



## Covariation and quantifier polarity: What determines causal attribution in vignettes?

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### Abstract

Tests of causal attribution often use verbal vignettes, with covariation information provided through statements quantified with natural language expressions. The effect of covariation information has typically been taken to show that set size information affects attribution. However, recent research shows that quantifiers provide information about discourse focus as well as covariation information. In the attribution literature, quantifiers are used to depict covariation, but they confound quantity and focus. In four experiments, we show that focus explains all (Experiment 1) or some (Experiments 2–4) of the impact of covariation information on the attributions made, confirming the importance of the confound. Attribution experiments using vignettes that present covariation information with natural language quantifiers may overestimate the impact of set size information, and ignore the impact of quantifier-induced focus.

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*Den divorced Angie, Maureen loves Billy, Ian hates Phil—but why? Making causal attributions about social situations is a core part of every day human cognition. A prominent idea about how people make causal attributions is that they use covariation information, the observed co-occurrence of two events (Kelley, 1967). More recently, covariation theory in its many guises assumes that people are exposed to instances of*

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events in the real world, and from these instances they compute co-occurrence between the events to make causal attributions (Cheng & Novick, 1990; Försterling, Buhner, & Gall, 1998; Hewstone & Jaspers, 1987; Hilton & Slugoski, 1986; Orvis, Cunningham, & Kelley, 1975; Pruitt & Insko, 1980; Sutton & McClure, 2001).

The crucial assumption of covariation theory is that the set size of agents in a target event determines causal attribution. For instance, if a large set of people like Mary, and Fred likes Mary, then Mary is perceived as the cause of the liking, all other things being equal. On the other hand, if a small set of people like Mary, and Fred likes Mary, then the cause of Fred's liking is more likely to be attributed to Fred. So the number of people that like Mary is critical in order to make a causal attribution. The number of different agents participating in an event gives consensus information, one kind of covariation information. Other crucial sources of covariation information are the set size of patients (distinctiveness information) and the number of occasions the agent and patient participate in the target event together (consistency information).

The emphasis in all instantiations of covariation theory is on the *perception* of behaviour, and the resulting inferences made from the experience of events. Causal attribution is likened to the problem of perceiving visual properties of the environment: the cognizer is striving to extract stable features of the social environment, such as intention, desire, sentiment and ability, just as he or she extracts stable features of the visual environment such as size, shape and colour (Heider, 1958; Kelley, 1967). One consequence of aligning causal attribution with visual perception is that the role of language has remained of peripheral interest in social cognition. In fact, the role of language generally remains a relatively neglected area of research in social psychology (Robinson, 2001). But much of real-life social reasoning is crucially done through talk (Anderson & Beattie, 1996).

Although there has been an emphasis on perception and relative neglect of language by experimental social psychologists, when testing covariation theory participants are not normally presented with real events, but rather with short texts, to which they have to attribute cause (e.g. Cheng & Novick, 1990; Försterling et al., 1998; Hilton & Slugoski, 1986; McArthur, 1972). The underlying assumption seems to be that making causal attributions is the same if you have directly perceived an event and if you are told about such an event. The basics of covariation theory are often presented in textbooks using such vignette examples (e.g. Aronson, 1992; Fiske & Taylor, 1991).

There are very few studies that examine covariation theory where participants are presented with sets of real events that differ in consensus, distinctiveness or consistency. One of these was that of Feldman, Higgins, Karlovac, and Ruble (1976), who showed participants videos of someone choosing an item, and other people either agreeing or disagreeing with that choice. Participants made use of consensus information but only when that was the only source of information. Other studies investigating whether people spontaneously seek covariation information find that people do search for such information, but less than would be expected. Fewer than a quarter of questions asked before making a causal attribution request covariation information (Garland, Hardy, & Stephenson, 1975). And covariation information is requested less for events that are script deviations (e.g. an argument in a restaurant) than for events that are non-scripted (e.g. John laughs at the comedian) (Beattie & Anderson, 1995).

Asking people to make causal attributions from vignettes reflects how people often reason about causes, since information about set sizes and frequencies is gathered not only through direct observation of the world, but also through language. In the present paper we show that many vignette studies taken to support covariation theory confound two variables in the provision of covariation information: (1) information about set size, and (2) the focus-directing properties of the quantifiers used. We argue that covariation information *per se* may be of less importance in causal attribution than previously assumed.

The confound of set size and quantifier focus has been present in the literature since it occurred in McArthur's (1972) seminal work, which is a citation classic.<sup>1</sup> McArthur presented participants with passages like the following:

1. Almost everyone who hears the comedian laughs at him. John does not laugh at almost any other comedian. In the past, John has almost always laughed at the same comedian.

Participants had to make a causal attribution to the target event *John laughs at the comedian*. Set size information, in such vignettes, is presented through quantifiers, like *almost everyone*, *not... almost any*, *everyone*, *many*, *hardly anyone*, *few*, and *nobody* (e.g. Cheng & Novick, 1990; Hewstone & Jaspers, 1987; Hilton & Jaspers, 1987; Hilton, Smith, & Kim, 1995; McArthur, 1972, 1976; Pruitt & Insko, 1980; Ruble & Feldman, 1976; Rudolph, 1997; Smith & Miller, 1979; Sutton & McClure, 2001; Van Overwalle, 1998; Van Overwalle & Heylighen, 1995). The assumption is that the difference between quantifiers is in the set sizes they denote, and so any difference in causal attribution must be due to set size. But set size is not the only information conveyed by quantifiers (Moxey & Sanford, 2000). Rather, quantifiers have been shown to lead to emphasis on particular aspects of the situation being denoted.

Klima (1964) distinguished positive and negative quantifiers. Although negative quantifiers can have an explicit negative marker, as in *not many*, they need not, as in *few*. However, negative quantifiers alone license negative polarity items such as *anymore*. Moxey and Sanford (1987) and Sanford, Moxey, and Paterson (1996) showed that positive and negative quantifiers differ in their focus properties, as illustrated in (2)–(3). Whereas the positive quantifiers in (2) focus attention on the fans that went to the game, the negative quantifiers in (3) focus attention on the fans that did not go to the game, as the continuations make clear.

2. A few/Nearly all of the fans went to the game. They enjoyed it greatly.
3. Few/Not quite all of the fans went to the game. They watched it on TV instead.

Importantly, the set that is in focus does not depend on the amount denoted by the quantifier. Sanford et al. (1996) had participants indicate the proportions they thought quantifiers denoted in 30 different contexts, and found that *few* (negative) and *a few* (positive) denoted about 14%, while *not quite all* (negative) and *nearly all* (positive) both denoted 95%. But in attribution studies all quantifiers denoting small amounts

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<sup>1</sup> According to Web of Science, McArthur's article has been cited 402 times (31st December 2004).

(*hardly anyone, few, not... almost any, and nobody*) have been negative quantifiers, whereas all quantifiers denoting large amounts (*everyone and many*) have been positive quantifiers (e.g. Cheng & Novick, 1990; McArthur, 1972; Rudolph, 1997; Sutton & McClure, 2001).

These observations raise the possibility that when covariation is presented in vignettes for assessing causal attribution it is quantifier focus, not set size, that determines causal attributions. Barton and Sanford (1990) provided data supporting this possibility, based on scenarios like (4):

4. John enjoys walking his dog when he's in town. A few other people enjoy walking their dogs when they are in town.

Participants considered there to be nothing remarkable about John in this case. But when *a few* was changed to *few*, they assumed something was unusual about John (i.e. he was attributed causality). This shows an influence of quantifier focus rather than set size, because the set sizes denoted by *few* and *a few* are indistinguishable. The negative quantifier (*few*) draws attention to the group of people who do not walk their dogs and this makes John seem unusual in that he does.

The key issue for the present paper is what influences the use of consensus information—is it set size or quantifier focus? As well as properties of the quantifier affecting the kind of causal attributions made, the verb also plays a crucial role. When people use language to depict an event they have to choose a perspective on what they wish to describe (Clark, 1997). For example, the same event could be described as *John frightened Mary* or *Mary feared John*. In the first description John is in focus, whereas in the second Mary is in focus; the first description implies that John is actively doing something to make Mary scared, whereas in the second no such implication is made. *Frightened* and *feared*, along with *embarrassed*, *admired*, *respected* and *amused* are examples of verbs with *implicit causality bias*. Such verbs influence which argument of a verb is taken to be the cause. For example, if asked to make a causal attribution to *John embarrassed Mary*, participants typically attribute cause to John (NP1); however, in *John admired Mary*, they typically attribute cause to Mary (NP2) (Brown & Fish, 1983; Garvey & Caramazza, 1974; McArthur, 1972). Clearly, then, the kind of event for which a causal attribution is being made needs to be considered carefully. In the following experiments we used both NP1 and NP2 biasing implicit causality verbs in order to control for the information provided by the verb.

We examined causal attribution by manipulating set size and focus in an orthogonal design, using the positive and negative quantifiers in (2) and (3). We then measured causal attributions in a number of different ways. People make causal judgements in many different situations: they can provide a reason for an event during the telling of a story, they can be asked to reflect on why a certain event happened as it did, and they can be asked to choose between alternatives as the likely cause of an event. Studies of causal attribution typically pose a causal question or ask participants to rate a causal statement. The exact wording of the question can influence the kind of causal attributions participants make (Crocker, 1981; White, 2003). It is not at all obvious that one way of framing a causal question would reflect “true” causal reasoning more than any other. Therefore, we

explore a range of ways of eliciting causal judgements with the goal of establishing how set size, quantifier focus and implicit causality bias are used when making causal attributions. Crucially, we are interested in the relative impact of set size information and quantifier focus.

In Experiment 1 we used a continuation method in order to elicit causal attributions. In the task people write continuations following a sentence of the form *X verbed Y because....* We chose the continuation method because it provides an implicit measure of causal attribution, akin to the kind of attribution made during discourse. In Experiment 2 we asked people an explicit causal question, and they had to provide a reason for the target event. This shares some of the properties of the continuation task, in that participants have to write a reason for the event, but differs in that participants are asked to reflect on why that might be so. In Experiments 3 and 4, we asked participants to make a choice between possible causes of the target event.

## 1. Experiment 1

Our predictions may be framed through example (5):

5. [Few/A few/Not quite all/Nearly all] of the people pleased Paul. Ellen pleased Paul because...

According to covariation theories, quantifiers denoting a small amount (*few* and *a few*) should lead to high numbers of NP1 attributions (i.e. to Ellen). In contrast, quantifiers denoting large amounts (*nearly all* and *not quite all*) should lead to NP2 attributions (i.e. to Paul). But according to the quantifier focus account, if attention in (5) is drawn to the group of people who did not please Paul by using a negative quantifier (i.e. *few* or *not quite all*) then Ellen, who did please Paul, should be special in some way, and thus considered the cause. On the other hand, if attention is drawn to the group of people who did please Paul (i.e. *a few* or *nearly all*), then attribution should go towards Paul. This pattern should hold regardless of set size. Finally, we would also expect an effect of implicit causality bias.

### 1.1. Method

#### 1.1.1. Participants

Thirty-four undergraduate students from the University of Glasgow were paid three pounds to participate.

#### 1.1.2. Materials and design

Booklets were prepared consisting of 48 materials, containing 24 NP1 and 24 NP2 implicit causality biasing verbs, each paired with one male and one female name, with male and female names occurring equally often in each position (see Appendix). Experimental items consisted of a sentence which provided covariation information, followed by the target event. The covariation information provided was consensus

information, quantifying over the subject noun phrase. The quantifiers used were either positive or negative, and denoted either small or large amounts: *few*, *a few*, *not quite all*, and *nearly all*. The design of the experiment was 2 (set size: small vs. large)  $\times$  2 (polarity: negative vs. positive)  $\times$  2 (implicit causality bias: NP1 vs. NP2). Exactly one version of an item appeared in each booklet, and all booklets contained six items from each condition. Each booklet was presented in a different random order.

### 1.1.3. Procedure

Participants received a booklet and were asked to read each item and then write a continuation to the target fragment so that it was a complete sentence.

### 1.1.4. Coding

Participants' responses were coded by noting the noun phrase to which they attributed causality. A NP1 attribution was one that referred to the subject of the target as the cause, while a NP2 attribution referred to the object. Responses that did not refer to either noun phrase, or that were ambiguous about the intended referent were discarded, but accounted for only 2.6% of the data.

## 1.2. Results and discussion

Continuations were analysed using 2 (set size)  $\times$  2 (polarity)  $\times$  2 (implicit causality bias) ANOVAs, one treating participants ( $F_1$ ) as the random effect, the other treating items ( $F_2$ ) as the random effect. All factors were treated as within participants and items, apart from implicit causality bias, which was treated as a between items factor. Results for the NP1 continuations are presented here, although statistically indistinguishable results were obtained when analysing NP2 continuations. All results are significant at the .05 level or better, unless stated otherwise.

There was a main effect of implicit causality bias [ $F_1(1,33)=405$ ;  $F_2(1,46)=1066$ ] with NP1 biasing verbs giving rise to more NP1 continuations ( $M=4.9$ ) than NP2 biasing verbs ( $M=0.9$ ). As predicted by the focus theory, negative quantifiers led to more NP1 continuations ( $M=3.1$ ) than positive quantifiers ( $M=2.7$ ) [ $F_1(1,33)=19.7$ ;  $F_2(1,46)=10.1$ ]; see Fig. 1. However, despite a numerical trend there was no reliable effect of set size on causal attributions [ $F_1(1,33)=2.6$ ,  $P=.10$ ;  $F_2(1,46)=1.7$ ,  $P=.20$ ]: small set size ( $M=2.9$ ), large set size ( $M=2.8$ ). This provides no support for the covariation account. There were no other main effects or interactions (all  $F_s < 1$ ). Further analysis showed that implicit causality bias was the largest effect ( $\eta_p^2 = .925$ ),<sup>2</sup> followed by quantifier focus ( $\eta_p^2 = .374$ ), with set size being very weak ( $\eta_p^2 = .072$ ). So, while there is a clear effect of polarity, the effect of set size seems to be negligible.

The new findings here are that set size did not significantly influence the effect of consensus information, *contra* the predictions of covariation theory, while there was a large and reliable influence of quantifier polarity.

<sup>2</sup>  $\eta_p^2$  is presented for these studies (rather than  $\eta^2$ , for example) as it is not masked by the most powerful factor, and so gives a better estimate of how important each factor is independently.

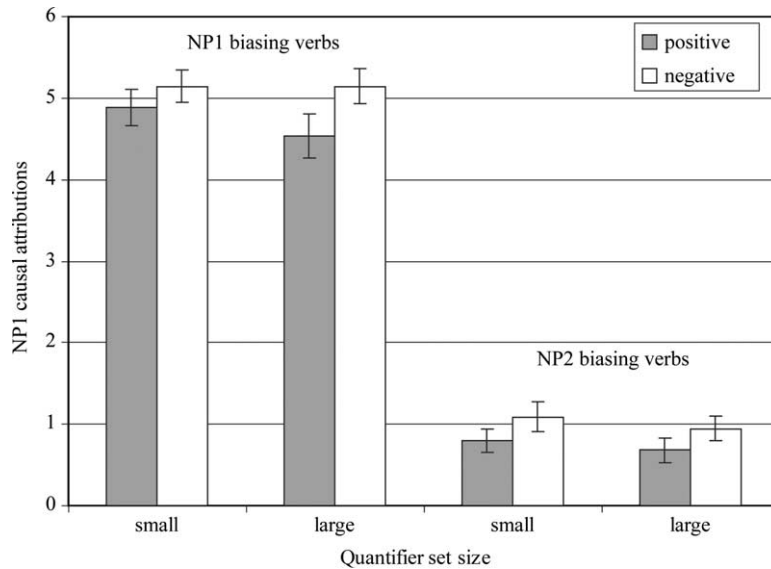


Fig. 1. Number of causal attributions made to NP1 as a result of implicit causality bias, set size and quantifier polarity information in Experiment 1.

Why the lack of utilisation of set-size information? One possibility is that when making implicit causal judgements, as in this study, participants are not in a deliberative mode of reasoning. Previous work suggests that there are two modes of reasoning: associative versus rule-based reasoning (Sloman, 1996), also known as reflexive versus reflective reasoning (Lieberman, Gaunt, Gilbert, & Trope, 2002). The associative or reflexive system processes information rapidly, in parallel and unconsciously; whereas the rule-based or reflective system is slow, sequential, limited in information processing capacity, and conscious. If participants were reasoning using the associative system then they may not have considered the influence of set size information. However, if we can engage the more deliberative mode by, for example, asking an explicit causal question, then participants should utilise set size information more heavily than they did in Experiment 1.

To test this, in Experiment 2, participants were asked to make an explicit causal attribution. If asking an explicit question engages a more deliberative mode of causal reasoning then participants should use set size information as well as quantifier polarity and implicit causality bias.

## 2. Experiment 2

In this experiment, we used an explicit measure of causal attributions. Participants were presented with the same materials as in Experiment 1, but they were asked an explicit causal question (e.g. *Why did Ellen please Paul?*).

## 2.1. Method

### 2.1.1. Participants

Twenty-four further undergraduate students from the University of Glasgow were paid three pounds to participate. Two of the participants did not complete the experiment, and were excluded from the analyses.

### 2.1.2. Materials and design

The materials and design were the same as in Experiment 1. Participants were presented with the covariation information and the target sentence. This was followed by a question (e.g. *Why did Ellen please Paul?*) to which the participants had to provide a written answer.

### 2.1.3. Procedure

Participants were told to read each of the passages carefully and then provide an answer to the question in the space provided.

### 2.1.4. Coding

Participants' responses were coded by noting the noun phrase to which they attributed causality. A NP1 attribution was one that referred to the subject of the target as the cause, while a NP2 attribution referred to the object. Responses that did not refer to either noun phrase, or that were ambiguous were discarded, but accounted for only 1.4% of the data.

## 2.2. Results and discussion

As in Experiment 1, results for the NP1 continuations are presented here, although statistically indistinguishable results were obtained when analysing NP2 continuations. See Fig. 2. There was a main effect of implicit causality bias [ $F_1(1,21)=225$ ;  $F_2(1,46)=519$ ] with NP1 biasing verbs giving rise to more NP1 continuations ( $M=4.9$ ) than NP2 biasing verbs ( $M=0.9$ ). As predicted by the focus theory, negative quantifiers led to more NP1 continuations ( $M=3.3$ ) than positive quantifiers ( $M=2.7$ ) [ $F_1(1,21)=11.2$ ;  $F_2(1,46)=18.5$ ]. Unlike Experiment 1, there was also an effect of set size on causal attributions [ $F_1(1,21)=5.7$ ;  $F_2(1,46)=3.8$ ,  $P<.06$ ]: small set size ( $M=3.1$ ), large set size ( $M=2.8$ ). Finally, there was an interaction between polarity and set size [ $F_1(1,21)=5.9$ ;  $F_2(1,46)=3.7$ ,  $P<.06$ ]. Polarity affected causal attributions for quantifiers denoting small amounts (the contrast between *few* and *a few* [ $t_1(1,21)=1.7$ ;  $t_2(1,47)=2.1$ ]), and for large amounts (the contrast between *not quite all* and *nearly all* [ $t_1(1,21)=4.3$ ;  $t_2(1,47)=3.9$ ]). In contrast, set size only affected causal attributions for positive quantifiers (*a few* versus *nearly all* [ $t_1(1,21)=3.1$ ;  $t_2(1,47)=3.9$ ]) but not negative quantifiers (*few* versus *not quite all*, both  $ts < 1$ ).

Implicit causality bias was the strongest effect ( $\eta_p^2 = .915$ ), followed by polarity ( $\eta_p^2 = .348$ ), and then set size ( $\eta_p^2 = .212$ ). So, as in Experiment 1, we found a substantial effect of polarity. Additionally, we found a reliable effect of set size. Asking an explicit causal question gave rise to a larger effect of set size information than when an implicit question was asked (i.e. set size was only a small effect,  $\eta_p^2 = .072$ , in Experiment 1).



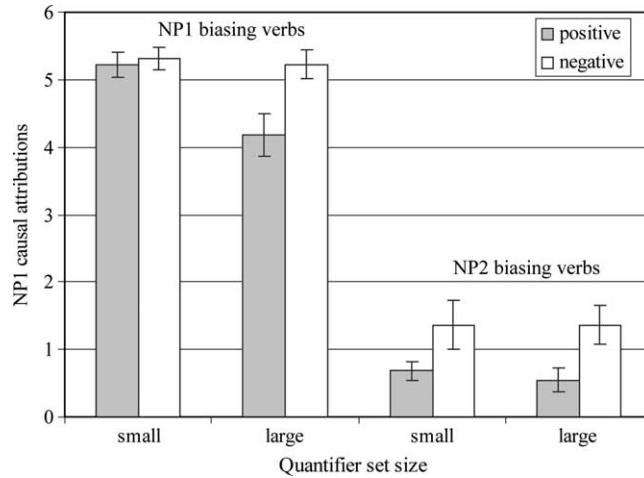


Fig. 2. Causal attributions made based on implicit causality bias, set size and polarity information in Experiment 2.

This suggests that it is the type of reasoning that participants are engaged in which affects whether or not set size information will be utilised when making causal attributions.

It could be argued that the small effect of set size but larger effects of quantifier polarity and implicit causality bias in Experiments 1 and 2 are the result of the continuation method we employed which taps discourse focus effects. So, participants might be making causal attributions on the basis of which discourse entities are the most salient, due to on the verb and the quantifier. When participants are asked to reflect on their causal attributions, for example, through an explicit causal question, then this may lessen the impact of discourse focus by making them weigh each source of information more thoroughly. A rating scale task, like the explicit question in this experiment, may encourage participants to be more reflective.

To further explore the relative contributions of set size and quantifier polarity, we conducted two studies using rating scales. [Semin and Marsman \(1994\)](#) argued that there are actually two separate types of causal inferences that people can make: an event instigation inference (i.e. who brought about the target event by doing something), and a dispositional inference (i.e. did the target event happen because of some trait or property of the participants). While Experiments 1 and 2 do not distinguish the two types of inference, Experiment 3 forced participants to make an event instigation inference, and Experiment 4 asked participants to make a dispositional inference instead.

### 3. Experiment 3

#### 3.1. Method

##### 3.1.1. Participants

Twenty-four further undergraduate students from the University of Glasgow were paid three pounds to participate.

### 3.1.2. Materials and design

The materials and design were the same as in Experiments 1 and 2. The only change was the way that the participant made their causal attribution. Instead of asking participants to produce a continuation to the target fragment ending in *because*, or a continuation to an explicit question such as *Why did Ellen please Paul?*, participants were asked to make an explicit causal attribution to the target event *Ellen pleased Paul* on a rating scale consisting of a line, labelled at one end *sure it's something Ellen did*, and at the other end *sure it's something Paul did*.

### 3.1.3. Procedure

Participants were told to make a decision about the cause of the main event. They marked a rating scale with a cross, based on their judgment. The distance of each cross was measured in millimetres, with 0 indicating causal attribution to NP1 and 100 indicating attribution to NP2.

## 3.2. Results and discussion

See Fig. 3. NP1 biasing verbs gave rise to slightly more NP1-like attributions ( $M=41$ ) than NP2 biasing verbs ( $M=58$ ) [ $F_1(1,23)=24.9$ ;  $F_2(1,46)=194$ ]. There was a main effect of polarity with negative quantifiers leading to more NP1-like attributions ( $M=43$ ) than positive quantifiers ( $M=56$ ) [ $F_1(1,23)=50.3$ ;  $F_2(1,46)=85.8$ ]. There was also a reliable effect of set size on causal attributions, with quantifiers denoting a small set size giving rise to more NP1-like attributions ( $M=40$ ) than those denoting a large set size ( $M=59$ ) [ $F_1(1,23)=33.6$ ;  $F_2(1,46)=188$ ]. Finally, there was an interaction of implicit

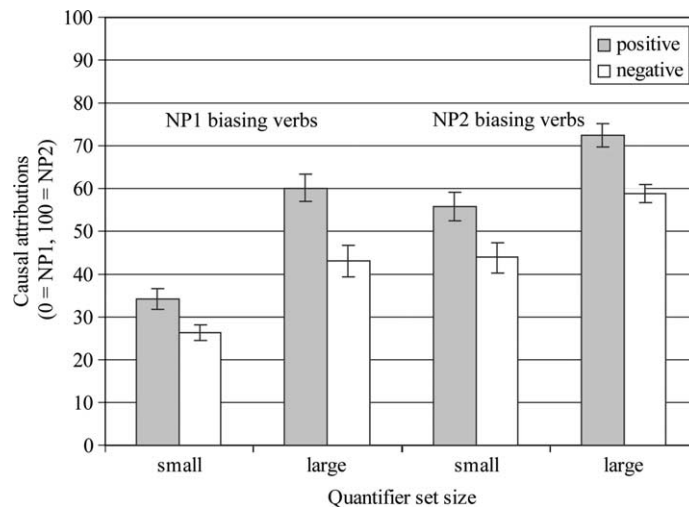


Fig. 3. Causal attributions made based on implicit causality bias, set size and polarity information in Experiment 3 (note that more NP1 attributions are reflected by means closer to 0).

causality bias and polarity [ $F_1(1,23)=6.3$ ;  $F_2(1,46)=4.0$ ]. The effect of polarity was greater for NP1 biasing verbs than for NP2 biasing verbs.

In Experiments 1 and 2, implicit causality bias was the largest effect size, followed by polarity, with the smallest effect size coming from set size. However, in this experiment polarity was the largest effect ( $\eta_p^2 = .686$ ), followed by set size ( $\eta_p^2 = .593$ ) and implicit causality bias ( $\eta_p^2 = .521$ ).

Experiment 3 shows a different pattern of causal attributions to the first two experiments. There is a greater weighting of polarity information, as well as a substantial effect of set size information and implicit causality bias. In Experiment 4, participants made a dispositional inference to tap directly into whether there is something special about one of the characters.

## 4. Experiment 4

### 4.1. Method

#### 4.1.1. Participants

Twenty-four further undergraduate students from the University of Glasgow were paid three pounds to participate.

#### 4.1.2. Materials and design

The materials and design were the same as Experiment 3. The only change was the causal attribution participants made. Instead of asking participants to choose whether the agent or patient had done something to bring about the target event, the rating scale consisting of a line, labelled at one end *sure there's something special about Ellen*, and at the other end *sure there's something special about Paul*, corresponding to a dispositional inference to the agent or the patient.

#### 4.1.3. Procedure

Participants were told to make a decision about the cause of the main event. They marked a rating scale with a cross, based on their judgment. The distance of each cross was measured in millimetres, with 0 indicating causal attribution to NP1 and 90 indicating attribution to NP2.

### 4.2. Results and discussion

See Fig. 4. NP1 biasing verbs gave rise to slightly more NP1-like attributions ( $M=43$ ) than NP2 biasing verbs ( $M=49$ ), but this was marginal by participants [ $F_1(1,23)=3.7$ ,  $P<.07$ ;  $F_2(1,46)=11.8$ ]. There was a main effect of polarity with negative quantifiers leading to more NP1-like attributions ( $M=40$ ) than positive quantifiers ( $M=52$ ) [ $F_1(1,23)=22.9$ ;  $F_2(1,46)=52.2$ ]. There was also a reliable effect of set size on causal attributions, with quantifiers denoting a small set size giving rise to more NP1-like attributions ( $M=38$ ) than those denoting a large set size ( $M=54$ ) [ $F_1(1,23)=29.2$ ;  $F_2(1,46)=113$ ]. Finally, there was an interaction of set size and polarity [ $F_1(1,23)=6.9$ ;

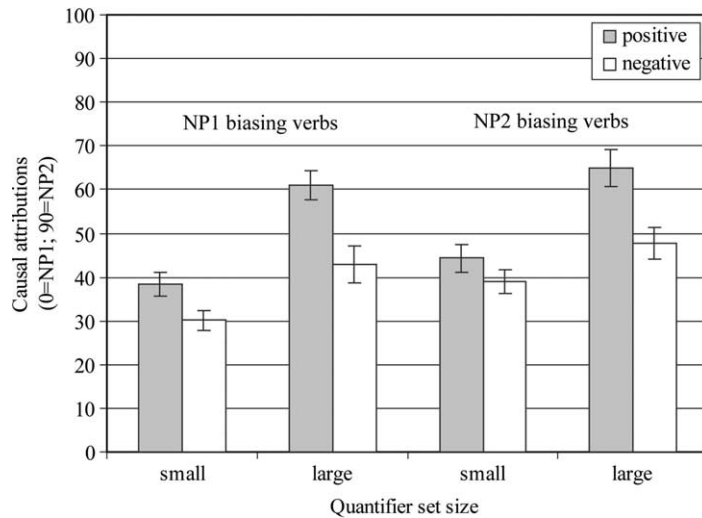


Fig. 4. Causal attributions made based on implicit causality bias, set size and polarity information in Experiment 4 (note that more NP1 attributions are reflected by means closer to 0).

$F_2(1,46) = 11.3$ ]. The effect of polarity is greater for quantifiers denoting large set size than for those denoting small set size.

In this experiment, set size ( $\eta_p^2 = .559$ ) and polarity ( $\eta_p^2 = .499$ ) were the strongest effects, with a smaller contribution from implicit causality bias ( $\eta_p^2 = .14$ ). This contrasts to the previous three studies where implicit causality bias was one of the strongest effects, but is in accord with [Semin and Marsman's \(1994\)](#) finding that when making causal dispositional inferences participants do not rely greatly on implicit causality bias.

## 5. General discussion

Situations for testing how causal attributions are made often use vignettes depicted in language, and descriptions of attribution in textbooks frequently allude to these studies. Consensus, and other covariation information, is introduced through natural language quantifiers, in a manner that has led to a confounding of set size information and quantifier polarity. In the present studies, we found that the focus directing properties of quantifiers had a reliable effect on attribution patterns. In contrast, set size information was not consistently used across different tasks: set size information had *no* impact when an implicit measure of causality was used (Experiment 1), but did have an impact when an explicit question was asked (Experiment 2), and had an even more substantial impact when participants were forced to make a choice between two participants (Experiments 3 and 4).

Previous studies have concluded that covariation information is the most important cue to causal attributions because covariation information over-rides implicit causality bias information when the two are pitted against each other ([McArthur, 1972](#); [Rudolph, 1997](#);

Table 1  
Summary of effect sizes (as  $\eta_p^2$ ) for implicit causality bias, polarity and set size information in Experiments 1–4

	Implicit causality bias	Polarity	Set size
Experiment 1	.93	.37	.07
Experiment 2	.93	.35	.21
Experiment 3	.52	.69	.59
Experiment 4	.14	.50	.56

van Kleeck, Hillger, & Brown, 1988). The results of our experiments question the generality of these conclusions. Although we find that covariation information is a more important cue than implicit causality bias in Experiments 3 and 4, this was not the case in Experiments 1 and 2 where we found that information about the implicit causality bias led to larger effects than covariation information. While the use of implicit causality bias and set size information shifted across response types, the use of quantifier focus had a much more consistent effect across experiments (see Table 1).

The implication of the consistent use of quantifier focus information, but inconsistent use of set size information across experiments, is that the case for frequency of co-occurrence driving attribution is weakened, and in some cases may even be wrong. The reason this is crucial is that covariation theory is one of the most influential accounts of how people make causal attributions, and the strongest evidence for covariation theory in social psychology comes from such vignette studies.

Our primary purpose was to investigate the influence of quantifier polarity on the use of consensus information, pitting polarity against set size, but we can also make observations about the use of implicit causality information in the verb. The fact that the implicit causality bias was the strongest effect in Experiments 1 and 2 is in line with studies using the continuation methodology (Rudolph & Försterling, 1997). That it was a smaller effect in Experiments 3 and 4, where attributions were made on a rating scale, is also in agreement with previous studies (McArthur, 1972; Rudolph, 1997; van Kleeck et al., 1988). Why the difference between these studies?

One explanation for the differential utilisation of information with different response formats is that the continuation methodology is more sensitive to discourse coherence effects than the rating scales. In the continuation task, the participant has to produce a response which gives both a causal attribution, and that also produces a coherent discourse. So, entities that are high in discourse salience may be taken to be better candidates for the cause of the event. Other manipulations which affect discourse structure, such as the use of an active or passive structure (e.g. Hoffman & Tchir, 1990; Kasof & Lee, 1993; Rudolph & Försterling, 1997), or whether covariation information is “given” or “new” (Krosnick, Fan, & Lehman, 1990), have been shown to affect causal attributions too.

Fugelsang and Thompson (2003) propose a two-stage model for causal attributions. In stage one participants recruit knowledge about the possible causal candidates, and in stage two they consciously evaluate the empirical evidence. We suggest that discourse structure is part of what determines causal reasoning in stage one, while explicit questions encourage more conscious evaluation in stage two. So, in Experiments 1 and 2 discourse

coherence plays a strong role and participants relied on the associative or reflexive system; as the experiment engages more explicit attributions in Experiments 2 (where an explicit question was asked) and in Experiments 3 and 4 (with the rating scales) participants are encouraged to be in a more deliberative mode, consciously weighing the different sources of information, and thus engaging the rule-based or reflective system. We suggest that as the causal question asked is made more explicit, participants are encouraged to engage in more conscious deliberation, and thus engage in more rule-based reasoning consistent with normative models such as Kelley's (1967) attribution theory, and other covariation theories.

It has been argued that much of our everyday cognition and rationality is based on the associative system (Evans & Over, 1996), which makes the results of Experiments 1 and 2 even more striking—it suggests that in everyday reasoning people do not weigh set size information very highly. The effect of quantifier focus is compatible with the view that qualitative information is used to make causal attributions. So, if it is pointed out that there are people who do not do X, and John does X, then there is something unusual about John that brings about him doing X. Attention is not just directed to the size of the set of people who did not do X; rather it is directed to focus on the quantifier.

The confound between set size and quantifier focus holds for all kinds of covariation information, not just consensus information. It is certainly applicable to distinctiveness information, which is manipulated using the same quantifiers that are used for consensus information. Furthermore, the confound is also present for consistency information. Consistency is manipulated by using frequency adverbs, most commonly *often* and *rarely*. *Often* denotes a large set and is positive, whereas *rarely* denotes a small set but is negative (Barton & Sanford, 1990; Moxey & Sanford, 2000). We hypothesise, in certain situations, that focus may well be more important than set size for distinctiveness and consistency information too. Finally, we should point out that the use of extreme terms to convey covariation information (*never*, *always*, *none*, *all*) is also a confound between focus and amount, so that it is impossible to say whether frequency or focus information is the crucial factor in attribution.

In this paper we have shown that rather than making attributions solely based on covariation, as determined by set size, people also base their attributions on the focus directing properties of quantifiers. Although this entails people not using relevant information in their reasoning, such behaviour is commonplace in everyday reasoning. Rather than simply applying the logic of covariation, we propose that people apply qualitative principles of argumentation that rely on features towards which attention is drawn.

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**Appendix**

QUANTIFIER was *few, a few, nearly all or not quite all*

- 1 QUANTIFIER of the people charmed Rose. Thomas charmed Rose
- 2 QUANTIFIER of the people embarrassed Rachel. Alan embarrassed Rachel
- 3 QUANTIFIER of the people scandalized Luke. Kathy scandalized Luke
- 4 QUANTIFIER of the people impressed Pamela. Derek impressed Pamela
- 5 QUANTIFIER of the people mystified Amy. Adam mystified Amy
- 6 QUANTIFIER of the people inspired Trevor. Lorna inspired Trevor
- 7 QUANTIFIER of the people baffled Donna. Tony baffled Donna
- 8 QUANTIFIER of the people intrigued Joan. Patrick intrigued Joan
- 9 QUANTIFIER of the people terrified Michael. Meg terrified Michael
- 10 QUANTIFIER of the people amazed Mary. Mick amazed Mary
- 11 QUANTIFIER of the people hurt Emma. Donald hurt Emma
- 12 QUANTIFIER of the people offended Jack. Samantha offended Jack
- 13 QUANTIFIER of the people shocked Rob. Kate shocked Rob
- 14 QUANTIFIER of the people pleased Paul. Ellen pleased Paul
- 15 QUANTIFIER of the people amused Elizabeth. Bob amused Elizabeth
- 16 QUANTIFIER of the people troubled Noel. Carol troubled Noel
- 17 QUANTIFIER of the people delighted Edward. Gemma delighted Edward
- 18 QUANTIFIER of the people distracted Nicola. Daniel distracted Nicola
- 19 QUANTIFIER of the people irritated Roy. Debbie irritated Roy
- 20 QUANTIFIER of the people fascinated Susan. Barry fascinated Susan
- 21 QUANTIFIER of the people upset John. Gail upset John
- 22 QUANTIFIER of the people unnerved Fraser. Beth unnerved Fraser
- 23 QUANTIFIER of the people worried Simon. Veronica worried Simon
- 24 QUANTIFIER of the people frightened Jean. Stephen frightened Jean
- 25 QUANTIFIER of the people pitied Charles. Sue pitied Charles
- 26 QUANTIFIER of the people despised Diana. Peter despised Diana
- 27 QUANTIFIER of the people admired Suzanne. Arnold admired Suzanne
- 28 QUANTIFIER of the people respected Grant. Claire respected Grant
- 29 QUANTIFIER of the people desired Henry. Jennifer desired Henry
- 30 QUANTIFIER of the people honoured Beryl. Philip honoured Beryl
- 31 QUANTIFIER of the people trusted Liz. Gordon trusted Liz
- 32 QUANTIFIER of the people mourned Theresa. David mourned Theresa
- 33 QUANTIFIER of the people liked Matthew. Ruth liked Matthew
- 34 QUANTIFIER of the people hated Richard. Sally hated Richard
- 35 QUANTIFIER of the people envied Catherine. Douglas envied Catherine
- 36 QUANTIFIER of the people noticed Graeme. Barbara noticed Graeme
- 37 QUANTIFIER of the people feared Eileen. James feared Eileen
- 38 QUANTIFIER of the people suspected Alisdair. Emily suspected Alisdair
- 39 QUANTIFIER of the people disliked Jonathan. Sandra disliked Jonathan
- 40 QUANTIFIER of the people loathed Ian. Nancy loathed Ian
- 41 QUANTIFIER of the people detested Sarah. Kevin detested Sarah

- 42 QUANTIFIER of the people dreaded Callum. Joyce dreaded Callum  
 43 QUANTIFIER of the people worshipped Neil. Melissa worshipped Neil  
 44 QUANTIFIER of the people distrusted Ann. Keith distrusted Ann  
 45 QUANTIFIER of the people loved Jane. Andrew loved Jane  
 46 QUANTIFIER of the people valued Caroline. Craig valued Caroline  
 47 QUANTIFIER of the people adored Anna. Jake adored Anna  
 48 QUANTIFIER of the people resented Bruce. Charlotte resented Bruce

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