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Deductive and inductive conditional inferences: Two modes of reasoning

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Deductive and inductive conditional inferences: Two modes of reasoning

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A number of single- and dual-process theories provide competing explanations as to how reasoners evaluate conditional arguments. Some of these theories are typically linked to different instructions—namely deductive and inductive instructions. To assess whether responses under both instructions can be explained by a single process, or if they reflect two modes of conditional reasoning, we re-analysed four experiments that used both deductive and inductive instructions for conditional inference tasks. Our re-analysis provided evidence consistent with a single process. In two new experiments we established a double dissociation of deductive and inductive instructions when validity and plausibility of conditional problems were pitted against each other. This indicates that at least two processes contribute to conditional reasoning. We conclude that single-process theories of conditional reasoning cannot explain the observed results. Theories that postulate at least two processes are needed to account for our findings.

Keywords: Analytical reasoning; Conditional reasoning; Double dissociation; Probabilistic reasoning; State-trace analysis.

Human reasoning deviates in many ways from the norm provided by standard deductive logic. A typical finding is that the content of presented arguments can influence the reasoning outcome independent of the logical

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status of the argument. One prominent example is the so-called *belief bias*; that is, the finding that reasoners are more likely to accept believable conclusions than unbelievable conclusions (e.g., Evans, Barston, & Pollard, 1983, Klauer, Musch, & Naumer, 2000). These and other *content effects* have led to a major paradigm shift in psychological theories on human reasoning (see Johnson-Laird, 2008, for a brief historical overview). Earlier theories suffered from what has been called logicism (Evans, 2002); that is, the assumption that formal logic provides the basis for human reasoning. Given the pervasive evidence of deviations from formal logic, most contemporary theories incorporate mechanisms that are incommensurate with standard logic (but see, e.g., O'Brien & Manfrinati, 2010; Rips, 1994).

In the current paper we will focus on one form of human reasoning that has received special attention and rich theoretical development in the past years: conditional reasoning from if-then statements (see Oaksford & Chater, 2010, for a current overview). The present study is in part motivated by the observation that certain theoretical positions tend to be confounded with the experimental methods typically used in empirical tests of these positions. Proponents of more analytical theories of reasoning typically use instructions stressing logical validity and encourage participants to ignore the specific content of the arguments and their prior knowledge, whereas proponents of probabilistic theories typically use instructions stressing inductive strength or plausibility of the arguments, thereby focusing participants on the specific contents and their prior knowledge. Proponents from either theoretical position argue, at least implicitly, that the assumed mechanism is responsible for reasoning under both types of instructions, and hence one position must be correct and the other one incorrect (see e.g., Oaksford & Chater, 2007; Schroyens & Schaeken, 2003). Here we use a conditional inference task to show a double dissociation of the two types of instructions when plausible but invalid and implausible but valid problems are pitted against each other, to show two things: (a) neither of the aforementioned positions is fully able to explain the results presented here, and (b) at least two processes contribute to conditional reasoning. This study adds to the current debate on what the effects of different reasoning instructions are (e.g., Evans, 2002; Heit, 2007; Heit & Rotello, 2010; Markovits, Lortie Forgues, & Brunet, 2010; Rips, 2001; Rotello & Heit, 2009).

Conditional problems typically consist of (a) the conditional rule, the major premise, in which two propositions p, the antecedent, and q, the consequent, are linked in the form "if p, then q" ($p \rightarrow q$), (b) a minor premise which is p, q, or one of their negations ($\neg$), and (c) a conclusion. Specifically there are two affirmation problems, *modus ponens* (MP: $p \rightarrow q$, p: q) and *affirmation of the consequent* (AC: $p \rightarrow q$, q: p), as well as two denial problems, *modus tollens* (MT: $p \rightarrow q$, $\neg q$: $\neg p$) and *denial of the antecedent*

(DA: $p \rightarrow q$, $\neg p$: $\neg q$). Under the traditional logical interpretation of the conditional as the truth-functional material implication only MP and MT are logically valid inferences, whereas AC and DA are not logically valid (Edgington, 2008). In the conditional inference task naïve reasoners are asked to judge either the validity or the likelihood of conclusions for the four conditional problems.

CONTENT EFFECTS IN CONDITIONAL REASONING

In conditional reasoning, content is typically manipulated via background knowledge related to perceived *necessity* and/or *sufficiency* of *p* for *q* (Thompson 1994, 2000). For causal conditionals (i.e., *p* and *q* are related as cause and effect), this background knowledge is typically operationalised by two types of counterexamples: *alternatives* and *disablers* (for reviews see Beller & Kuhnmünch, 2007; Politzer, 2003). In the presence of alternatives—that is, of incidents other than *p* sufficient for *q*—perceived necessity is decreased. In the presence of disablers—that is, of incidents that prevent *q* in the presence of *p*—perceived sufficiency is decreased. For example, consider the conditional "*If water has been poured on a campfire, then the fire goes out*". One can easily imagine alternatives to the presented cause to have the effect that the fire goes out. For example, the fire may go out on its own or be smothered with a blanket or sand. Hence there are many alternatives to water being poured on a campfire and the perceived necessity of *p* (pouring water on a campfire) should be low for *q* (the campfire goes out). However, it is more difficult to find appropriate disablers for this conditional. For example, one could use too little water, but this possibility is less salient given the conditional rule. Hence there are only few disablers and perceived sufficiency of *p* for *q* should be high (for corresponding normative data see de Neys, Schaeken & d'Ydewalle, 2002, Table A1; for a discussion on whether perceived sufficiency/necessity and disablers/alternatives can be dissociated see Verschueren, Schaeken, & d'Ydewalle, 2005,).

Cummins and her colleagues (Cummins 1995; Cummins, Lubart, Alksnis & Rist, 1991) were among the first to show the effect of alternatives and disablers empirically. They asked one group of participants to generate alternatives and disablers for a set of conditional rules. Another group of participants was asked to judge whether or not the conclusions drawn from the four conditional problems MP, AC, MT, and DA could be accepted. Although the participants who were asked to judge the problems were not asked to generate counterexamples, their judgements were dependent on the number of counterexamples. The results were parallel for both affirmation and denial problems. The likelihood of accepting the invalid (i.e., DA and AC) problems was decreased in the presence of alternatives, and the likelihood of accepting the valid (i.e., MP and MT) problems was decreased in the presence of disablers. Similar results were obtained when not the number of alternatives/disablers but the association strength of alternatives/disablers with the conditional or the frequency with which the counter-examples occur was taken into account as a contributing factor (de Neys, Schaeken, & d'Ydewalle, 2003; Geiger & Oberauer, 2007; Quinn & Markovits, 1998). Returning to our example, the disabler (too little water) may be less strongly associated with the conditional and appear less frequently than the more salient alternatives (e.g., fire goes out on its own). In summary, salient (or *strongly linked*, Politzer, 2003) alternatives decrease acceptance of DA and AC and salient disablers decrease acceptance of MP and MT. To obtain a response pattern in line with formal logic one should therefore present conditionals with salient alternatives but without salient disablers (such as our example). To obtain a response pattern in opposition to formal logic one should present conditionals without salient alternatives but with salient disablers.

EXPLAINING CONTENT EFFECTS IN CONDITIONAL REASONING

Contemporary theories in conditional reasoning can be broadly classified by the number of processes assumed to explain the reasoning outcome. There are two classes of theories that assume one basic process at the heart of conditional reasoning: analytical and probabilistic theories. The analytical theories assume that reasoning itself is still analytical, although the outcome is influenced by content. In the influential mental model framework (Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991), it is assumed that content modulates the way conditionals are represented, but that inferences are still drawn in a deductive way from these representations (Johnson-Laird & Byrne, 2002; Johnson-Laird, Byrne, & Schaeken, 1992; Markovits & Barouillet, 2002, Schroyens & Schaeken, 2003). Probabilistic theories of reasoning (Oaksford & Chater, 2007; Oaksford, Chater, & Larkin, 2000) assume that reasoners extract probabilities from conditional problems. These probabilities (such as the conditional probability of *q* given *p*) are then used to evaluate the problem. The specific content is assumed to determine the extracted probabilities. From a probabilistic position, reasoning is seen as a rational process determined by the perceived probabilities (for an analytic version of probabilistic theories based on non-monotone logic see, e.g., Pfeifer & Kleiter, 2010).

Interestingly these theoretical accounts, analytical and probabilistic, are typically related to differing experimental methods, especially to different instruction types. Instructions in experiments within the mental model framework (e.g., Quinn & Markovits, 2002) follow what has been called the "deduction paradigm" (Evans, 2002): they typically stress the notion of deductive validity (henceforth referred to as deductive instructions). Participants are instructed to treat the conditional rule as always true and to accept only those conclusions that are valid based on the *form* of the argument; that is, independent of the specific content. The response is given via binary (e.g., valid – invalid) or ternary (e.g., valid – invalid – unsure) response options. Experiments carried out from a probabilistic position (e.g., Oaksford et al., 2000) are typically designed to tap *everyday* or *pragmatic* reasoning (Oaksford & Chater, 2001, 2007). As a consequence, instructions typically do not stress logical necessity but inductive strength, and highlight that participants should consult their prior knowledge (henceforth inductive[1] instructions). Furthermore, the response is given on a graded response scale, asking, for example, how likely it is that a given conclusion holds. Given that the different theoretical positions are confounded with the used instructions, the question is whether or not different instructions lead to different reasoning outcomes. If so, can any of these single-process theories explain conditional reasoning comprehensively?

Theories that assume more than one process at the heart of conditional reasoning seem to be better suited to explain different results produced by different instructions. Most (if not all) of these theories can be subsumed under the label *dual-process theories*, indicating that basically two processes govern the reasoning process (Evans, 1982, 2006, 2007; Klauer, Beller, & Hütter, 2010; Oaksford & Chater, 2010, Part 4; Verschueren et al., 2005; for an overview see Evans, 2008). These theories typically distinguish between a process that is nonconscious, rapid, automatic, and high in capacity, called Type 1, from a process that is conscious, slow, and deliberative, called Type 2 (although not all theories ascribe all of these attributes to the postulated processes). One basic assumption of most theories is that Type 1 processes produce a default response, and Type 2 processes, given enough time, override or support the outcome of Type 1 processes by factors such as instructions (Evans, 2006), metacognitive judgements (Thompson, 2010), or content-specific effects (Verschueren & Schaeken, 2010; Verschueren et al., 2005; but see Handley, Newstead, & Trippas, 2011). In most dual-process theories content influences reasoning via Type 1 processes by heuristically retrieving relevant knowledge from memory (see Verschueren et al., 2005, for a dual-process model in which both processes are knowledge based).

In some dual-process theories the role of the instruction is explicit. For example, Evans (e.g., 2007) makes assumptions about the role of

[1] We use the terms deductive and inductive in the broadest possible sense. Deduction refers to all reasoning that entails the truth of the conclusion given the truth of the premises. Induction refers to all reasoning that does not entail the truth of the conclusion given the premises (this is also termed *abductive* reasoning).

instructions in conditional reasoning (e.g., more Type 2 involvement) and often uses both types of instructions in his recent studies (e.g., Evans, Handley, & Bacon, 2009, Experiment 1; Evans, Handley, Neilens, & Over, 2010). Klauer et al.'s (2010) model is explicitly developed for everyday reasoning under inductive instructions. In contrast, Verschueren et al. (2005) use binary response options without stressing logical necessity in the instructions, but do not justify this choice. Taken together, although some proponents of dual-process theories do acknowledge that different instructions may produce different outcomes, not all do so.

DISSOCIATING DEDUCTIVE AND INDUCTIVE CONDITIONAL REASONING

Based on this theoretical background, the question addressed here is whether different instruction types prompt different modes of reasoning that are empirical dissociable. In other words, do deductive instructions produce a deductive mode of reasoning and inductive instructions produce an inductive mode of reasoning?[2] Furthermore, can single-process theories explain both modes of reasoning or only dual-process theories? Direct evidence questioning the notion of a single mode of reasoning stems from experiments in domains outside conditional reasoning. Rips (2001) compared deductive and inductive instructions on a multiple-form reasoning task.[3] Furthermore, he simultaneously varied validity and plausibility of the presented problems. That is, he presented problems with matching validity and plausibility (i.e., valid and plausible, invalid and implausible) and problems where validity and plausibility were pitted against each other (i.e., valid and implausible, invalid and plausible). Using this design, Rips found a so called *double dissociation* (Dunn & Kirsner, 1988) for the problems with validity and plausibility pitted against each other: Under deductive instructions, deductively valid but implausible problems were more often accepted than deductively invalid but plausible problems (*validity effect*). The opposite was true under inductive instructions. Here plausibility predicted the results. Invalid but plausible problems were more often accepted than valid but implausible ones (*plausibility effect*). Furthermore, when validity and plausibility matched there were only minor differences as a function of instruction. This last finding strengthens the

[2] The two modes of reasoning are not synonyms for Type 1 and Type 2 processes. Rather, these distinctions are orthogonal to each other (see Rips, 2001). This aspect will be addressed in the General Discussion below.

[3] Rips (2001; as well as Heit & Rotello, 2005, see below) used multiple forms of reasoning, including conditional reasoning (i.e., MP arguments). However, as the presented results are averaged over all different forms of reasoning, the specific effect on conditional arguments remains unclear.

validity of a double dissociation and establishes a so-called reversed association (Dunn & Kirsner, 1988).

Establishing a double dissociation—that is, showing that the manipulation of at least two different variables selectively influences different tasks—is the most common method to determine whether certain results are compatible with a single process or not. Although the validity of inferences drawn from a double dissociation is intensely debated (e.g., Chater, 2003; Dunn & Kirsner, 1988, 2003), we agree with Baddeley (2003) in asserting the moderate position that double dissociations are useful statistical tools for accumulating evidence opposing one-process models. Therefore Rips' (2001) results provide strong evidence against any theory postulating that the responses under deductive and inductive instructions are generated from a single process via different (although monotonicly increasing) transformations. For example, theories positing that responses under both conditions reflect (monotone transformations of) perceived probabilities (Oaksford et al., 2000) or inductive strength are thereby ruled out. At the same time it is further ruled out that responses under both conditions reflect (different monotone transformations of) perceived deductive validity. For the current question of whether or not conditional reasoning under deductive and inductive instructions can be explained by single- or dual-process theories it is possible to design an experiment similar to the one conducted by Rips (2001). Indeed, we intend to show that manipulating one variable (i.e., validity) affects responses primarily under deductive instructions, whereas another variable (i.e., plausibility) affects responses primarily under inductive instructions in conditional reasoning.

Further evidence against a one-dimensional view of reasoning (i.e., a single process is able to account for reasoning) comes from a series of studies by Heit and Rotello (2005, 2008, 2010; Rotello & Heit, 2009). Unlike Rips (2001), Heit and Rotello did not manipulate plausibility to dissociate two modes of reasoning but, within a signal detection framework, showed that a one-process model was unable to account for the data observed under deductive and inductive instructions. Instead, a two-process model, one process pertaining to deductive validity and one pertaining to associative strength, was able to account for the data. However, like Rips (2001), Heit and Rotello mainly used non-conditional arguments, so their results do not directly address conditional reasoning.

In the domain of conditional reasoning a dissociation of inductive and deductive instructions has yet to be shown. We know of one study that was specifically targeted at comparing deductive and inductive instructions for conditional reasoning (Markovits & Handley, 2005, Experiment 1). In their study Markovits and Handley solely manipulated instruction type and problem (MP, AC, MT, and DA). They found differences between deductive and inductive instructions, but their results were also consistent with a simple threshold model (i.e., a single-process model). In particular, one underlying dimension of argument strength was able to account for reasoning under both kinds of instructions. As already argued above, one would not expect a double dissociation to emerge unless the problems are specifically constructed towards the end of establishing a double dissociation (one necessary condition being that an additional variable is manipulated over and above problem and instruction type). In other words, the absence of a double dissociation is non-diagnostic if these design features are not implemented.

We found three additional studies that used both deductive and inductive instructions on conditional reasoning tasks (Evans et al., 2009, Experiment 1; Evans et al., 2010; Weidenfeld, Oberauer, & Hörnig, 2005). All of these studies manipulated variables in addition to instruction type and problem. Weidenfeld et al. (2005) manipulated content of the conditional rule, Evans et al. (2009) manipulated content of the conditional rule and time pressure for judging the problems, and Evans et al. (2010) manipulated content of the conditional rule and, based on measured intelligence, split their sample into groups of high and low cognitive ability. However, none of these studies was designed to specifically compare deductive and inductive instructions in a design in which a double dissociation could be secured. Hence these studies either did not report a three-way interaction of instruction type by problem (MP, AC, MT, and DA) by a third variable, which would be the prerequisite of a double dissociation (Evans et al., 2009; Weidenfeld et al., 2005) or, when such an interaction was present (Evans et al., 2010), the data still did not exhibit a double dissociation.

Fortunately, there is a method related to double dissociation analyses for determining whether one or more dimensions are responsible for a certain result pattern; namely *state-trace analysis* (Bamber, 1979; Loftus, Oberg, & Dillon, 2004; Newell & Dunn, 2008), which we applied to the aforementioned four studies. State-trace analysis can be used when the factorial combination of all independent variables provides more than two cells for each of the two different tasks (i.e., the two instruction types). Central to state-trace analysis is the *state-trace plot*, a scatter plot in which both coordinates depend solely on the dependent variable and each different factorial combination of the independent variables creates one data point. In the following state-trace plots the y-axis represents responses under inductive instructions and the x-axis represents responses under deductive instructions. Moreover, each point represents one of the factorial combinations of the remaining independent variables. The crucial characteristic of the state-trace plot is whether or not the data points fall on a monotonically increasing or decreasing curve. If so, there is no evidence to reject a one-dimensional model. If they do not fall on a monotonically increasing or decreasing curve, the data must have been driven by more than one underlying dimension or process. In this latter case there would be evidence indicating that at least two processes contribute to the reasoning outcome. Unfortunately no method applicable to the data presented here has been developed to secure monotonicity or non-monotonicity of the state-trace plot statistically (Prince, Brown, & Heathcote, 2011; Newell & Dunn, 2008). Based on simulations, Loftus et al. (2004) claimed that $r_s = 1.0$ indicates monotonicity and all other values of r_s indicate non-monotonicity. However, simulations by Heathcote et al. (2010) revealed that values other than $r_s = 1$ frequently appeared when simulating data from a one-dimensional model. Thus they discourage the use of r_s in practice. Therefore we judge monotonicity by eye, but additionally provide r_s. Given this problem of how to statistically secure monotonicity or non-monotonicity, our own experiments were designed to allow us to conduct the statistically well-developed double-dissociation analysis. Furthermore, Dunn and Kirsner (1988) show that a certain double dissociation (i.e., a reversed association, as in Rips, 2001, and the one we aim for) is equivalent to a non-monotonic state-trace plot. Hence, such a double dissociation implies non-monotonicity in terms of state-trace analysis.

State-trace plots that provided deductive and inductive instructions in the domain of conditional reasoning from the four studies known to us are presented in Figure 1. Each point represents the responses to one of the four conditional problems. MP, AC, MT, and DA are represented by different symbols. Borrowing from the logic of double dissociations, and Rips' (2001) findings that the manipulation of at least two different variables (in addition to two different tasks, here deductive and inductive instructions) is a prerequisite for a dissociation, we plotted data points for all factorial combinations of the independent variables (i.e., one data point per cell). Manipulations of content of the conditional rule are represented by differences in shade (Evans et al., 2009, 2010; Weidenfeld et al., 2005). The differences in time pressure of the task (Evans et al., 2009) and cognitive ability (Evans et al., 2010) are represented by different sizes of the data points (see figure caption for more details).

Consider the state-trace plot of Markovits and Handley's (2005, i.e., the leftmost panel in Figure 1) data. Allowing for a small amount of measurement error (i.e., DA, AC, and MT are on the same level for inductive responses within a small error tolerance) there is a monotonic function connecting the four data points indicating that a one-dimensional model may be responsible for the results. The data of the remaining three studies are more difficult to interpret. Visual inspection of the state-trace plots permits no clear interpretation regarding monotonicity or non-monotonicity. Besides not providing a clear picture regarding the underlying dimensionality there is another difference between Markovits and Handley's (2005) data and the remaining three studies. In the latter, under deductive

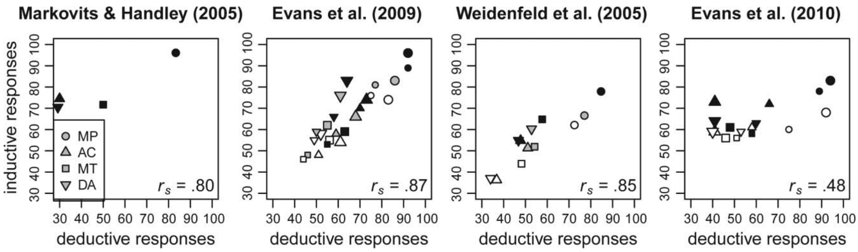

Figure 1. State-trace plots from four studies on conditional reasoning with both inductive and deductive instructions. If data points within one plot lie on a monotonically increasing curve, this is evidence for a one-dimensional model of deductive and inductive reasoning. Different problems are represented by different symbols. For Evans et al. (2009) black points represent conditional rules high in believability, grey points represent conditional rules medium in believability, and white points represent conditional rules low in believability. Furthermore, big points represent responses given under a free-time condition and small points represent responses given under a speeded-task condition. For Weidenfeld et al. (2005) black points represent causally forward conditional rules (i.e., *if cause then effect*), grey points represent non-causal conditional rules, and white points represent causally backward conditional rules (i.e., *if effect, then cause*). For Evans et al. (2010) black points represent conditional rules high in believability and white points represent conditional rules low in believability. Furthermore, big points represent responses from participants high in cognitive ability, and small points represent responses from participants low in cognitive ability. The corresponding r_s is shown in the lower right corner of each plot. Data from Evans et al. (2010) are taken from Table 2 for deductive responses and from Table 3 for inductive responses. Consult main text for interpretation of the plots.

instructions the valid problem MT was not judged to be more valid than the invalid problems AC and DA (i.e., MT is not more to the right than AC and DA). This means there was no validity effect for the denial inferences in Evans et al.'s (2009, 2010) and Weidenfeld et al.'s (2005) studies. These findings resemble meta-analytic results of Schroyens, Schaeken, and d'Ydewalle (2001, see also Schroyens & Schaeken, 2003) for conditional reasoning under deductive instructions showing a strong validity effect for affirmation problems, but hardly any validity effect for denial problems. However, a validity effect under deductive instructions is required for a dissociation as elaborated above. Therefore we analysed affirmation and denial problems separately, where possible (Figure 2; the state-trace plots of Markovits & Handley, 2005, would only consist of two data points each and are therefore omitted). Another reason for this split was that response bias (such as affirmation bias) is likely to affect affirmation and denial problems differently. This difference may interact with instruction type, thus potentially leading to evidence against a one-dimensional view based on misleading and superficial differences in response bias.

Inspection of the affirmation problems (upper row of Figure 2) provides further support for a one-dimensional view of deductive and inductive

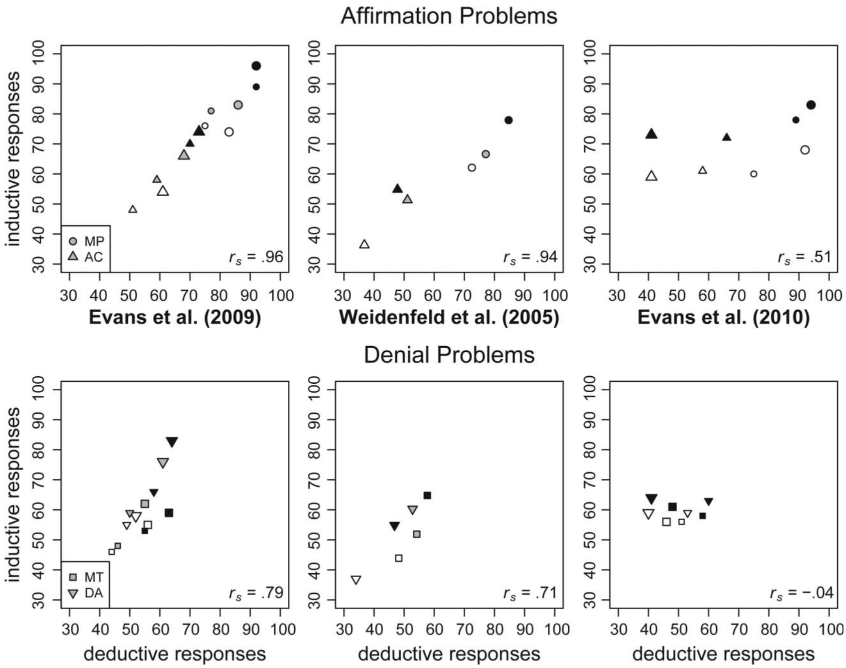

Figure 2. State-trace plots of affirmation (upper row) and denial (lower row) problems from three studies on conditional reasoning with both inductive and deductive instructions and manipulation of at least one additional variable. See caption of Figure 1 for details on what differences in shading and size represent. The corresponding r_s is shown in the lower right corner of each plot. Consult main text for interpretation of the plots.

conditional reasoning. The data points from the first two studies (Evans et al., 2009; Weidenfeld et al., 2005) lie almost perfectly on monotonically increasing curves. The results from the third study (Evans et al., 2010) are more difficult to interpret. Depending on the amount of measurement error, either a curve midway between high-belief (i.e., the black) data points and low-belief (i.e., the white) data points would fit the data, thereby indicating monotonicity. Alternatively two lines, one connecting the low-belief and one connecting the high-belief data points, would be more appropriate, thereby indicating non-monotonicity. For the denial problems (the lower row of Figure 2) the picture is less clear. Due to the absence of a validity effect the data points form a cluster rather than a curve, and interpretations regarding the dimensionality of the underlying processes seem unwarranted.

This brief review indicates that results are not inconsistent with single-process models for conditional affirmation problems. Results from the denial problems are inconclusive. This contrasts with results from non-conditional reasoning tasks indicating that at least two processes contribute to the reasoning outcome (Heit & Rotello, 2010; Rips, 2001; Rotello & Heit, 2009). This state of affairs is especially unsatisfactory considering the fact that single-process accounts have been most fully developed for conditional reasoning. For example, Oaksford et al.'s (2000) model posits that perceived probability of the conclusion given the minor premises underlies the responses under inductive and deductive instructions alike (see Oaksford & Chater, 2001, 2007). To add to the evidence that inductive and deductive instructions for conditional problems prompt two distinct modes of reasoning we conducted two experiments described in the following.

Following Rips (2001) we presented problems with matching validity and plausibility as well as problems where validity and plausibility were pitted against each other to establish a double dissociation. Under deductive instructions we expected validity of the problems to predict judgements, whereas under inductive instructions we expected plausibility of the problems to predict judgements. To present problems with these features in the framework of causal conditional reasoning we manipulated perceived sufficiency and necessity by presenting conditionals with varying numbers of salient disablers and alternatives. The conditional problems with matching validity and plausibility were constructed from conditionals with few and non-salient disablers, but with salient alternatives; that is, high sufficiency but low necessity of p for q. Henceforth we will call these conditionals *prological conditionals* as they should promote a response pattern in line with formal logic as already explained. The conditional problems where validity and plausibility were pitted against each other were constructed from conditionals with salient disablers and few and non-salient alternatives; that is, with low sufficiency but high necessity of p for q. We will call these latter conditionals *counterlogical conditionals*, as they should promote a response pattern contrary to formal logic as already explained.

EXPERIMENT 1

In the first experiment we selected four conditionals from the literature (see Appendix 1) with few and non-salient disablers, but with salient alternatives (i.e., prological conditionals) as the basis for the problems which matched in terms of validity and plausibility. To construct problems where validity and plausibility were pitted against each other (i.e., problems from counterlogical conditionals) we simply reversed the order of p and q of the prological conditionals. Through this reversal, disablers became alternatives and vice versa (Cummins, 1995; Thompson, 1994).

Consider the example (one of the prological conditionals used in the first experiment): *If water has been poured on a campfire, then the fire goes out*. This conditional (as well as the other three used in the first experiment) describes a causal relation (p is the cause for q) in which there are many alternatives to p that could cause q, (e.g., the fire goes out on its own), and few disablers that prevent q in the presence of p. Now consider the valid affirmation problem MP for this conditional: *Water has been poured on a campfire. How valid is the conclusion/How likely is it that the fire goes out?* The absence of any salient disablers suggests that the proposed outcome is plausible. Hence both validity and plausibility suggest strong endorsement. Now consider the invalid affirmation problem AC: *A campfire goes out. How valid is the conclusion/How likely is it that water has been poured on it?* Here, salient alternatives question the plausibility of the conclusion. Hence both validity and plausibility suggest weak endorsement. For the prological conditionals we therefore predicted little difference in judgements between deductive and inductive instructions. Furthermore, as MP is valid and plausible and AC invalid and implausible, endorsement should be stronger for MP than for AC under both instructions.

For the counterlogical conditionals an effect was conditionally linked to one of many causes (now p is the effect caused by q). Consider the above conditional in reversed direction: *If a campfire goes out, then water has been poured on it*. This conditional now has few alternatives for p in light of q (i.e., the few and non-salient former disablers, e.g., too little water), but many disablers; that is, cases other than q that could be responsible for p (i.e., the former alternatives, e.g., goes out on its own). Now consider the valid affirmation problem MP for this conditional: *A campfire goes out. How valid is the conclusion/How likely is it that water has been poured on it?* Due to the presence of disablers the plausibility of this argument is questionable. Hence, although the problem is logically valid, plausibility suggests weak endorsement. Now consider the invalid affirmation problem AC: *Water has been poured on a campfire. How valid is the conclusion/How likely is it that the fire goes out?* Here, the absence of salient alternatives makes it a plausible problem and suggests strong endorsement. However, AC is not valid. For the counterlogical conditionals we therefore predicted an interaction of instruction with validity of the problem. Specifically, we will test for the following double dissociation for the counterlogical conditionals: Under deductive instructions, MP should be endorsed significantly more strongly than AC (validity effect); conversely, under inductive instructions, AC should be endorsed significantly more strongly than MP (plausibility effect).

The same predictions should in principle hold for the denial problems (MT and DA). But in accordance with the aforementioned meta-analytic results (Schroyens et al., 2001), and our brief review, it was doubtful whether a sufficiently strong validity effect would emerge for the denial problems under deductive instructions to establish a full double dissociation. Therefore, in the following, we inspected affirmation and denial problems separately.

As already mentioned, studies with deductive instructions typically use binary or ternary response options, whereas studies with inductive instructions typically use a graded response scale. When comparing both instruction types, each accompanied with its typical response scale, one needs to transform at least one of the response scales. For example, Markovits and Handley (2005) compared the mean percentage of acceptance in the deductive condition (e.g., accepting 3 out of 4 problems is transformed to a score of .75) with mean endorsement in the inductive condition (e.g. two times 5 and two times 6 on a 7-point response scale is transformed to .79). Although this is one way of making both scales comparable, it is unknown whether this transformation adequately captures the responses given by the participants, or whether another possible transformation would be more appropriate. For example, Evans et al. (2010) simply dichotomised the responses under inductive instructions at the midpoint of the scale. Others (Evans et al., 2009; Rips, 2001; Weidenfeld et al., 2005) circumvented this problem by providing binary response options for both conditions (e.g., valid – invalid versus strong – not strong; Rips, 2001). However, in applying this method one loses the benefits of a graded response scale for the inductive condition. This seems very unsatisfactory considering theories that highlight that conditionals are transformed into probabilities that determine responses (e.g., Oaksford et al., 2000). Therefore we decided to collect responses on a graded response scale in both conditions.

This decision may seem odd given recent results by Markovits et al. (2010), who showed that it is not the instruction type but rather the type of response option (graded versus binary) that drives differences. But unlike Markovits et al. we used a stronger manipulation of instruction type. Specifically, under deductive instructions our participants are asked to assume the truth of the premises and to disregard background knowledge, whereas Markovits et al. simply asked participants whether "the conclusion could be logically drawn from the given information" (2010, p. 487).

Method

Participants. A total of 40 students from the University of Freiburg (20 per condition) participated in this study in exchange for 3.50 € ($M_{\text{age}} = 23.2$, range 18–31 years). Participants had no training in formal logic.

Materials and procedure. Participants had to judge either the deductive validity (deductive instructions) or the likelihood (inductive instructions) of a conclusion drawn from a conditional problem. Each participant worked on four different conditional rules. For each participant two of the four conditionals were randomly selected to be presented as prological conditionals. The other two conditionals were presented as counterlogical conditionals. For each conditional the four problems MP, AC, MT, and DA were administered. The so-called converse inferences, MP', AC', MT', and DA', with polarity of the conclusion inverted (Oaksford et al., 2000), were also presented as filler items. Each session was divided into two blocks separated by a short break. In each block we presented all four conditional rules together with all four inference problems. The only difference between the blocks was the polarity of the conclusion, which was randomly assigned. In each block the rules appeared in random order. For each rule all four inference problems were successively presented, but in random order. In total each participant worked on 32 problems, 16 per block.

Under deductive instructions, participants were instructed to judge whether a presented conclusion followed from a rule and an observation (i.e., the minor premise) based only on the logical form of the problem. They were instructed that this implies considering the rule to be true ("in one hundred percent of the cases and without any exception") even when knowing that this might not be the case in real life. Furthermore, they were told that judgements should be made irrespective of the plausibility of the problem. For each problem participants were presented with the rule and an observation. Then they were asked: "Given the validity of this rule and this observation: How valid is the conclusion that ... from a logical perspective?" ["Wie gültig ist aus logischer Sicht die Folgerung, dass ... "] The three dots were replaced by the corresponding conclusion. Participants were asked to indicate their answer on a scale ranging from 0 to 100. Instructions clarified that participants were to mark 0 when they judged the conclusion to be invalid and 100 when they judged the conclusion to be valid. Furthermore they read: "When you are unsure, you can indicate the degree to which you think the conclusion is valid by selecting a number between 0 and 100."

Under inductive instructions participants were instructed to judge the probability of a conclusion given rule and observation. For each problem, participants were presented with the rule and an observation. Then they were asked: "How likely do you think it is that ... ?" ["Wie groß schätzen Sie die Wahrscheinlichkeit, dass ... "] Again, the dots were replaced with the corresponding conclusion. Participants were asked to indicate their answer on a scale ranging from 0% to 100%. Instructions clarified that participants were to mark 0% when participants judged the conclusion to be highly unlikely, to mark 100% when they judged the conclusion to be highly likely, and to mark 80% when they judged the conclusion to be 80% probable. Under both instruction types it was clarified that rules should only be viewed unidirectional. That is, instructions stated that the rule "*if p, then q*" does not imply "*if q, then p*".

Results and discussion

We collapsed mean responses for each participant over the conditionals separately for each type of conditional rule (prological vs counterlogical) and problem (MP vs AC & MT vs DA). The filler items (MP', AC', MT', and DA') were not analysed. Mean responses to the problems and English translations of the conditional rules are given in Appendix 1. As is apparent from Figures 3 and 4, the data do not meet all assumptions for classical inferential statistics (i.e., normality and homoscedasticity). Therefore the critical prediction of the double dissociation is tested with assumption-free permutation tests following Hothorn and colleagues (Hothorn, Hornik, van de Wiel, & Zeileis, 2006, 2008). In the case of between-participants comparisons, so-called exact statistics are provided (also known as randomisation tests), for the within-participant comparisons (i.e., stratifying by participant) the results are based on 100.000 bootstrapped Monte Carlo samples. The same pattern of significant and non-significant results is obtained when standard t tests are used.

Affirmation problems. We entered the data into a 2 (between participants) $\times$ 2 $\times$ 2 (within participants) analysis of variance (ANOVA) with instruction (deductive vs inductive), type of the conditional rule (prological vs counterlogical) and problem (MP vs. AC) as factors. Among others (see Table 1), we found the expected three-way interaction of instruction by type by problem, $F(1, 38) = 10.73$, $p = .002$, depicted in Figure 3, left panel. This interaction was the prerequisite for the predicted double dissociation.

Results confirmed the main prediction: the dissociation of validity and plausibility when both were pitted against each other (i.e., the crossover interaction of the inner problems in Figure 3, left panel). Under deductive instructions participants showed stronger endorsement for the valid but implausible MP problem than for the invalid but plausible AC problem, $Z = 2.34$, $p = .02$ (validity effect). Under inductive instructions we found the reverse pattern. Participants showed lower endorsement for the valid but implausible MP problem than for the invalid but plausible AC problem, $Z = -2.98$, $p = .001$ (plausibility effect). Furthermore, participants under deductive instructions showed stronger endorsement for the valid but implausible MP problem than participants under inductive instructions, $Z = 3.90$, $p < .001$. Participants under inductive instructions showed stronger endorsement for the plausible but invalid AC problem than participants under deductive instructions, $Z = -2.270$, $p = .02$.

For problems where validity and plausibility matched (i.e., the outer problems in Figure 3, left panel), we also found the predicted results. Namely, under both instructions participants showed stronger endorsement for MP (valid and plausible) than for AC (invalid and implausible),

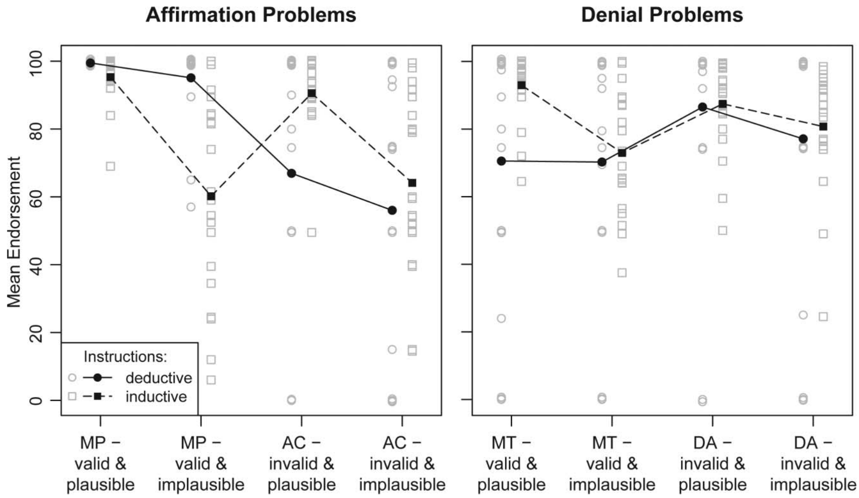

Figure 3. Mean responses (in black) from deductive and inductive instructions on the affirmation (left panel) and denial problems (right panel) from Experiment 1. The significant three-way interactions of instruction × type of the conditional rule × problem are plotted to show the interaction of validity with plausibility. For the outer problems validity and plausibility match (problems constructed from prological conditional rules), whereas for the inner problems they are pitted against each other (problems constructed from counterlogical conditional rules). The cross-over interaction in the left panel depicts the critical double dissociation of validity and plausibility. The raw data is plotted in grey to show the dispersion of the data. If two or more data points would have overlapped in the figure, a small amount of random jitter (uniformly distributed from –0.7 to 0.7) was added to make them distinguishable.

$Z = 3.21$, $p < .001$, and $Z = 3.43$, $p < .001$, respectively, for deductive and inductive instructions. However, participants in the deductive condition showed stronger endorsement for MP problems than participants in the inductive condition, $Z = 2.38$, $p < .001$, whereas there was no difference in endorsement for AC, $Z = –.72$, $p = .48$.

Denial problems. We entered the data into the above-described 2 × 2 × 2 ANOVA with instruction (deductive vs inductive), type of the conditional rule (prological vs counterlogical) and problem (here, MT vs DA). Again, among others (see Table 1), we found the expected three-way interaction of instruction by type by problem, $F(1, 38) = 4.12$, $p = .049$, depicted in Figure 3, right panel.

Results did not confirm the prediction of a double dissociation. Under deductive instructions we did not find a validity effect. Participants did not show stronger endorsement for the valid but implausible MT problem than for the invalid but plausible DA problem, $Z = –1.83$, $p = .07$, rather the

TABLE 1
Experiment 1

Factor	*df*	*MSE*	*F*	η^2	*p*
		Affirmation problems			
Instruction	1, 38	1072.42	.13	.00	.72
Type (of Conditional Rule)	1, 38	187.90	.06	.00	.81
Problem	1, 38	1007.21	13.01***	.26	< .001
Type × Instruction	1, 38	187.90	3.09	.08	.09
Problem × Instruction	1, 38	1007.21	12.44**	.25	.001
Type × Problem	1, 38	498.48	29.62***	.44	< .001
Type × Problem × Instruction	1, 38	498.48	10.73**	.22	.002
		Denial problems			
Instruction	1, 38	1615.52	1.37	.35	.25
Type (of Conditional Rule)	1, 38	338.60	.13	.00	.72
Problem	1, 38	884.58	1.78	.05	.19
Type × Instruction	1, 38	338.60	3.72	.09	.06
Problem × Instruction	1, 38	884.58	1.19	.03	.28
Type × Problem	1, 38	174.88	18.99***	.33	< .001
Type × Problem × Instruction	1, 38	174.88	4.13*	.10	.049

Results of the two three-way ANOVAs with instruction (deductive vs inductive), type of the conditional rule (prological vs counterlogical) and problem (MP vs AC and MT vs DA) as the factors for both affirmation and denial problems from Experiment 1. MSE represent mean squared errors for the corresponding error term.
*$p < .05$. **$p < .01$. ***$p < .001$.

results even tended to point in the opposite direction. Furthermore, they did not show stronger endorsement for the valid and plausible MT than for the invalid and implausible DA, $Z = –.65$, $p = .53$.

Interestingly, under inductive instructions the results confirmed the predictions. We did find the predicted plausibility effect. When validity and plausibility were pitted against each other participants showed stronger endorsement for the invalid but plausible DA problem than for the valid but implausible MT problem, $Z = –2.42$, $p = .01$. When validity and plausibility matched, participants showed stronger endorsement for the plausible and valid MT problem than for the invalid and implausible DA problem, $Z = 2.72$, $p < .001$. This indicates that, when naïve reasoners were freed from the task of determining the validity of the denial problems, they were able to use disablers/alternatives to judge plausibility.

Comparisons between the two instruction types did not provide much insight. The only differences were found for the valid and plausible MT. Under deductive instructions participants endorsed this particular problem less than under inductive instructions, $Z = –2.40$, $p = .01$. For the other three problems we found no differences, *p*s $> .70$.

Multiple testing. To control for multiple testing (e.g., Shaffer, 1995) we restricted the probability of committing a Type I error to $\alpha = .05$ separately for the set of significance tests conducted for affirmation problems and for the set of tests conducted for denial problems. For each set we computed four tests on the problems from the counterlogical conditionals: two (one for each instruction type) comparing the valid (MP or MT) to the invalid (AC or DA) problems and two comparing responses under deductive instructions to responses under inductive instructions for valid and invalid problems, respectively. Using Holm-Bonferroni correction (Holm, 1979; i.e., the smallest p-value is tested against $\alpha/4$, the second-smallest against $\alpha/3$, and so forth, until the first test is non-significant in this sequence of tests) the pattern of significance did not change (the same is true if one uses the p-values from standard t tests instead). For affirmation problems all four tests passed the corrected critical alpha. For denial problems only one test was significant prior to the correction ($p = .01$); this test remained significant after correction. The other three tests passed neither the uncorrected nor corrected alpha-level. Hence results remained unchanged when controlling for multiple testing.

Summary

The first study confirmed the predictions that naïve reasoners can adopt either a deductive or an inductive mode of reasoning. When asked to judge the validity of conditional problems, participants showed higher endorsement for valid than for invalid problems. When asked to judge the plausibility of conditional problems, participants showed higher endorsement for plausible than implausible problems. However, this dissociation was restricted to the affirmation problems. The absence of the dissociation for the denial problem was driven by responses under deductive instructions. Participants did not show a validity effect (i.e., participants did not show stronger endorsement for valid than invalid problems). This is in line with previous findings showing that participants more readily discriminate valid from invalid problems among affirmation problems than among denial problems (Schroyens et al., 2001). For denial problems under inductive instructions, plausibility predicted the results. That is, participants showed stronger endorsement for plausible than for implausible problems.

EXPERIMENT 2

With the second experiment we wanted to replicate the results of the first experiment and, furthermore, implement changes to rule out possible alternative explanations and broaden the scope of our findings. The most important change was that we used different contents for the prological and counterlogical conditionals. In the first experiment we had used the same content in both types, but reversed the rule (from "if *p* then *q*" to "if *q* then *p*") to construct counterlogical from prological conditionals. As a consequence valid problems from the prological conditionals and invalid problems from the counterlogical conditionals (and vice versa) were exactly the same when looking at the conditional problem without the conditional rule (but note that no participant saw problems with the same contents for the prological and the counterlogical conditionals; see Method section of Experiment 1). For example, when ignoring the conditional rule, both MP for one of the prological and AC for the respective reversed counterlogical conditional used in Experiment 1 state: *Water has been poured on a campfire. How valid is the conclusion/How likely is it that the fire goes out?* Furthermore, the prological conditionals always were of the form "if cause, then effect", whereas the counterlogical conditionals always were of the form "if effect, then cause", a distinction that has been referred to as one between causal versus diagnostic conditionals (Ali, Chater, & Oaksford, 2011; Ali, Schlottmann, Shaw, Chater, & Oaksford, 2010). Prological and counterlogical conditionals in Experiment 2 used different contents and were all causal conditionals. In all cases, *p* was the cause for *q*. This removed the confounding of prological and counterlogical conditionals and causal direction.

The second major change was that we provided participants with problems not only from prological (i.e., few and non-salient disablers, but salient alternatives) and counterlogical (i.e., salient disablers, but few and non-salient alternatives) conditionals, but also from conditionals that had both salient disablers and salient alternatives. These conditionals should neither facilitate nor oppose a response pattern in line with formal logic and, therefore, we will call them neutral conditionals. For the neutral conditionals the salient disablers should reduce endorsement for the valid problems (MP and MT) and the salient alternatives should reduce endorsement for the invalid problems (AC and DA). These additional conditionals should provide evidence for using counterexamples (i.e., disablers and alternatives) as a means for selectively influencing endorsement rates. Furthermore, we wanted to show that not all manipulations lead to the proposed dissociation, but that it is critical to oppose valid and implausible with invalid and plausible problems to produce the double dissociation of deductive and inductive instructions. This protects our interpretation from possible alternative explanations in terms of shallow directional response biases affecting MP (forward inference) and AC (backward inference) differentially as a function of instruction.

Method

Participants. A total of 56 students from the University of Freiburg (28 per condition) participated in this study in exchange for 3.50 € ($M_{\text{age}} = 22.7$, range 19–29 years). Participants had no training in formal logic.

We excluded one participant with conspicuous data from the deductive condition. This participant took less than 6 seconds per problem (mean of remaining participants = 16 seconds) and his mean response for MP problems was 51.9 (more than 4 *SD* below the mean in the deductive condition). The pattern of results did not change when including this participant.

Materials and procedure. The procedure was the same as in Experiment 1 except for the following changes. We provided participants with three different types of conditional rules, prological, neutral, and counterlogical, taken from the literature (three of each type, see Appendix 2). Each participant was presented with all of the conditional rules. Each session was divided into three blocks, separated by short breaks. In each block we presented one randomly selected conditional rule of each type; that is, we presented problems for three rules in each block. The order of the conditional rules within each block was randomly determined. For each rule all four inference problems, MP, AC, MT, and DA, were successively presented, but in random order. We did not use the converse inferences in this experiment. In total each participant worked on 36 problems, 12 per block.

We constructed problems with matching plausibility and validity from the prological conditionals (i.e., few and non-salient disablers, but salient alternatives) and problems with validity and plausibility pitted against each other from the counterlogical conditionals (i.e., salient disablers, but few and non-salient alternatives, see Appendix 2). The neutral conditionals had salient disablers as well as salient alternatives.

Results and discussion

As in Experiment 1 we collapsed mean responses for each participant over the conditional rules for each type of conditional rule and problem. Mean responses to the problems and English translations of the conditional rules can be found in Appendix 2. (Due to computer memory limitations we were not able to provide exact statistics for the permutation tests in Experiment 2, so all direct comparisons are based on 100.000 bootstrapped samples. The same pattern of significant and non-significant results emerges when standard t tests are used.)

Affirmation problems. We entered the data into a 2 (between participants) × 3 × 2 (within participants) ANOVA with, in order, instruction (deductive vs inductive), type of the conditional rule (prological vs neutral vs counterlogical), and problem (MP vs AC) as factors. Note that for all *F*-tests with type of conditional as a factor we provide Greenhouse-Geisser corrected values. Among others (see Table 2) we found the expected three-way interaction of instruction by type by problem, $F(1.72, 91.18) = 4.84$, $p = .01$, depicted in Figure 4, upper panel, the prerequisite for the double dissociation.[4]

As in Experiment 1 we found the double dissociation of validity and plausibility (i.e., the crossover interaction of the inner problems in Figure 4, upper panel) for the affirmation problems from the counterlogical conditionals where validity and plausibility were pitted against each other: Under deductive instructions we found the validity effect, $Z = 2.90$, $p = .002$; under inductive instructions we found the plausibility effect, $Z = –2.48$, $p = .01$. Furthermore, participants under deductive instructions showed stronger endorsement for MP, $Z = 4.22$, $p < .001$, and weaker endorsement for AC, $Z = –2.50$, $p = .01$, than participants under inductive instructions.

For problems where validity and plausibility matched (i.e., the outer problems in Figure 4, left panel, constructed from the prological conditionals), we also replicated the findings: Under both instructions participants showed stronger endorsement for MP than for AC, $Z = 4.62$, $p < .001$, and $Z = 4.80$, $p < .001$, respectively, for deductive and inductive instructions. However, participants under deductive instructions showed stronger endorsement for MP, $Z = 2.65$, $p < .001$, and tended to endorse AC less strongly, $Z = –1.87$, $p = .06$, than participants under inductive instructions.

The results for the problems constructed from the neutral conditionals exhibited a similar pattern as the results for the problems constructed from the prological conditionals: Under both instructions participants showed stronger endorsement for MP than for AC, $Z = 4.28$, $p < .001$, and $Z = 3.56$, $p = .001$, for deductive and inductive instructions respectively. Additionally, participants under deductive instructions showed stronger endorsement for MP, $Z = 4.18$, $p < .001$, and tended to endorse AC less strongly, $Z = –1.80$, $p = .07$, than participants under inductive instructions. Inspection of Figure 4 indicates that the difference for MP between inductive and deductive instructions is more pronounced for neutral conditionals than for prological conditionals.

Denial problems. We entered the data into a 2 × 3 × 2 ANOVA with instruction (deductive vs inductive), type of the conditional rule (prological

[4] When running the same analysis as in Experiment 1 (i.e., omitting the problems with the neutral conditionals) the 3-way interaction remained significant, $F(1, 53) = 6.49$, $p = .01$.

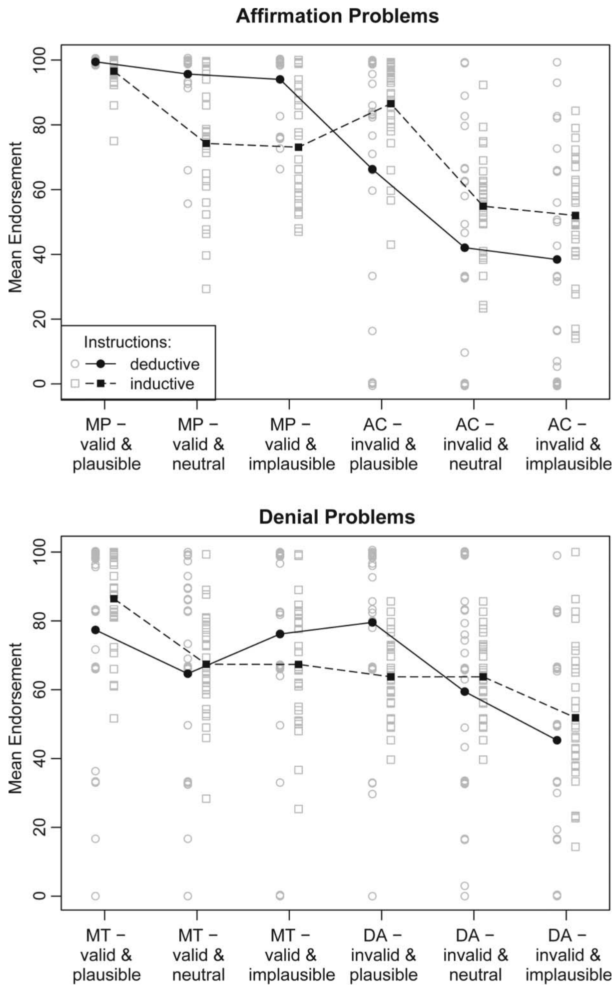

Figure 4. Mean responses (in black) from deductive and inductive instructions on the affirmation (upper panel) and denial problems (lower panel) of Experiment 2. The significant three-way interactions of instruction × type of the conditional rule × problem are plotted to show the interaction of validity with plausibility. For the outer problems validity and plausibility match (problems constructed from prological conditional rules), whereas for the inner problems they are pitted against each other (problems constructed from counterlogical conditional rules). The problems depicted in-between are constructed from the neutral conditionals. The raw data is plotted in grey to show the dispersion of the data. If two or more data points would have overlapped in the figure, a small amount of random jitter (uniformly distributed from –0.7 to 0.7) was added to make them distinguishable.

TABLE 2
Experiment 2

Factor	*df*	*MSE*	*F*	η^2	*p*
		Affirmation problems			
Instruction	1, 53	894.54	.01	.00	.94
Type (of Conditional Rule)	1.87, 99.05	180.76	29.32 ***	.36	< .001
Problem	1, 53	978.22	87.13 ***	.62	< .001
Type × Instruction	1.87, 99.05	180.76	3.83 *	.07	.03
Problem × Instruction	1, 53	978.22	19.78 ***	.27	< .001
Type × Problem	1.72, 91.18	267.53	63.93 ***	.55	< .001
Type × Problem × Instruction	1.72, 91.18	267.53	4.84 *	.08	.01
		Denial Problems			
Instruction	1, 53	852.26	1.33	.02	.25
Type (of Conditional Rule)	1.98, 104.74	297.76	22.01 ***	.29	< .001
Problem	1, 53	1300.62	4.67 *	.08	.04
Type × Instruction	1.98, 104.74	297.76	1.51	.03	.23
Problem × Instruction	1, 53	1300.62	.47	.02	.50
Type × Problem	1.95, 103.16	248.62	59.78 ***	.53	< .001
Type × Problem × Instruction	1.95, 103.16	248.62	3.09 †	.06	.05

Results of the two three-way ANOVAs with instruction (deductive vs inductive), type of the conditional rule (prological vs neutral vs counterlogical) and problem (MP vs AC and MT vs DA) as the factors for both affirmation and denial problems from Experiment 2. MSE represent mean squared errors for the corresponding error term. All *F*-tests comprising type of conditional as a factor report the Greenhouse-Geisser corrected values.
†$p < .1$. *$p < .05$. **$p < .01$. ***$p < .001$.

vs neutral vs counterlogical) and problem (here, MT vs DA). The three-way interaction of instruction by type by problem, depicted in Figure 4, lower panel, was only marginally significant, $F(1.95, 103.16) = 3.09$, $p = .051$.[5]

As in Experiment 1 we did not find a dissociation of deductive and inductive instructions for denial problems. This was, again, due to participants not distinguishing valid from invalid problems under deductive instructions: We did not find a validity effect for problems constructed from neither the counterlogical, $Z = -.43$, $p = .69$, nor the neutral conditionals, $Z = .58$, $p = .57$. Interestingly, for problems constructed from the prological conditionals we did find a validity effect, $Z = 3.15$, $p < .001$. For the latter problems, where validity and plausibility matched, this effect cannot be disentangled from a plausibility effect.

Under inductive instructions we found the predicted plausibility effect. For problems constructed from the prological conditionals, participants

[5] When running the same analysis as in experiment 1 (i.e. omitting the problems with neutral conditionals) the 3-way interaction was significant, $F(1, 53) = 4.84$, $p = .03$.

showed stronger endorsement for the (plausible) MT problem than for the (implausible) AC problem, $Z = 4.32$, $p < .001$. For problems constructed from the counterlogical conditionals they showed stronger endorsement for the (plausible) AC problem than for the (implausible) MT problem, $Z = -3.80$, $p < .001$. Interestingly, for problems constructed from the neutral conditionals we did not find any differences, $Z = 1.04$, $p = .31$. As is apparent from Figure 4, lower panel, there were no differences between deductive and inductive instructions, all ps $> .12$.

Multiple testing. Using Holm-Bonferroni correction (Holm, 1979), the pattern of significance did not change for the tests examining the cross-over interaction of the problems with validity and plausibility pitted against each other (the same is true if one uses the p-values from standard t tests instead). For affirmation problems all four tests passed the corrected critical alpha (all ps $< .012$). For denial problems, only the test examining the plausibility effect in the inductive condition was significant prior to controlling ($p < .001$), and it was significant afterwards.

Summary

The second experiment almost exactly replicated the findings of the first experiment: For affirmation problems we found the expected dissociation of deductive and inductive conditional reasoning, but not for denial problems. Furthermore, the implemented changes rule out possible alternative explanations for the results from the first experiment based on the reversal of the conditional rule, the causal direction of the conditional rules, or on the specific contents used in Experiment 1.

Adding a third type of (neutral) conditionals revealed that only when using a particular manipulation of the content, namely pitting validity and plausibility against each other, did the predicted double dissociation emerge. This strengthens the interpretation of the double dissociation in that both validity and plausibility appear to be the relevant dimensions on which participants focus under deductive and inductive instructions, respectively. Furthermore (replicating, e.g., Cummins et al., 1991), the response patterns under inductive instructions revealed the validity of using disablers and alternatives as a means of selectively influencing endorsement to MP and AC problems (see Figure 4, upper panel). The presence of disablers (neutral and counterlogical conditionals) decreased endorsement for MP compared to the absence of disablers (prological conditionals). However, the presence of alternatives (neutral and prological conditionals) decreased endorsement for the AC as compared to the absence of alternatives (counterlogical conditionals).

GENERAL DISCUSSION

Taken together, our two experiments provide evidence for a dissociation of two modes of conditional reasoning. When pitting validity and plausibility of conditional arguments against each other, validity predicts endorsement under deductive instructions and plausibility predicts endorsement under inductive instructions. This shows that the effect of validity outweighs the effect of plausibility under deductive instructions and the effect of plausibility outweighs the effect of validity under inductive instructions. Furthermore, this double dissociation indicates that at least two processes or latent variables must have produced the responses under deductive and inductive instructions (Dunn & Kirsner, 1988). That is, single-process theories are unable to predict the results found under the two different modes of conditional reasoning. Our study extends findings by Rips (2001) and Heit and Rotello (2005, 2008, 2010; Rotello & Heit, 2009) to the domain of conditional reasoning.

One may wonder whether this conclusion really holds given that we only found the dissociation for affirmation inferences. But, when considering the relevant literature this pattern is not at all surprising. As already said, the validity effect, the prerequisite for the double dissociation, is generally bigger for affirmation than denial inferences (e.g., Schroyens et al., 2001, for abstract materials). When using naturalistic causal conditionals (as we did), Evans et al. (2010) found virtually no difference between acceptance rates of MT (51%) versus DA (49%) under deductive instructions. This pattern even reversed for low-ability participants (55% versus 57%, for whom the validity effect was still present for affirmation inferences, 82% versus 62%). Furthermore, Evans et al. (2010, Table 6) show that even high-ability participants under deductive instructions are unable to deductively reason about MT inferences but rather resort to the believability of the conditional to judge the validity of the MT inference. Taken together, MT seems to be too difficult for naïve reasoners for a validity effect to emerge (see Schroyens & Braem, 2011, for a mental model based explanation of this effect). Hence, one cannot expect to find a double dissociation for denial inferences if one leg of the double dissociation rests on this validity effect. Furthermore, showing this dissociation for affirmation inferences only is sufficient for the claim that conditional reasoning per se cannot be explained by a single process.

Based on our findings we postulate, in line with other recent work (e.g., Evans, 2007; Heit & Rotello, 2010), that theories on conditional reasoning need to explicitly account for the effect of instruction and, furthermore, need to be able to allow for differential effects of reasoning and knowledge (i.e., validity and plausibility) under both types of instruction. Theories that do not do so, as the single-process theories outlined in the introduction, cannot fully account for the pattern of data presented here, and hence do not provide a comprehensive account of conditional reasoning. One reason is that these theories usually do not make explicit how effects of the different instructions should be accommodated. Let us consider, nevertheless, whether reasonable assumptions on such effects could enable these theories to account for the present double dissociation.

In the probabilistic theory of conditional reasoning by Oaksford et al. (2000) the probability of MP is defined as $P(MP) = 1 - e$ and AC as $P(AC) = (a(1-e))/b$ with a and b being the subjective probabilities of p and q events, respectively, and e an exceptions parameter, quantifying the subjective probability of rule violations, $e = P(\neg q|p)$. A natural manner to incorporate the effects of instructions would appear to be to assume that strong deductive instructions imply a decreased exceptions parameter e, that is, $e_{ded} < e_{ind}$. Entering the different exceptions parameters into the equations leads one to predict a main effect of instruction type. Under deductive instructions the probabilities for MP and AC should both be increased relative to inductive instructions—if e decreases, $P(MP) = 1 - e$ increases as does $P(AC) = (a(1-e))/b$. This prediction is consistent with our results for MP, but contradicts those obtained for AC. It is possible to account for the present results pattern if additional instruction effects are permitted on the a and/or b parameters of the model, but it is difficult to see how this could be justified on psychological grounds within Oaksford et al.'s probabilistic reasoning theory.

A similar conclusion can be drawn for the single-process theories based on the mental model framework (Markovits & Barrouillet, 2002; Schroyens & Schaeken, 2003). Take for example the version of Markovits and Barrouillet (2002), which is explicitly designed to handle the effects of alternatives and disablers. It states that an inference is drawn if no mental model containing a counterexample is represented. Hence the presence of disablers should reduce endorsement of MP and the presence of alternatives should reduce endorsement of AC as each heightens the probability of representing the respective mental model containing a counterexample. However, older adults are assumed to be able to inhibit disablers, leading them to accept MP even in the presence of disablers. A natural assumption to incorporate the instructional effects would therefore be that deductive instructions lead to stronger inhibition of counterexamples. Hence this version of the mental model theory can predict the pattern of results for MP under both instructions for prological and counterlogical conditionals. For prological conditionals (no salient disablers) it predicts no difference between the two instruction types. For counterlogical and neutral conditionals (salient disablers) it predicts higher endorsement for deductive than inductive instructions. In contrast, the pattern of results for AC cannot be predicted with this theory. Two possible readings of the theory regarding the effect of instruction are possible, but both fail to predict the observed data pattern. First, instruction type does not change the reasoning process and solely the presence or absence of alternatives should predict the pattern of results. This is not consistent with our results for counterlogical conditionals (i.e., a difference between the instruction types). Second, similarly to the MP inferences, deductive reasoning instructions could suppress the mental model containing the alternative condition. Then, as AC is drawn in the absence of this mental model, the theory would predict that AC is generally drawn under deductive instructions (see Markovits & Barrouillet, 2002, p. 20). This prediction is inconsistent with our results for AC under deductive instructions and with most of the literature showing that participants tend to endorse AC less than MP under deductive instructions. However, if it is assumed that deductive instructions lead to inhibition of counterexamples that conflict with the logical validity of the reasoning problem (i.e., of disablers, see De Neys, Schaeken, & d'Ydewalle, 2005), but to increased activation of counterexamples that promote responses in line with logical validity (i.e., of alternatives), then the present dissociation would be obtained. Note, however, that this modification would effectively make the theory a dual-process theory, an inductive process being responsible for the retrieval of information from long-term memory and a deductive process being responsible for modulation of knowledge activation and inhibition in accordance with the logical validity of the problem.

At the same time it is not the case that all dual-process theories are able to predict our results. First, some theories (e.g., Klauer et al., 2010) explicitly account for reasoning under only one type of instruction. Clearly one would not expect this theory to account for the observed results. Second, other theories (e.g., Verschueren et al., 2005) do not explicitly take an effect of instruction or context into account. Whether these theories are able to account for the present results rests on what one assumes the effect of instruction type to be on the parameters of the model. For example, Verschueren et al.'s (2005) theory integrates Oaksford et al.'s (2000) probabilistic model with the mental model based theory by Markovits and Barrouillet (2002). Hence this model is likely to encounter the same difficulties discussed above for Oaksford et al.'s (2000) model and for Markovits and Barrouillet's (2002) account in incorporating the effects of instruction.

Regarding the current literature on dual-process theories in reasoning, we see two approaches that readily predict our results. The first approach is the recent formulation of a dual-process theory by Evans (2006, 2007) that is based on the distinction between heuristic (Type 1) and analytic (Type 2) processes that interact in many ways. His theory builds on mental models but deviates from Johnson-Laird's (1983, Johnson-Laird & Byrne, 1991) definitions as Evans' mental models do not only represent true possibilities but are epistemic in nature. They can represent states of belief and knowledge. Reasoning from such models follows three principles. First, people only consider one model at a time (the singularity principle). Second, people consider the model that is the most relevant in the current context (the relevance principle), depending on task features, current goals, and background knowledge. This implies that different models can be constructed depending on task features and goals as defined by the instructions. Third, models are evaluated with reference to the current goal (e.g., validity or plausibility of the presented argument) and accepted if satisfactory (the satisficing principle) relative to that goal, implying that satisficing criteria may differ according to instructions. As already exemplified, instruction type can enter this theory in at least two stages, in model construction and in model evaluation, and hence it is easily seen to be consistent with the present dissociation.

Furthermore, one important implication follows from these principles. Any outcome of a reasoning process can only be achieved if both processes contribute. Put differently, assuming that only heuristic processes are responsible for reasoning under inductive instructions and only analytic processes are responsible for reasoning under deductive instructions (i.e., substituting Type 1 processes with the inductive and Type 2 processes with the deductive mode of conditional reasoning) is too simplistic. This suggests that both background knowledge and deductive validity will have an impact on both inductive and deductive judgements, if with different weights.

A second approach that accommodates this idea was proposed by Rotello and Heit (2009; see also Heit & Rotello, 2005, 2008, 2010). As Rotello and Heit (2009, p. 1328) put it, it seems that "deductive and inductive judgements are based on different weighted combinations of at least two sources of underlying information". This idea is also supported by our findings. Under deductive instructions validity clearly influences the outcome (i.e., the validity effect), but plausibility does so too, a finding that stimulated a lot of research on content effects under deductive instructions (e.g., Thompson, 1994). This is best illustrated by comparing problems with salient counterexamples and problems without salient counterexamples (but with same logically validity) under deductive instructions. In Experiment 2, under deductive instructions (see Figure 4), MP from prological conditionals (i.e., few salient disablers) was endorsed significantly more strongly than MP from neutral conditionals, $Z = 1.82$, $p = .01$, and MP from counterlogical conditionals, $Z = 2.41$, $p = .02$ (both associated with salient disablers). Similarly, AC from counterlogical conditionals (i.e., few salient alternatives) was endorsed significantly more strongly than AC from neutral conditionals, $Z = 3.50$, $p < .001$, and AC from prological conditionals, $Z = 3.39$, $p < .001$ (both associated with salient alternatives). Convergent evidence comes from Evans et al.'s (2010, Table 6) modelling, which showed that even under deductive instructions belief in the conditional plays an important role (this influence is much larger under inductive than under deductive instructions, mean R^2 of .72 under inductive versus .31 under deductive instructions).

Conversely, reasoning under inductive instructions also appears to be influenced by two types of information. This can be illustrated by comparing valid and invalid problems that are equally plausible under inductive instructions (see Figure 4). In Experiment 2, under inductive instructions, MP from prological conditionals (i.e., few salient disablers) was endorsed significantly more strongly than AC from counterlogical conditionals (i.e., few salient alternatives), $Z = 2.97$, $p < .001$. Similarly, endorsement for implausible MP problems (i.e., salient disablers, averaged over counterlogical and neutral conditionals), is significantly higher than endorsement for implausible AC problems (i.e., salient alternatives, averaged over prological and neutral conditionals), $Z = 3.94$, $p < .001$. Convergent evidence comes from Liu and colleagues (Liu, 2003; Liu, Lo, & Wu, 1996; see also Klauer et al., 2010). They showed differences in endorsement rates between conditions in which standard conditional problems were presented and conditions in which the same problems were presented without the conditional rule. In both conditions, salient counterexamples had a strong impact on endorsement rates but the rule, where present, selectively enhanced endorsement of logically valid problems.

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APPENDIX 1

Mean responses to the conditional rules used in Experiment 1

#	*Conditional rule (translated to English)*	*Instruction*	*N*	*MP*	*AC*	*MT*	*DA*	*adapted from*
Prological Conditionals (few and non-salient disablers, salient alternatives)								
1	If a person's food went down the wrong way, then the person has to cough.	deductive	11	99.2 (0.4)	58.7 (48.8)	76.9 (41.0)	77.0 (40.8)	DN #5
		inductive	13	94.2 (9.7)	65.6 (29.2)	93.9 (6.1)	80.4 (18.7)	
2	If a person fell into a swimming pool, then the person is wet.	deductive	10	99.8 (0.4)	62.7 (48.3)	79.2 (34.6)	69.4 (47.9)	DN #6
		inductive	7	99.3 (0.8)	48.6 (38.2)	99.4 (0.5)	87.7 (18.6)	
3	If water was poured on a campfire, then the fire goes out.	deductive	10	99.4 (0.5)	52.0 (40.9)	70.5 (40.5)	79.5 (34.8)	DN #8
		inductive	13	95.5 (4.2)	71.9 (27.4)	93.8 (11.1)	80.6 (27.5)	
4	If a person ate a lot of salt, then the person is thirsty.	deductive	9	99.6 (0.5)	49.8 (49.9)	53.2 (50.9)	83.1 (35.2)	V #14
		inductive	7	92.9 (11.1)	62.4 (24.6)	83.1 (28.7)	74.9 (24.7)	
Counterlogical Conditionals (salient disablers, few and non-salient alternatives)								
5	If a person has to cough, then the person's food went down the wrong way.	deductive	9	92.7 (20.1)	74.1 (42.5)	74.2 (42.5)	99.6 (0.5)	
		inductive	7	61.7 (30.7)	88.9 (7.4)	67.3 (33.5)	95.7 (4.3)	
6	If a person is wet, then the person fell into a swimming pool.	deductive	10	99.2 (0.4)	64.6 (47.1)	57.6 (50.0)	84.3 (33.6)	
		inductive	13	49.8 (38.0)	99.0 (0.7)	80.2 (22.2)	96.4 (5.8)	
7	If a campfire goes out, then water was poured on this campfire.	deductive	10	97.3 (7.8)	64.7 (47.2)	83.6 (33.2)	89.6 (31.5)	
		inductive	7	86.4 (14.8)	78.0 (17.0)	82.3 (15.0)	82.7 (16.6)	
8	If a person is thirsty, then the person ate a lot of salt.	deductive	11	91.4 (21.3)	65.3 (44.9)	66.4 (45.1)	75.1 (40.0)	
		inductive	13	55.6 (30.9)	89.8 (15.3)	63.7 (22.7)	76.6 (24.6)	

The counterlogical conditionals were constructed by reversing the prological conditionals. Each participant saw all four contents, two randomly determined from the prological conditionals and the remaining two from the counterlogical conditionals. *N* is the number of participants who saw this conditional.

Numbers in brackets are the respective standard deviations.

DN = de'Neys, W., Schaeken, W., & d'Ydewalle, G. (2002). Causal conditional reasoning and semantic memory retrieval: A test of the semantic memory framework. *Memory & Cognition*, 30, 908–920. Appendix, Table A1.

V = Verschueren, N., Schaeken, W., & d'Ydewalle, G. (2005). A dual-process specification of causal conditional reasoning. *Thinking & Reasoning*, 11, 278–293. Appendix 1.

APPENDIX 2

Mean responses to the conditional rules used in Experiment 2

#	*Conditional rule (translated to English)*	*Instruction*	*MP*	*AC*	*MT*	*DA*	*adapted from*
Prological Conditionals (few and non-salient disablers, salient alternatives)							
1	If a person fell into a swimming pool, then the person is wet.	deductive	99.4 (0.6)	34.6 (40.3)	71.6 (42.6)	51.0 (44.6)	DN #6
		inductive	96.1 (9.7)	54.2 (30.5)	87.2 (24.3)	78.9 (23.6)	
2	If a dog has fleas, then it will scratch itself from time to time.	deductive	99.4 (0.6)	47.1 (41.4)	82.1 (36.2)	39.0 (45.9)	V #11
		inductive	95.0 (7.8)	56.7 (18.6)	84.8 (18.9)	42.4 (32.1)	
3	If you prick a soap-bubble, then it will pop.	deductive	99.5 (0.6)	33.6 (41.6)	78.3 (36.8)	46.0 (44.5)	V #20
		inductive	98.5 (2.7)	45.1 (31.8)	87.3 (20.6)	34.3 (33.5)	
Neutral Conditionals (salient disablers, salient alternatives)							
4	If a person studies hard, then the person will get a good grade in the test.	deductive	95.6 (11.2)	46.5 (44.2)	71.1 (38.0)	72.2 (36.3)	DN #3
		inductive	82.1 (16.9)	70.1 (18.9)	70.9 (17.0)	67.8 (17.2)	
5	If a person has turned on the air conditioner, then the person feels cool.	deductive	95.8 (19.2)	44.1 (45.7)	70.1 (43.6)	49.9 (45.4)	DN #4
		inductive	70.4 (30.0)	50.4 (29.8)	74.3 (21.5)	73.7 (21.0)	
6	If a person drinks a lot of coke, then the person will gain weight.	deductive	95.7 (15.8)	35.6 (39.5)	52.7 (47.1)	56.3 (43.0)	V #5
		inductive	70.3 (26.3)	44.0 (22.8)	57.1 (28.4)	49.8 (22.2)	
Counterlogical Conditionals (salient disablers, few and non-salient alternatives)							
7	If you water a plant well, then the plant stays green.	deductive	93.2 (21.3)	71.1 (42.9)	80.4 (36.6)	84.7 (28.9)	V #2
		inductive	84.4 (14.0)	82.1 (23.2)	79.3 (19.3)	86.9 (12.9)	
8	If a person brushes his/her teeth, then the person will not get cavities.	deductive	96.7 (10.1)	54.1 (43.5)	69.0 (40.4)	70.8 (40.9)	V #3
		inductive	79.3 (17.6)	81.6 (20.5)	69.8 (26.4)	82.0 (15.3)	
9	If a girl had sexual intercourse, then she is pregnant.	deductive	92.1 (20.0)	73.7 (44.4)	79.1 (37.1)	83.3 (35.7)	V #17
		inductive	55.6 (38.2)	95.9 (10.1)	52.9 (37.5)	95.0 (10.3)	

All Participants saw all nine conditional rules with all problems.
Numbers in brackets are the respective standard deviations.
DN = de'Neys, W., Schaeken, W., & d'Ydewalle, G. (2002). Causal conditional reasoning and semantic memory retrieval: A test of the semantic memory framework. *Memory & Cognition*, 30, 908–920. Appendix, Table A1.
V = Verschueren, N., Schaeken, W., & d'Ydewalle, G. (2005). A dual-process specification of causal conditional reasoning. *Thinking & Reasoning*, 11, 278–293. Appendix 1.