.74$, $p < .05$,
815 $MSE = 591$). There was also an interaction between the two factors ($F_1(1,25) = 64.41$,
816 $p < 0.001$, $MSE = 4362$; $F_2(1,25) = 10.75$, $p < .005$, $MSE = 1342$). The causal strength
817 ratings showed similar trends: no antecedent effect (F_1 and $F_2 < 1$), a significant effect of
818 consequent polarity ($F_1(1,25) = 9.38$, $p < .005$, $MSE = 2.27$; $F_2(1,25) = 3.45$, $p = .074$,
819 $MSE = .70$) and a significant interaction ($F_1(1,25) = 98.43$, $p < .001$, $MSE = 8.44$;
820 $F_2(1,25) = 12.80$, $p < .001$, $MSE = 2.60$). Inspecting the means, it appears that doubly
821 negated conditionals were judged as more probable (and more causally strong) than oth-
822 ers, resulting in both the main effect and interactions. The correlation between the two
823 dependent measures, across sentences, was .87.

824 We do not attach much theoretical significance to the effects of polarity, as the exper-
825 imenters arbitrarily chose sentences in each class. The presence of negated components

Table 10

(a) Mean (SD) probability of conditional estimates in Experiment 3

	Consequent polarity	
	Affirmative	Negative
Antecedent polarity		
Affirmative	56.5 (12.9)	52.1 (13.8)
Negative	42.5 (13.8)	64.1 (11.6)

(b) Mean (SD) causal strength ratings in Experiment 3

	Consequent polarity	
	Affirmative	Negative
Antecedent polarity		
Affirmative	3.46 (.54)	3.18 (.63)
Negative	2.82 (.41)	3.69 (.46)

826 might have increased probability judgments merely because affirmative statements tend to
 827 refer to sets that are ‘rarer’ than their contrast classes. The pattern of correlations of prob-
 828 ability judgments with our key measures was broadly similar for each group, so we will not
 829 break subsequent analyses down by polarity.

830 4.2.2. Correlation and regression analyses

831 Table 11 shows both correlations and regressions across the whole set of 32 sentences.
 832 We have changed the notation in this table so that A represents antecedent and C conse-
 833 quent regardless of negated components. For example, consider the counterfactual ‘If
 834 alternative fuels had become widely available 5 years ago, then the price of petrol would

Table 11

Correlations and regressions computed across sentences using mean ratings for all participants in Experiment 3

	Probability of conditional	Causal strength
<i>(a) Correlations between judged probability of conditionals and judged causal strength with various probabilities computed from the truth table task</i>		
Hypotheses		
Conjunctive probability	.62*	.65*
Material conditional	.69*	.67*
Conditional probability	.83*	.80*
Delta-p rule	.69*	.72*
Other		
P(A)	.09	.14
P(C A)	.40*	.38*
P(C ¬A)	−.08	−.14
<i>(b) Multiple regressions using three independent predictors (β weights)</i>		
P(A)	.06	.13
P(C A)	.87*	.85*
P(C ¬A)	−.26*	−.34*

Note: A and C represent true antecedent cases and ¬A and ¬C false antecedent cases, regardless of the presence of negated components in the conditionals.

835 not have remained high.’ In that case, $P(C|A)$ would represent the probability that the
836 price of petrol would *not* have remained high given that alternative fuels had become avail-
837 able and so on. The correlations presented in Table 11 are thus directly comparable to
838 those for the previous experiments.

839 Table 11(a) shows a similar pattern of correlations to those observed in the previous
840 experiments. We then tested for differences between these correlations. The correlation
841 with conditional probability was higher than that with the material conditional and with
842 the conjunction probability. This time, the correlation with conditional probability was
843 not significantly higher than that with the delta-p rule. Subsequently, we performed multi-
844 ple linear regressions on mean ratings across the 32 sentences with the same predictors as
845 for Experiment 1, for both probability of conditional and causal strength judgments (see
846 Table 11(b)). The results are strikingly similar to those for the indicative conditionals
847 investigated in Experiments 1 and 2. Conditional probability remains the best predictor
848 of both probability and causal strength judgments. There is also a negative but much
849 smaller effect of $P(C|\neg A)$, which corresponds to $P(q|\neg p)$ for the previous experiments.
850 As previously, we also computed regressions for individual participants, with the results
851 shown in Table 5(c). These analyses confirm strong support for the conditional probability
852 hypothesis, as in Experiments 1 and 2. There is a striking similarity between the results on
853 the probability of counterfactuals and those on the probability of causal indicative condi-
854 tionals. This similarity is itself the first experimental support for the theoretical argument
855 that these conditional constructions are closely related to each other.

856 5. General discussion

857 In a series of three experiments, we investigated the subjective probability of causal
858 indicative conditionals (Experiments 1 and 2) and closely related counterfactuals (Exper-
859 iment 3). We examined four hypotheses about the subjective probability of one of these
860 conditional. First, it is the subjective conjunctive probability of its antecedent and conse-
861 quent: the conjunctive probability hypothesis. Second, it is the subjective probability of the
862 material conditional: the material conditional hypothesis. Third, it is the conditional sub-
863 jective probability of its consequent given its antecedent: the conditional probability
864 hypothesis. Fourth, it depends on the delta-p rule: the delta-p rule hypothesis.

865 The support for the conditional probability hypothesis was extremely strong in all our
866 experiments. There was no support at all for the material conditional hypothesis, and very
867 little for the conjunctive probability hypothesis. The delta-p rule hypothesis received very
868 modest support, as shown in the weak negative effect of $P(q|\neg p)$. The conditional proba-
869 bility hypothesis is a consequence of the Ramsey test of conditionals, and our results are
870 consistent with psychological accounts grounded in the Ramsey test. The first of these was
871 that of Rips and Marcus (1977), who were also influenced by the kind of conditional found
872 in Stalnaker (1968). Much more recently, there has been a growing trend to explain think-
873 ing and reasoning about conditionals in terms of conditional probability. (See Evans &
874 Over, 2004, for a review, and Oaksford, 2006, for comment, and Evans et al., 2005; Kauf-
875 mann, 2005; Oaksford, 2005; Oberauer et al., in press, for later work.)

876 The rest of the paper is organized as follows. We will begin by discussing our findings in
877 more detail. We will then consider the implications of our findings for the most influential
878 psychological account of conditionals: the mental model theory of Johnson-Laird and
879 Byrne (1991, 2002). This theory implies the conjunctive probability hypothesis and, in

880 some of its features, the material conditional hypothesis. Opposing theories are based on
881 the Ramsey test and the conditional probability hypothesis. In these theories, the causal
882 conditionals and counterfactuals we studied are Adams conditionals or Stalnaker condi-
883 tionals, and so we will discuss these conditionals. Finally, we will turn our attention to
884 the covariation and causal proposals, which imply that causal conditionals and counter-
885 factuals make explicit statements about covariation or causation. We will conclude with
886 a summary of our findings and their importance.

887 5.1. Findings

888 Previous work has demonstrated a close relation between the probability of abstract,
889 basic indicative conditionals and conditional probability, supporting the conditional prob-
890 ability hypothesis (Evans et al., 2003; Hadjichristidis et al., 2001; Oberauer & Wilhelm,
891 2003; Over & Evans, 2003; but see also Girotto & Johnson-Laird, 2004). The present stud-
892 ies extended tests of this hypothesis to non-basic conditionals that, like almost all natural
893 language conditionals, are not independent of content and background knowledge. These
894 were causal indicative conditionals (Experiments 1 and 2) and related counterfactuals
895 (Experiment 3) that are central to everyday discourse and decision making.

896 In Experiments 1 and 2, we used four categories of indicative conditionals defined (on
897 the basis of a prior rating study) to be high in antecedent and consequent probability
898 (HH), high in antecedent but low in consequent probability (HL) and, analogously, the
899 low-high (LH) and low-low (LL) cases. This was mostly done in order to ensure a spread
900 of probabilities across materials to facilitate our correlation and regression analyses. This
901 manipulation allowed for an indirect test of the conditional probability hypothesis. This
902 hypothesis predicts that ratings will increase with high consequent probability because,
903 all else being equal, a high $P(q)$ should lead to higher estimates of $P(q|p)$. They did. In fact,
904 ratings were significantly higher when antecedent as well as consequent probabilities were
905 high. The antecedent effect cannot be predicted by the conditional probability hypothesis,
906 but it may nevertheless be related to its foundation in the Ramsey test. It may be that when
907 the antecedent p is unlikely, as it is in LL cases, some people find it hard to add p hypo-
908 thetically to their beliefs. This may occur particularly if q is also improbable so that ' $p \& q$ '
909 is a difficult possibility to imagine. In such cases, a shallow response might simply be to
910 reject the conditional as unbelievable. Where the Ramsey test is fully implemented, how-
911 ever, one would expect the overwhelming evaluation of the indicative conditional to be
912 based on the conditional probability, $P(q|p)$.

913 We have much more sensitive data analyses available in our experiments here than in
914 earlier experiments to test the conditional probability hypothesis. We can compare judg-
915 ments made by the same participants to the same set of materials of both component prob-
916 abilities and probability of the conditional. These analyses do not rely on the wide initial
917 classification of conditional statements at all, but on multiple regression analyses per-
918 formed across the whole set of sentences as actually rated by this group of participants.
919 These analyses—see Tables 4(b), 8(b) and 11(b)—show that by far the best predictor of
920 $P(\text{if } p \text{ then } q)$ is $P(q|p)$, in line with the conditional probability hypothesis. This is also
921 the case if the regressions are carried out on individual participants and then collated
922 (Table 5).

923 Previous research on basic conditionals (see Evans et al., 2003; Oberauer & Wilhelm,
924 2003) showed a strong minority tendency in line with the conjunctive probability hypoth-

925 esis, in that some participants equated $P(\text{if } p \text{ then } q)$ with $P(p \ \& \ q)$. What evidence is there
926 for this hypothesis in the current study of non-basic conditionals? One consequence is that
927 people should find these conditionals more believable when $P(p)$ is high. This was the case
928 in that people gave higher ratings to HH and HL than to LH and LL conditionals,
929 although further inspection suggests that this finding was mostly driven by low ratings
930 to LL conditionals rather than high ratings to HH conditionals. In the more sensitive
931 regression analyses, $P(p)$ had no measurable effect in Experiments 1 and 3 but showed
932 up as a weak predictor in Experiment 2. On balance, the influence of conjunctive proba-
933 bility is a lot weaker for these realistic conditionals.

934 Experiment 3 supports the existence of a relation between counterfactuals and con-
935 ditional probability, like Experiments 1 and 2 did for causal indicative conditionals. A
936 finding of Experiments 2 and 3 was that people's judgments of the probability of indic-
937 ative or counterfactual conditionals and of the causal strength between the antecedent
938 and consequent events were very highly correlated. This might seem to provide support
939 for the causal proposal. However, for conditionals and causal strength, by far the
940 strongest predictor of judgments was the conditional probability, $P(q|p)$, rather than
941 the delta- p rule. The latter implies that $P(q|\neg p)$ should be an equally strong negative
942 predictor. Where $P(q|\neg p)$ had an effect, it was very much weaker. We will now consid-
943 er the implications of our results for theoretical accounts of conditionals in natural
944 language.

945 5.2. *Implications for mental model theory*

946 Rips and Marcus (1977) were the first to propose what came to be known as mental
947 model representations, of conjunctive and disjunctive propositions, in their version of
948 the Ramsey test (Evans & Over, 2004, pp. 53–56). Mental models of conjunctions can rep-
949 resent conditional probability judgments, provided that some of these models are repre-
950 sented as more probable than others (Evans & Over, 2004, Ch. 9; Over & Evans, 2003).
951 This representation of conditional probability is possible because $P(q|p)$ is high when
952 $P(p \ \& \ q)$ is higher than $P(p \ \& \ \text{not-}q)$, and low when $P(p \ \& \ \text{not-}q)$ is higher than $P(p \ \& \ q)$.
953 There are also possible ways of indicating mental links between mental models that
954 could represent conditional probability judgments (Evans & Over, 2004, Ch. 9). Our
955 results certainly do not disconfirm the use of a general mental models framework to
956 explain thinking and reasoning about conditionals, but rather imply that a modification
957 and extension of the framework is necessary. This implication applies especially to the
958 mental models theory of conditionals in Johnson-Laird and Byrne (2002).

959 Johnson-Laird and Byrne have long held that people's initial representation of an indic-
960 ative conditional is a mental model of the conjunction, 'p & q,' plus some indication that
961 other models are implicit. They would predict a conjunctive probability response, and
962 there is a tendency to give this response in experiments on basic conditionals (Evans
963 et al., 2003; Girotto & Johnson-Laird, 2004; Oberauer & Wilhelm, 2003). However, we
964 found only very weak signs of it in our results on non-basic conditionals. Johnson-Laird
965 and Byrne (1991) would also have predicted a material conditional pattern. Johnson-Laird
966 and Byrne (2002) still represent some causal conditionals, as we would classify them, as
967 material conditionals. As we pointed out above, they do this (p. 655) with their example,
968 'if a patient has malaria then she has a fever.' Yet the material conditional pattern was
969 entirely absent from our data.

970 Johnson-Laird and Byrne (2002) helpfully introduce the distinction between basic and
971 non-basic conditionals. Background knowledge affects the interpretation of non-basic con-
972 ditionals, and by relying on this fact, they should be able to modify their theory to explain
973 why there is not a conjunctive probability response to non-basic conditionals. They also
974 claim (p. 673) that ‘semantic modulation’ can make conditionals about temporal or spatial
975 relations and possibly causal relations or mechanisms. As we have suggested above, one
976 might use semantic modulation to argue for a covariation proposal or a causal proposal
977 for at least some conditionals, with the right semantic content. But both of these proposals
978 imply the delta-p rule hypothesis, and we found only very modest support for that. Sch-
979 royens and Schaeken (2004) argue that Johnson-Laird and Byrne could relatively easily
980 modify their theory to explain why there is a tendency to give the conditional probability
981 response as the probability of basic conditionals. However, it is unclear how Johnson-
982 Laird and Byrne (2002) could revise their particular theory to imply the conditional prob-
983 ability hypothesis for non-basic conditionals.

984 To make predictions about the probability of non-basic conditionals, Johnson-Laird
985 and Byrne will finally have to break completely with the material conditional hypothesis.
986 They cannot continue to claim (as on p. 651) that it is valid to infer ‘if p then q’ from ‘not-
987 p’ alone or from q alone. These inferences, the so-called paradoxes of the material condi-
988 tional, are valid if and only if the conditional is the material conditional (Evans & Over,
989 2004, pp. 19–21). These are invalid inferences when, as a result of semantic modulation, ‘if
990 p then q’ means ‘p raises the probability of q,’ or ‘p causes q,’ as obviously neither of these
991 statements follows from ‘not-p’ alone or from q alone. These inferences are also invalid if
992 $P(\text{if } p \text{ then } q)$ is the conditional probability (Adams, 1998; Edgington, 1995). Johnson-
993 Laird and Byrne will need new account of which inferences are valid, and which are inval-
994 id, for non-basic conditionals.

995 There is additionally the problem of accounting for the probability of non-basic condi-
996 tionals. People make probability judgments about these conditionals by using heuristics,
997 causal models, or other non-extensional procedures. But the mental model theory of John-
998 son-Laird and his collaborators so far only applies to extensional probability judgments
999 (Johnson-Laird et al., 1999, p. 63).

1000 If the extensional material conditional is not the ordinary conditional of natural lan-
1001 guage, then what is? We will consider two possibilities, the Adams conditional and the
1002 Stalnaker conditional. Both of these conditionals were founded on the Ramsey test and
1003 have influence some psychologists (see Evans & Over, 2005, for a review and Oaksford,
1004 2006, for comment). Rips and Marcus (1977) used the conditional of Stalnaker (1968)
1005 as the basis of their psychological theory. But before considering the Stalnaker condi-
1006 tional, we return to Adams conditional, which we introduced in the discussion of Experiment
1007 1.

1008 5.3. *The adams conditional*

1009 An Adams conditional, of the form ‘if p then q,’ is evaluated by means of the Ramsey
1010 test and its probability, $P(\text{if } p \text{ then } q)$, is exactly the conditional probability $P(q|p)$. Edg-
1011 ington (1995, 2003) argued that this conditional can represent both the indicative and
1012 counterfactual conditionals of natural language. There is a truth value gap for Adams con-
1013 ditionals with false antecedents: the conditionals have a subjective probability (or believ-
1014 ability) but no objective truth value in not-p cases. People do use the ordinary words ‘true’

1015 and ‘false’ in ‘not-p’ cases, but supporters of the Adams conditional can point out that
1016 these words are ambiguous in natural language. For example, the words ‘true’ and ‘false’
1017 do not mean the same applied to scientific statements and to expressions of moral princi-
1018 ples or other subjective matters. Applied to a conditional in ‘not-p’ cases, these words can
1019 only express, for supporters of the Adams conditional, high or low confidence in the con-
1020 ditional. There is evidence that basic conditionals are Adams conditionals, but whether
1021 non-basic conditionals are Adams conditionals is a much more difficult question to answer
1022 (Evans & Over, 2004, Ch. 7 & Ch. 9).

1023 An Adams conditional is not equivalent to an explicit statement that p raises the prob-
1024 ability of q , as in (3) above, nor that p causes q , as in (4) above. A conditional probability
1025 $P(q|p)$ can be high when p does not raise the probability of q and when p does not cause q .
1026 For example, $P(q|p)$ can be high simply because $P(q)$ is high. Does this mean that support-
1027 ers of the view that these conditionals are Adams conditionals cannot account for the
1028 weak negative effect of $P(q|\neg p)$ in the current studies? Not necessarily, for they can argue
1029 that the use of a conditional *pragmatically* suggests, in certain ordinary contexts, that p
1030 raises the probability of q or that p causes q . Consider for example:

1031 (6) If you take extra vitamin C, then your cold will be gone in three days.

1032

1033 In most contexts, asserting (6) would be misleading, and very bad advice, if extra vita-
1034 min C was not a causal factor raising the probability that the cold will be gone in 3
1035 days. The argument would be that there is often a *pragmatic implicature* when a condi-
1036 tional like (6) is asserted: that not taking extra vitamin C will make it probable that the
1037 cold will last longer than 3 days (Evans & Over, 2004, pp. 158–159). This inverse impli-
1038 cature could cause a second conditional, ‘if not- p then not- q ,’ to be added to the original
1039 representation. A Ramsey test on this added conditional would be believable to the
1040 extent that $P(\neg q|\neg p)$ is high. A positive effect of this probability is the same as a nega-
1041 tive effect of its complement $P(q|\neg p)$. Hence, our secondary finding could be accounted
1042 for by pragmatic implicature. It is worth noting that pragmatic implicatures, unlike
1043 semantic implications, are open to individual interpretation and can be ‘cancelled’ in
1044 some contexts (Grice, 1989). Future studies could investigate contexts in which possible
1045 implicatures would normally be cancelled. For example, a doctor who asserted (6) could
1046 do so in a context in which she had already expressed some doubt about the claim that
1047 extra vitamin C shortens the length of colds. She might then be taken by her patient as
1048 making an ‘even if’ assertion. That is, even if extra vitamin C is taken, the cold will still
1049 be gone in 3 days.

1050 5.3.1. The Stalnaker conditional

1051 There is also the possibility, as presupposed originally by Rips and Marcus (1977), that
1052 the conditionals we studied are not Adams conditionals but rather Stalnaker conditionals
1053 (Stalnaker, 1968, 1975). Stalnaker (1968) held that, when in the Ramsey test we make the
1054 smallest possible change to our belief state to suppose p consistently, we are thinking
1055 about the closest possibility in which p holds. The notion of the closeness of possibilities
1056 has inspired work in cognitive psychology on how people understand conditionals in gen-
1057 eral and counterfactuals in particular (Rips & Marcus, 1977; Evans & Over, 2004). It has
1058 also led to research in judgment and decision making and social psychology on how people
1059 conceive and respond to the closeness of possibilities and counterfactuals (Byrne, 2005;

1060 Kahneman & Miller, 1986; Kahneman & Varey, 1990; Mandel et al., 2005; Roese, 1997,
1061 2004, 2005; Teigen, 1998, 2005).

1062 In Stalnaker's analysis, indicative and counterfactual conditionals are non-truth func-
1063 tional conditionals that are always either true or false—there are no truth value gaps. A
1064 Stalnaker conditional is true in TT possibilities and false in TF possibilities, but unlike
1065 an Adams conditional, a Stalnaker conditional *does* have a truth value in FT and FF pos-
1066 sibilities. It is true in FT, or true in FF, if and only if TT is closer than TF as a possibility
1067 to FT, or to FF. Stalnaker (1968, 1975) takes his approach to both indicative and coun-
1068 terfactual conditionals, with only a pragmatic difference between them (Evans & Over,
1069 2004).

1070 To illustrate, assume that (1)—‘if the cost of petrol increases then traffic congestion will
1071 improve’—is a Stalnaker conditional, and that the cost of petrol will not increase (the
1072 world is in a FT or FF state). Now consider the closest possible state of the world in which
1073 the cost of petrol increases. Perhaps there are many people in Government who want to
1074 put an extra tax on petrol to increase its cost, and they almost have enough votes to make
1075 this tax change. That would make the tax change the closest possibility in which the cost of
1076 petrol goes up, and (1) will be true if traffic congestion improves in that closest possibility.
1077 If it does not improve in that closest possibility, then (1) is false. A material conditional, of
1078 the form ‘not-p or q,’ is truth functional and is of course always true in FT and FF pos-
1079 sibilities. But a Stalnaker conditional is not truth functional: it is only *sometimes* true in
1080 FT and FF possibilities.

1081 Stalnaker (1968) argued that the probability of a conditional, $P(\text{if } p \text{ then } q)$, in his anal-
1082 ysis is the conditional probability, $P(q|p)$, given by the Ramsey test. However, the proba-
1083 bility of a Stalnaker conditional is not in general identical with the conditional probability
1084 (as famously proved by Lewis, 1976; see also Bennett, 2003, for a review of work on Lew-
1085 is's proof and Evans & Over, 2004, Ch. 2, for an account of it in a psychological context).
1086 Nevertheless, it can be argued that Stalnaker's theory was ‘almost right’ (Lewis, 1976), and
1087 that the probability of a Stalnaker conditional is often too close, in many ordinary con-
1088 texts, to the conditional probability for a difference to be easily found in experiments
1089 (Evans & Over, 2004, pp. 28–30).

1090 It may be that people use the Ramsey test, in bounded thought, as a quick and generally
1091 effective way to get close enough to the probability of a Stalnaker conditional. The points
1092 we made above about pragmatic implicature for Adams conditionals can also be made for
1093 Stalnaker conditionals. For example, the use of (6) as a Stalnaker conditional could have
1094 the same pragmatic implicatures that (6) would have as an Adams conditional. Moreover,
1095 supporters of Stalnaker can also explain the low ratings given to LL conditionals in our
1096 data. The LL case, in which both p and q are improbable, represents a distant possibility,
1097 and people may use a ‘closeness’ or ‘proximity’ heuristic (Roese, 2004; Teigen, 1998, 2005)
1098 as a quick way to reject such a conditional as highly improbable. (This heuristic takes very
1099 close possibilities to be highly probable and very distant ones to be highly improbable.)
1100 Since the probability of a Stalnaker conditional will often be very close to the conditional
1101 probability, supporters of Stalnaker, such as Rips and Marcus, could use this fact to
1102 explain why the conditional probability hypothesis is so strongly supported by our results.

1103 5.3.2. *The covariation and causal proposals*

1104 Causal indicative conditionals, and related counterfactuals, may be neither Adams con-
1105 ditionals nor Stalnaker conditionals, but a stronger conditional, as implied by both the

1106 covariation and causal proposals. Suppose a conditional, ‘if p then q,’ means that p raises
1107 the probability of q, as the covariation proposal states, or that p causes q, as the causal
1108 proposal states. As we have already pointed out, an Adams conditional is weaker than
1109 the statement that p raises the probability of q, or that p causes q. A Stalnaker conditional
1110 is also weaker than either of these statements. As a Stalnaker conditional, (1) would be
1111 true if a petrol cost increase was followed, in a mere coincidence, by traffic congestion
1112 improvement. The covariation and causal proposals might also be able to explain our con-
1113 firmation of the conditional probability hypothesis and our other results.

1114 Consider again the findings in Experiment 2 and Experiment 3 of a high correlation
1115 between the judged probability of the conditional and causal strength judgments. This cor-
1116 relation could be taken as evidence for the causal proposal: that a conditional like (1) is
1117 equivalent in meaning to an explicit causal statement like (4). In that case, the negative
1118 effect of $P(q|\neg p)$ in Experiment 2 would not be pragmatic but rather semantic. The del-
1119 ta-p rule is too simple on its own to measure causal strength, but $P(q|p) - P(q|\neg p)$ must
1120 normally be positive before one would say that p is a ‘cause’ of q (Cheng, 1997; Pearl,
1121 2000). As observed earlier, however, we found only a weak negative effect of $P(q|\neg p)$ in
1122 participants’ judgments of causal strength.

1123 The weakness of both negative effects of $P(q|\neg p)$ could be the result of a well known
1124 bias studied in the literature on contingency judgment. It is well established that people
1125 tend to focus too much on the a and b cells, rather than the c and d cells, of a 2×2 con-
1126 tingency table when tested on the delta-p rule (Anderson, 1990; Kao & Wasserman, 1993;
1127 Shanks, 1995; Stanovich & West, 1998). This tendency would be equivalent, in our results,
1128 to placing too much emphasis on $P(q|p)$ rather than $P(q|\neg p)$, in spite of understanding the
1129 conditional as a causal assertion. The weakness of the negative effects of $P(q|\neg p)$ in our
1130 results could simply be the result of this bias, which may arise because focusing more
1131 on $P(q|p)$ than on $P(q|\neg p)$ is often an effective heuristic for judging correlation or causal
1132 strength in ordinary affairs (Anderson, 1990; Cheng, 1997; Over & Green, 2001; Shanks,
1133 1995; Stanovich & West, 1998).

1134 Previous discussions in the literature of the delta-p rule have almost always been direct-
1135 ly related to explicit statements of correlation or causation, such as (3) and (4) above.
1136 There is not extended work in linguistics, philosophical logic, or psychology that tries
1137 to explain the meaning of some type of conditional in terms of the delta-p rule. For exam-
1138 ple, as far as we are aware, no normative logic for a conditional has ever been formulated
1139 on the basis that its formal semantics is given by the delta-p rule. Owing to the bias that
1140 could explain the weak negative effect of $P(q|\neg p)$, more work will have to be done theo-
1141 retically and experimentally before it can be definitely determined whether or not the del-
1142 ta-p rule is basic to the semantics of causal conditionals and counterfactuals.

1143 6. Conclusions

1144 In this paper, we have provided the first experimental psychological evidence on the
1145 subjective probability of causal indicative conditionals, and closely linked counterfactu-
1146 als, commonly used in natural language. We have shown that these conditionals cannot
1147 be material, truth functional conditionals. Our results strongly disconfirm the material
1148 conditional hypothesis, which is implied by Johnson-Laird and Byrne (1991) and still
1149 found in aspects of Johnson-Laird and Byrne (2002). We have also shown that evidence
1150 for a conjunctive probability response, predicted by Johnson-Laird and Byrne (1991,

2002), is very weak. We have found that people's confidence in causal conditionals and related counterfactuals is predominantly determined by the conditional probability, $P(q|p)$, as implied by the conditional probability hypothesis, which is implied in turn by the Ramsey test. We have studied, for the first time, possible relations between probability judgments about causal and counterfactual conditionals, causal strength judgments, and the delta-p rule. We have found a weak effect of the delta-p rule and pointed out how this could be connected to a bias in contingency judgment. An extended mental models framework may be able to explain our results, but it is an open question whether these are best explained by the supposition that natural language conditionals are Adams conditionals, Stalnaker conditionals, or stronger conditionals. The only way to make progress is to integrate the study of conditionals with the psychology of causal judgment (Sloman, 2005) and, more generally, with work on probability in judgment and decision making (Evans & Over, 2004). Only this integration can tell us how the Ramsey test is implemented in detail, by the use of deductive and inductive inferences, heuristics, and causal models for probability judgment. In this paper, we have taken an important step in that direction by demonstrating how very closely probability judgments about causal and counterfactual conditionals are related to conditional probability judgments.

7. Uncited references

Over (1993), Over (2004), Roberts (1998), Stanovich and West (2003).

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