An Affective Social Tie Mechanism

Theory, Evidence, and Implications

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Abstract

This paper presents substantial evidence of a simple social tie mechanism that endogenizes people's care about other individuals under the influence of interaction experiences. The mechanism is rooted in scientific studies from various disciplines. For our evidence, we propose and estimate a dynamic model of tie formation using different experimental datasets regarding public goods, test its within-sample and out-of-sample predictive performance, and compare it with other models. In addition to the support obtained for the mechanism, we find that the effects of interaction experiences show substantial persistence over time, and that only a minority looks ahead to strategically influence the behavior of interaction partners. Furthermore, our model appears to track the often volatile behavioral dynamics of the different datasets remarkably well. Additional evidence is presented of a neural substrate of the tie mechanism, based on a recent (fMRI) application of the estimated model, and of the explanatory power of our model regarding other extant experimental findings. Implications for private and public governance and topics for future research are discussed.

Keywords: social ties, public good, social preferences, affect, experiment

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A tendency in the West to see emotions as soft and social attachments as messy has made theoreticians turn to cognition as the preferred guide of human behavior. We celebrate rationality. This is so despite the fact that psychological research suggests the primacy of affect: that is, that human behavior derives above all from fast, automated emotional judgements, and only secondarily from slower conscious processes.

Frans de Waal (2006)

1 Introduction

Enduring affective social ties, also labeled affectional bonds or interpersonal attachments, play a crucial role in human lives. People's health, happiness, and economic welfare depend on them, and this dependence goes together with a need to belong (Baumeister and Leary 1995, Reis et al. 2000, Helliwell and Putnam 2004, Campbell and Loving 2012). Starting with maternal care, they continue to play an important role throughout our lives in, for example, peer groups, romantic relationships, and professional relationships within and outside organizations. Characteristic of affectional bonds is that they are dynamic, develop via emotional experiences in social interactions with specific individuals, and generalize across contexts and time. Bonds developed in one context and time period are likely to impact the behavior of interaction partners in another context or future time period. For example, friendship relationships developed at work are not restricted to the work environment but carry over to other settings and show some duration ("once a friend, always a friend"). Developmental psychology, furthermore, shows that there is also a social learning aspect to it. The literature on attachment (Bowlby 2005, Mikulincer and Shaver 2007) provides abundant evidence that early childhood experiences with the primary caregiver form the basis of the development of a particular attachment style that influences the quantity and quality of bonding later in life.[1] A growing number of evolutionary studies argue in favor of the adaptive value (fitness) of bonding for (non)human animals in relation to their extremely limited brain capacities to deal with the deep environmental uncertainty and potential dangers they are confronted with (see Seyfarth and Cheney 2012). There is also suggestive evidence now of the neurobiological drivers of bonding and of the related social approach and avoidance motivational systems, as we will further discuss below.

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[1] Interestingly, some evidence also exists for the proposition that an individual's *social value orientation* (SVO), defined as stable preferences for payoff distributions concerning oneself and a (randomly selected) other individual, is partially rooted in interaction experiences early in life and further shaped by such experiences during adulthood (van Lange et al. 1997). We will come back to this below.

In the economics literature, affective social ties have been hinted at in the past and found to be important in various private and public economic contexts, such as resource sharing, the control of externalities, collective action, and fair business dealings (Simon 1952, Ackerlof 1982, 1983, Becker 1974, 1981, Granovetter 1973, 1985, Coleman 1984, 1990, Uzzi 1996, 1999).[2] A timely example concerns the debate in finance about the relative merits of relationship banking versus transactional or arms-length banking (Boot 2000). Extensive empirical evidence shows that firms having relationships with banks enjoy various benefits, such as improved credit availability and insurance from these banks, while the banks in their turn face lower costs by obtaining more proprietary information (e.g. Beck et al. 2014). Affect appears to play an important role in the development of these relationships (Uzzi 1999).[3] Affective relations with bank lending officers are beneficial for firms that are seeking financing, because they motivate partners to share private resources.[4] There is also substantial experimental evidence, both from the lab and the field, of the importance of affective social ties like friendships for economic behavior, for example, related to cooperation (Harrison et al. 2011, Appicella et al. 2012), giving (Leider et al. 2009, Goeree et al. 2010, Braňas-Garza et al. 2012), coordination and conflict (Reuben and van Winden 2008), trust and trustworthiness (Glaeser et al. 2000, Abbink et al. 2006), and norm enforcement (Goette et al. 2012).

In stark contrast to their widely attested importance, so far the development and testing of a formal structural model of affective social ties has been neglected in economics, a task to which we turn in this paper. Existing models of social preferences (see Camerer 2003, Sobel

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[2] In *The Theory of Moral* Sentiments, Smith referred to (habitual) sympathy as an underlying factor driving affective (kin and non-kin) relationships. In his view, affective social ties abound even in competitive business environments: “Colleagues in office, partners in trade, call one another brothers; and frequently feel towards one another as if they really were so. Their good agreement is an advantage to all (…)” (Smith [1759] 1971, p.224). Edgeworth, in his classic book *Mathematical Psychics*, referred to a “coefficient of effective sympathy” as a possible weight attached to someone else’s utility (Edgeworth 1881, p53). And Marshall, in his famous *Principles of Economics*, referred to the importance of « old associations » for explaining the reluctance of workers to migrate: »There are often strong friendships between employers and employed (…) » (Marshall [1890] 1961, p226) .

[3] A bank lending officer quoted by Uzzi (1999, p488) puts it this way: “A relationship on a social basis tends to break a lot of ice and develop a multidimensional relationship that's more than cold facts, interest rates, and products. It's an emotion-based bond . . . that's so important to have . . . [because] the customer will let us know about problems early, so we can correct them.” And another such officer notes: “After he [the entrepreneur] becomes a friend, you want to see your friend succeed and that goes along many lines.” (Uzzi 1999, p489).

[4] In response to the 2008 financial crisis, the Kay Review (2012) has pleaded for the restoration in the financial sector of such deeper caring relationships, and to weaken the current role of transactional cultures. For a more general concern about the weakening of social ties in Western societies, see the Sarkozy Report (Stiglitz et al. 2009).

2005, Fehr and Schmidt 2006, Cooper and Kagel 2013) miss out on one or more of the aforementioned characteristics of affectional bonding. Specifically, the dynamics of the development of the weight attached to the utility of another individual, including the *persistence* of the effects of interaction experiences across time and contexts, is not modeled. These models are typically static equilibrium models, offering no explanation of the dynamics that are key in the study of bonding.[5]

An exception is the theoretical social ties model of van Dijk and van Winden (1997; vDvW, for short), developed in the context of the private provision of a local public good. Based on arguments and findings of social scientists regarding the impact of social interaction on the sentiments that interaction partners develop towards each other[6], they formalized a social tie between an individual *i* and another individual *j* as a dynamic weight (α_{ijt}) attached to *j*'s utility in i's extended utility function. The dynamics of this weight (tie) depends on "impulses" (I_{ijt}) determined by the other's behavior compared to a reference point, which is taken to be one's own behavior (contribution to the public good). Impulses are assumed to modulate the weight in an automatic way, through affective processes happening at the autonomic level, which cannot be directly controlled.[7] This affective tie mechanism – where the current tie and impulse determine the new tie: $\alpha_{ijt+1} = f(\alpha_{ijt}, I_{ijt})$ – makes the agent's social preferences endogenous and specific to each interaction partner. For given thus adapted preferences, the standard assumption is maintained that (extended) utility is maximized. In other words, what this model adds to the standard model is the assumption that people experience feelings based on their emotional appraisal of the reward value of an interaction, which then influence their attitude and attachment towards the interaction partner, making

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[5] That is why experimental applications of these models focus on the last period(s) of repeated games assuming that sufficient learning to play an equilibrium has taken place; see e.g. Fehr and Schmidt (1999, p851) and Levine (1998, p599). Apart from offering no explanation of the evolution of play it is also questionable whether stability is indeed reached towards the end of an interaction (see, for instance, the individual contribution patterns of the public good experiments presented in section 4).

[6] Homans (1950), Simon (1952), Granovetter (1973, 1985), Frijda (1986), Coleman (1990), Baumeister and Leary (1995). See also Lawler 2001.

[7] See Camerer et al. (2005) on the role of automatic and affective neural processes versus controlled and cognitive processes in economic decision making. The role of emotions is more and more acknowledged in economics. Examples regarding individual decision making concern the impact of regret, disappointment, and anxiety (Loomes and Sugden 1982, 1986, Caplin and Leahy 2001). Examples regarding social decisions relate to envy, anger, guilt, and the interaction between affect and deliberation (Kirchsteiger 1994, Bosman and Van Winden 2002, Battigalli and Dufwenberg 2007, Loewenstein and O'Donoghue 2007). For an excellent introductory textbook on emotions, see Oatley & Jenkins (1996). An emotion arises when an event is being appraised as relevant to one's interests. Emotions have a direct hedonic quality. The processes underlying emotions are unconscious. Emotions involve physiological changes (arousal, visceral responses) and bodily changes, like facial expressions. Central to an emotion is an action tendency. Affect is a general term for emotions, moods, feelings, and sentiments.

their concern for others intrinsically dynamic. Whereas a positive tie represents a positive (liking) relationship, a negative tie stands for a negative (antagonistic) relationship. As demonstrated by vDvW, using a differential equations analysis, their "dual process" model leads to predictions that can be very different from the standard Nash predictions and allows for studying the interaction dynamics. We will return to this in greater formal detail in the next section.

The affective social ties model and study presented in this paper keeps vDvW's general idea of a tie being determined by affective impulses but differs strongly in various other respects. First of all, our formal (discrete instead of continuous time) model can be empirically applied and tested. This gives us the opportunity to directly estimate and test the (relative) performance of our model, including the proposed specification of the tie mechanism.[8] To that purpose we will use our own as well as some other datasets from behavioral public good experiments for estimation, test the within-sample and across-samples performance of our model, and compare its performance with other models. The estimated model is further used for an (elsewhere reported) model-based fMRI analysis, linking brain activity data to the individually estimated parameter values of the tie mechanism, to look for neurobiological evidence.[9] The main relevant findings of this analysis will be mentioned in the paper. From a structural modeling point of view we do not only adapt but also extend the (myopic) vDvW model in an important direction, which is to allow for strategic forward-looking behavior. Because substantial evidence, that we will refer to, shows that people are severely constrained in their capacity to plan ahead and act strategically, and to keep a simple tractable model, we will do so by formulating a two-period model. Furthermore, our model incorporates an explicit specification of the tie mechanism, where a tie is updated by a simple weighted combination of the existing tie and the currently experienced impulse, that is: $\alpha_{ijt+1} = \delta_{i1}\alpha_{ijt} + \delta_{i2}I_{ijt}$. Recent evolutionary and neuroscientific studies, that we shortly discuss next, are supportive of this approach as a proximate mechanism.

In their literature review of the evolutionary origins of affective bonding among humans and nonhuman animals (primates, but also hyenas, elephants, and dolphins, for example) – which may have originally evolved in the context of mother-infant attachment

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[8] For some indirect support for the affective social ties mechanism, see Brandts et al. (2009), where emotions are found to mediate an effect of the behavior of counterparts in a repeated prisoner's dilemma game on the distributional preferences of the subjects measured after the game, concerning payoff combinations for the subject and her or his counterpart in the game.

[9] See our companion paper Bault et al. (2015).

(Numan and Young 2015) – Seyfarth and Cheney (2012) argue that bonds can be adaptive (fitness improving) even for genetically unrelated individuals.[10] Furthermore, they argue that bonds often involve cooperative interactions that are separated in time and differ in context (like a common currency), and also that they are built, at least in part, on the memory and the emotions associated with past interactions, summed over time and continually updated. The latter is clearly supportive of the social tie mechanism that we propose. This also holds for the view of Schino and Aureli (2009) that bonding involves an implicit emotional bookkeeping of service episodes, with their persistence implying a tolerance of temporary imbalances in services given and received.[11] By making decisions on the basis of these continually updated emotional states associated with interaction partners an excessive cognitive overload is avoided.[12] Recent neurobiological research suggests that some of the genetic and hormonal mechanisms found to be important for bonding among nonhuman animals (such as rodents and monkeys) are also at work in humans. In particular, the neuropeptide oxytocin – and the genetic coding for its receptors in the brain – has attracted attention as an evolutionary highly conserved modulator of social responses such as attachment in maternal care and pair-bonding. Studies have associated oxytocine with generosity, trust, motivation to engage in social bonding and contact, affiliative responses under stress, social memory, and emotional empathy (the vicarious feeling of an emotion, but not cognitive empathy), and, on the other hand, with positive interaction experiences (like social support, massage, and warm touch), while oxytocin deficiencies are associated with autistic traits, for example (for references, see: Carter 1998, Uvnäs-Moberg 1998, Pedersen 2004, Heinrichs et al. 2009, Campbell 2010, Insel 2010, Kemp and Guastella 2011, Meyer-Lindenberg et al. 2011).[13] Although research findings in this field need further confirmation, as some of them are conflicting or otherwise

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[10] This is relevant because the genetic relatedness among hunter-gatherers may have been much lower than is often presumed. Hill et al. (2011) analyze the co-residence patterns of 32 present-day foraging societies and find that primary kin generally make up less than 10% of a residential band. Instead, they find large interaction networks of unrelated individuals, suggesting that inclusive fitness cannot explain extensive cooperation in hunter-gatherer bands. See also Apicella et al. (2012) on the Hazda hunter-gatherers.

[11] Schino and Aureli argue against the emphasis on expected future returns in standard learning theory for explaining the behavior of primates, because of the observation that reciprocation can occur over longer time frames than reasonably allowed for by temporal discounting and the inability of animals to foresee future events: “We need to explore alternative proximate mechanisms that are based on past, not future, events.” (Schino and Aureli 2009, p58). It is an empirical question to what extent humans among the primates are different.

[12] First, it avoids complicated calculations of uncertain future rewards in a complex environment; second, a detailed episodic memory is not needed; and, third, via emotional mediation (see also de Waal 2008) a common currency is provided for different kinds of services.

[13] Furthermore, genetic polymorphisms in the oxytocin receptor gene are associated with performance on the SVO task (Israel et al. 2009).

problematic[14], they are at least suggestive for oxytocin being a neurobiological driver of positive affectional bonding in social interactions. But what about the negative bonding – and its implied "your pain is my gain" – that is also predicted as a possibility by the social ties model?[15] It is interesting to note here that some recent studies also associate oxytocin with negative social behavior and interactions, such as jealousy and aggression towards antagonists (Shamay-Tsoory et al. 2009, De Dreu et al. 2010, Bartz et al. 2011). This raises the possibility that oxytocin may be involved in both positive and negative bonding (affective tie formation). Of particular relevance in this context is the social-approach/withdrawal hypothesis of Kemp and Guastella (2011) which proposes that oxytocin facilitates, more generally, approach-related social emotions – including not only positive emotions like affection, but also negative emotions such as anger, aggression, envy, and gloating – and inhibit withdrawal-related social emotions (such as the perception of anger or experience of fear). Oxytocin's assumed relationship with the reduction of uncertainty about the predictive value of a socially relevant stimulus is seen as driver here (see also Meyer-Lindenberg et al. 2011). In this respect it is noted that our tie mechanism specification can be related to optimal (Bayesian) information extraction concerning the predictive reward value of an interaction partner, as we will show in the next section. On the basis of these relationships we conjecture that an even more direct link may exist between (the absolute value of) our social tie parameter and neural systems like oxytocin that are involved in bonding.[16] Notwithstanding this correspondence with learning, it is precisely this link with bonding, affecting the nature of the utility function (preferences), that differentiates our tie mechanism from standard learning models. From an evolutionary perspective this "shortcut" from individual experiences to automatic bonding is plausible, as adaptive agents can act on their environment but can also adjust their internal states (Friston 2010), in this case their social preferences. Both ways of adapting concern the learning of predictive relationships deserving selective attention, as in classical conditioning (Dayan et al. 2000).

The main findings of our study are the following. *First*, substantial support is obtained for the proposed social tie mechanism from the estimation and predictive performance of the

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[14] See e.g. Nave et al. (2015) on trust studies, and Walum et al. (2015) on statistical and methodological issues, more generally.

[15] Carter(1998) refers to "trauma" bonds as a potential outcome of negative social interaction, and suggests that aggressive behaviors need not be incompatible with attachment.

[16] Other peptides (e.g. vasopressin) and neurotransmitter systems (like dopamine) interact with oxytocin and have been found to be involved in other-regarding behavior and bonding as well (Carter 1998, Meyer-Lindenberg et al. 2011). The neural chemistry of these systems, furthermore, appears to be influenced by parental nurturing received during infancy (Pedersen 2004).

model involving three different datasets, a model-based fMRI analysis of brain activity data, a goodness-of-fit comparison with other models, and the (estimated) model's explanatory power regarding experimental findings related to some other experimental environments and games. Individuals develop affective ties (bonds) with others under the influence of positive or negative interaction experiences (impulses). The thus generated additional other-regarding utility is different from standard outcome related utility or procedural utility. *Second*, the estimated values of the tie parameters show a substantial persistence over time of the reciprocity-like effects of impulses. In dyads a decay of about 50% is observed, which implies a persistence of around four rounds of interaction, on average. *Third*, only a minority appears to look ahead to strategically influence the behavior of interaction partners. *Fourth*, the model appears to track the often volatile behavioral dynamics in the different datasets remarkably well, with an average contribution error of about 15% of the endowment. As will be discussed, these findings have important implications for the study of economic behavior and policy.

The organization of the paper is as follows. Section 2 is devoted to the presentation of the theoretical model, its behavioral implications, and its implementation for estimation and testing. Section 3 deals with our experimental design and procedures as well as the additional existing datasets that will be considered. Estimation and testing results are presented in section 4, followed by some evidence from other studies in section 5. Section 6 closes with a concluding discussion.

2 An Estimable Model of the Development of Affective Social Ties

In this section we first present our theoretical model. This is followed by a discussion of its theoretical implications and an implementation for estimation and testing.

2.1 The theoretical model

We start with a summary of the vDvW model.[17] In their continuous time model total instant utility of an individual i, denoted by V_i, is assumed to be determined by a weighted product of i's own utility P_i and the utility P_j of an interaction partner j: $V_i = P_i P_j^{\alpha_{ij}}$, where α_{ij} denotes an affective tie of i with j, expressing i's attachment to j. Utility is derived from a private consumption good x and a public good g: $P_h(x_h, g)$ $(h = i, j)$, where $g = g_i + g_j$ and $x_h = y_h - g_h$, with y_h denoting a given endowment or income. It follows that utility can be written as: $P_h(g_i, g_j)$. The development of α_{ij} over time is assumed to be determined by the existing tie and an emotional impulse I_{ij} generated by the contribution of j in comparison with a reference contribution, where the latter is taken to be a fraction ε_i of i's own contribution: $I_{ij} = g_j - \varepsilon_i g_i$. The following differential equation formally describes the development of the tie, the *tie mechanism*: $d\alpha_{ij}/dt = f_i(I_{ij}, \alpha_{ij})$. Individuals are assumed to be myopic and to simultaneously choose a contribution that maximizes their total utility, that is, V_i for individual i (given α_{ij} and j's contribution). Under some additional assumptions regarding the shape of the differential equation and the utility functions, the authors prove a number of propositions showing that social ties may substantially impact the voluntary provision and optimal regulation of local public goods compared to the standard model. For example, voluntary provision may converge to an efficient level (with $\alpha_{ij} = \alpha_{ji} = 1$) or, in case of negative ties, end up with a level worse than the standard Nash outcome. The model can be straightforwardly generalized to more than two players, and can be applied to other contexts than the private provision of public goods.

Although we keep the main idea of the social tie mechanism, we propose the following adapted and extended (discrete time) model for estimating and testing the explanatory power of the tie mechanism. Apart from the goal of an estimable model, a major reason is that we want to study the dynamics of social ties between individuals repeatedly

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[17] Their notation is slightly adapted, for later convenience.

interacting in a public good environment, which makes it important to allow for strategic (non-myopic) behavior in the model. Furthermore, we will present a simpler, but at the same time more flexible impulse function, which can be further supported by recent evidence from machine learning and neuroscience. For convenience, we continue to focus on dyads in the presentation, but will return to larger groups in the sequel.

Using the notation introduced above, we start with individual i's total utility V_{it} in time period (round) t of a finitely repeated public good game. Experimental evidence suggests that people's cognitive capacities to plan ahead and act strategically are severely limited. For example, Johnson et al. (2002) find limited lookahead instead of the game-theoretically prescribed backward induction in their finitely repeated bargaining game experiments. Bone et al. (2009) find that more than half of the subjects do not appear to be planning ahead in dynamic decision making tasks. Beauty contest (guessing) game experiments show that players typically use only 0-3 levels of strategic reasoning about what other players will guess (Camerer 2003). Neugebauer et al. (2009) find no difference in initial contributions in a finitely repeated public good game experiment between a treatment in which each round feedback is provided about others' contributions and a treatment where no such information is given, which is suggestive of the absence of strategic behavior in the former (as are the on average smaller contributions in the feedback treatment). According to Keser and van Winden (2000), the conditional cooperation that they observe in their finitely repeated public good game experiment appears to be characterized by limited future oriented and simple reactive behavior. Based on the "failure of backward induction" that Isaac et al. (1994) observed in their public good experiments they suggested a modeling approach where individuals view themselves as involved in a forward-looking intertemporal decision problem. They explored a two-period model, with no discounting, where an individual is assumed to believe that contributions have signaling content to others and considers a contribution (assumed to be kept constant across the two periods) "successful" if it is likely to lead to a larger payoff in the next period than the payoff resulting from complete free-riding. Although their (incomplete) model appears to be consistent with some aspects of the experimental data, the authors themselves point at a number of limitations. For example, the benchmark for success is arbitrary and there is a lack of differentiation between likelihoods of success. Moreover, the model predicts zero contributions as dominant strategy in the final period, when signaling becomes irrelevant, whereas the data show many deviations from this strategy. According to the authors: "any forward-looking model based on signaling must be complemented with an explanation for positive allocations to the group account in the final round" (Isaac et al. 1994, p26). Here, we retain their assumption of one-period forward-looking behavior, but develop a full model that can be estimated and, *inter alia*, explains non-zero contributions in the final period.

Specifically, we assume a two-period intertemporal utility function where total utility V_{it} is determined by the sum of current period's utility U_{it} and next period's utility U_{it+1}:

$$V_{it} = U_{it} + U_{it+1} \tag{1}$$

with utility a weighted sum of the payoffs from the public good game:

$$U_{it} = P_{it}(g_{it}, g_{jt}) + \alpha_{it} P_{jt}(g_{jt}, g_{it}) \tag{2}$$

Where the weight α_{ijt} represents *i*'s social tie with *j* in period *t*. In contrast to vDvW, we do not *a priory* restrict this parameter to the interval (–1, 1), but allow for cases where people might feel as much or even more strongly about the other than about themselves. We consider next the dynamics of α_{ijt} – which makes up the affective part of our dual-process model – and come back to the properties of the payoff functions below.

The following simple linear specification is proposed to describe the tie mechanism:

$$\alpha_{ijt+1} = \delta_{i1}\alpha_{ijt} + \delta_{i2} I_{ijt} \tag{3}$$

where the parameter δ_{i1} $(\delta_{i1} \geq 0)$ determines the impact of the existing tie α_{ijt}, and δ_{i2} $(\delta_{i2} \geq 0)$ the impact of the current impulse I_{ijt}. The former, δ_{i1}, will be called the *tie persistence* parameter, reflecting the influence of past experiences (impulses), while δ_{i2} is called the *tie impulse* parameter, which is supposed to capture the emotional impact of the impulse generated by the interaction partner's current behavior. For later reference, notice that with some decay (that is, $\delta_{i1} < 1$) a constant impulse I_{ij} will cause the tie to converge to: $\alpha_{ij} = [\delta_{i2}/(1 - \delta_{i1})]I_{ij}$. Now, consider that $\alpha_{ij} = 1$ leads to joint payoff maximization (efficiency), and let us normalize the impulse such that its normalized value $I_{ij}^{n} = 1$ when contributions are efficient.[18] Then, for an efficient equilibrium to be attainable the expression between hooks should also equal 1, and, thus: $\delta_{i1} + \delta_{i2} = 1$.

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[18] For simplicity, we assume here that contributions can be continuously adapted.

In the Introduction we mention evolutionary and neurobiological studies that appear to support our approach. Here, we will show that even a more formal foundation of our specification can be obtained by considering the optimal extraction of information in case of uncertainty. If bonding as an automatic response is indeed a proximate mechanism for survival and fitness, as argued in the Introduction, finding out in a simple though flexible way the predictive reward value of your interaction partner becomes very important then. To what extent can one expect to benefit from and get pleased by, or get hurt and frustrated by one's counterpart? Suppose that $I_{ijt} = v_{ijt} + \varepsilon_t$, with v_{ijt} the *true* reward (or punishment) contingency related to interacting with j and ε_t a normally distributed noise term with mean 0 and variance σ_I^2. Furthermore, let the subjective estimate of v_{ijt} be normally distributed with mean α_{ijt} and variance σ_{ijt}^2. Then, using Bayes' rule and some simplifying assumptions, it can be shown that the following update equation for the mean estimate applies: $\alpha_{ijt+1} = (1-\delta)\alpha_{ijt} + \delta I_{ijt}$, where: $\delta = \sigma_{ijt}^2 / \left(\sigma_{ijt}^2 + \sigma_I^2\right)$ (Anderson and Moore 1979, Dayan et al. 2000, Daw 2014; see also Behrens et al. 2007). Several comments are in order. First, note the *formal* correspondence with eq. (3), which becomes exact if $\delta_{i1} + \delta_{i2} = 1$. Moreover, this equation resembles the error-driven learning rule from standard reinforcement learning, with $\left(I_{ijt} - \alpha_{ijt}\right)$ the prediction error, except that the learning rate δ is here no longer a free parameter but turns out to be determined by the relative uncertainty about j's value, σ_{ijt}^2, and the stimulus related noise, σ_I^2. Note, however, that our social tie model goes beyond this by assuming that α_{ijt} becomes a weight attached to the payoff of the interaction partner – thereby affecting the nature of i's utility function – and is not just an appraisal of the other's specific behavior that can be exploited in the maximization of utility.[19] As argued in the Introduction, the additional step towards bonding (caring) distinguishes our tie mechanism from standard reinforcement learning models, where agents can act on their environment but do not adjust their internal states (here, preferences), even though both ways of adapting involve the learning of predictive relationships. With our experimental investigation we hope to shed some light on this issue. At this stage, however, we do not want to make any specific

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[19] It is more like a generalized experience-based appraisal of the weight to be imputed to the other in one's environment which motivates to care for (or hate) the other's well-being. Generalizations like this are commonly observed in psychology. A somewhat related effect is the well-known ''halo'' (''horn'') effect, that is, the tendency to like (dislike) a person based on limited (initial) experiences with that person (see Kahnemann 2011, Nisbett and Wilson 1977, Thorndike 1920). See further below on the ''Social Heuristic Hypothesis'' and Bowles (1998) on the role of generalization in the development of preferences.

assumptions about the parameters δ_{i1} and δ_{i2}, except that they are supposed to be nonnegative.

Regarding the initial sentiment α_{ij0} we will investigate two specific options. One is to take the standard no-ties model as point of departure and, thus, assume that $\alpha_{ij0} = 0$. Alternatively, we will explore whether the available data on people's social value orientation (SVO) can be used to that purpose, such that $\alpha_{ij0} = SVO$.[20] This is particularly interesting because we conjecture that an SVO is a (context weighted) integrator of affective social ties – reflecting the cumulative effect of an individual's interaction experiences –, for which some experimental evidence exists (Brandts et al. 2009, Murphy and Ackermann 2013).[21]

For the impulse I_{ijt} we take a more general specification than vDvW by allowing other contributions than i's own to be effective as reference contribution:

$$I_{ijt} = g_{jt} - g_{ijt}^{ref} \tag{4}$$

where g_{ijt}^{ref} is i's reference level regarding j's contribution for round t. In principle, the reference level may be exogenously (like a norm) or endogenously (like i's own contribution, as assumed by vDvW) determined. Several such options will be considered when we estimate the model. To normalize the scaling of the impulse we will sometimes divide the right-hand side of eq. (4) by the difference between the efficient contribution level and the reference level, in which case the normalized impulse becomes 1 if the other's contribution is efficient.

In this affective part of our model we concentrate on the (automatic) emotional appraisal of an interaction, contrary to social preferences models focusing on beliefs about intentions or (exogenously given) types of interaction partners, where attention is concentrated on the cognitive elaboration of interaction experiences (like the beliefs updating in the types model of Levine 1998).[22] This simplification is inspired by the findings of psychologists and neuroscientists, like Zajonc (1984) and LeDoux (1998), suggesting a

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[20] See footnote 1. For SVO measures, see: Liebrand 1984, van Lange 1999, Murphy and Ackermann 2014, Sonnemans et al. 2006.

[21] Fitting the here conjectured link with affective social ties is also the finding of Cornelissen et al. (2011) that perceived closeness appears to mediate between an individual's SVO and his or her donation in a Dictator game experiment. See further van Lange et al. (1997) for a lifetime perspective.

[22] Note that in our model perceived intentions may enter through the reference point that is used to gauge the friendliness of the other. We will return to the role of intentions in section 5.

primacy of affect (see also Kahneman 2011).[23] It is also supported by recent studies showing a difference in neural processing and impact on choice between described uncertainty (like the probability of success in a lottery) and experienced uncertainty (FitzGerald et al. 2010, Rakow and Newell 2010). The processes underlying tie formation cannot simply be chosen on command to achieve a certain goal. Preferences are adapted through autonomic responses to the social interaction. We assume that cognition kicks in to make an optimal decision given these preferences. To this cognitive part of our dual-process model we turn next.

Even though individuals may not be very sophisticated gamesmen[24], in a public good environment, they may be aware of behaviors like tit-for-tat, conditional cooperation, reciprocity, imitation or conformity – behaviors that are often observed in experiments[25] – and may want to exploit this perception. Because all these behaviors suggest that interaction partners may adapt their contributions in the direction of one's own contribution, we assume the following simple expectational process regarding the other's contribution:

$$g_{ijt+1}^{exp} = g_{ijt}^{exp} + \beta_i\left(g_{it} - g_{ijt}^{exp}\right) \tag{5}$$

where g_{ij}^{exp} denotes i's expectation of j's contribution level, and $\beta_i(\geq 0)$ indicates the anticipated responsiveness of j or i's lack of strategic behavior ($\beta_i = 0$); for convenience, β_i will be called the forward-looking *perceived influence* parameter. Finally, we assume that the contribution g_{it} will be chosen in line with the maximization of total utility V_{it} in eq. (1), subject to eqs. (2) − (5).

2.2 Behavioral implications

Before moving to the estimation procedure, we want to highlight some features of this model and discuss potential equilibria. *First of all*, the extended payoff function in eq. (2) implies that utility increases with positive bonds like friendships (and the reverse for enemies), which seems in line with the substantial extant evidence of the importance of close relationships for

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[23] Accordingly, the affective tie mechanism – and an SVO if integrator of such ties – may become relatively more important in driving behavior when there is little room or capacity for cognitive elaboration, such as under time pressure or cognitive load (see Cornelissen et al. 2011). This seems consistent, furthermore, with the "Social Heuristic Hypothesis" advanced by Rand et al. (2014), which postulates that we internalize strategies experienced as advantageous in our daily social interactions as automatic intuitive default responses, which are then overgeneralized to less typical settings (Rand and Epstein 2014).

[24] Since people have difficulty with forecasting their own as well as others' emotions (Loewenstein and Schkade 1999, Loewenstein 2000, Blumenthal 2004) sophistication in terms of strategizing the tie mechanism is not to be expected either, and is therefore neglected (see van Dijk and van Winden 1993).

[25] Axelrod (1984), Dal Bó and Fréchette (2011), Keser and van Winden (2000), Fischbacher et al. (2001), Carpenter (2004); see also Cartwright and Patel (2010).

happiness (Baumeister and Leary 1995, Kapteyn et al. 2010). Note that the extra utility generated by social ties, produced via social interaction, not only differs from standard outcome utility but is as such also different from procedural utility, that is, utility derived from decision-making procedures (Frey et al. 2004). *Secondly*, note that the future plays a role in two different ways: through the expected utility term U_{it+1} in V_{it} and the perceived influence parameter β_i, if positive. The latter makes it possible that public good contributions are made for purely strategic reasons (as in "pulsing" (Isaac et al. 1985)), without any social tie being involved. This renders two potential explanations for the decay of contributions towards the end of a finitely repeated game, the so-called "end-effect": (a) strategic contributions are no longer possible, and (b) in case of a positive social tie, the anticipation of a breakup and its concomitant loss of utility (cf. eqs. (1) and (2)) induces negative emotions like frustration and anger which may evoke more self-regarding behavior (Bowlby 2005, Baumeister and Leary 1995).[26] *Thirdly*, while standard selfish behavior can be retrieved still as a special case, requiring that $\alpha_{ij0} = \delta_{i2} = 0$ in eq. (3), also various well-known social preferences can be obtained depending on certain parameter configurations, for example: altruism $(\alpha_{ij0} > 0, \delta_{i1} = 1, \delta_{i2} = 0)$, spitefulness $(\alpha_{ij0} < 0, \delta_{i1} = 1, \delta_{i2} = 0)$, and direct reciprocity or tit-for-tat $(\alpha_{ij0} = 0, \delta_{i1} = 0, \delta_{i2} > 0)$. Furthermore, if individuals take their own contribution as reference contribution $g_{ijt}^{ref} = g_{it}$, and $\delta_{i2} > 0$, their behavior may resemble inequality aversion. To illustrate, consider a repeated symmetric public good game with costly contributions. Observing that counterpart contributes less than oneself will in that case not only imply a disadvantageous inequality but also a negative emotional impulse which motivates to lower one's contribution in the next round, in the direction of restoring equality (given counterpart's contribution). Similarly, observing a higher contribution than one's own will not only imply an advantageous inequality but also a positive impulse which motivates to raise one's contribution next round, again in the direction of restoring equality. *Finally*, what our model adds to these various forms of social preferences is that it also allows for endogenous enduring ties via the persistence of reciprocity-like effects of impulses, requiring

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[26] According to Bowlby (2005, pp65-66) the breaking up of an affectional bond is likely to induce a reproach-like response towards the deserter, especially in case of a sudden loss. Bowlby gives as evolutionary argument that it would be extremely dangerous in the wild to lose contact with attachment figures. Of course, these forces will be stronger the closer the relationship (like between mother and infant). However, Baumeister and Leary (1995. p503) in their survey paper on the need to belong conclude that : " people strongly and generally resist the dissolution of relationships and social bonds. Moreover, this resistance appears to go well beyond rational considerations of practical or material advantage." In terms of our model, the anticipation of no more contribution from an interaction partner might induce a negative impulse to the current social tie evoking more selfish behavior.

that both $\delta_{i1} > 0$ and $\delta_{i2} > 0$. Importantly, these parameters can be estimated as we will show below, which disciplines the model. Other model implications related to (in)direct reciprocity, affective networks, and in- and out-group distinctions will be discussed in section 5.

To address the issue of potential equilibria, we need to become more specific regarding the payoff functions in eq. (2), where we will focus on *i* (*mutatis mutandis* the same holds for *j*). In our experiment and the other experiments that will be used for testing the model, which all employ a symmetric public good game, this function has the following shape: $P_{it} = m\left(g_{it} + g_{jt}\right) + f(g_{it})$, where the first term shows the public payoff, with *m* a constant marginal per capita return on contributions, and *f*(.) denotes a strictly concave private payoff function (strictly convex in g_{it}), which makes V_{it} a strictly concave function of *i*'s total payoff as well.[27] Contribution decisions are made simultaneously. The change in total utility from contributing one extra unit can be expressed as follows:

$$(6)\ V_{it}(g_{it}+1) - V_{it}(g_{it}) = \left(1+\alpha_{ijt}\right)(1+\beta_i)m - MC(g_{it}) - \alpha_{ijt}MC^j\left(g_{it}\middle|\beta_i > 0, g_{ijt}^{exp}\right)$$

The first term shows the benefit of the extra contribution to the public good, which increases in both the social tie α_{ijt} and the perceived influence parameter β_i. The second term, $MC(g_{it}) = f(g_{it}) - f(g_{it}+1)$, denotes the private costs of contributing one extra unit, which is positive and increasing in g_{it}. The third term, $MC^j(\cdot) = f\left(g_{ijt+1}^{exp}(g_{it})\right) - f\left(g_{ijt+1}^{exp}(g_{it}+1)\right)$, indicates the expected private cost for *j* that results from influencing *j*'s contribution, which is also positive and increasing in g_{it}. Note that MC^j plays a role only if *j*'s behavior is perceived to be manipulable ($\beta_i > 0$) *and* *j*'s utility matters ($\alpha_{ijt} > 0$). For simplicity, we assume that symmetry also holds for the model parameters and that the reference contribution is time-invariant, which allows the following notation: α_0, β, δ_1, δ_2, and g^{ref}. Furthermore, we assume that ties decay ($\delta_1 < 1$) and that in equilibrium: $g_{ijt}^{exp} = g_{jt}$. For $\beta = 0$ (non-strategic behavior) it is easily seen that any contribution level from the closed set $[0, y]$ can be sustained as an equilibrium with social ties. Any contribution level can be generated by fixing an appropriate tie parameter α (which ranges from $-\infty$ to $+\infty$), while, given this contribution level and the reference contribution, any enduring α can be

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[27] Through the non-linearity of *f*(.) corner solutions, as in standard linear public good games where contributing either nothing or everything is optimal, can be avoided which is helpful for the empirical identification of the parameters.

generated by an appropriate value of $\delta_2/(1-\delta_1)$ (which ranges from 0 to $+\infty$; see eqs. (3) and (4)). Ties can be positive or negative depending on whether the equilibrium contribution is larger or smaller than the reference contribution.[28] Assuming a reference contribution that is smaller than the efficient contribution, an efficient equilibrium, with $\alpha = 1$, exists. In that case, the normalized impulse equals 1 (see below eq. (4)), so that with this normalization $\delta_2/(1-\delta_1) = 1$ (and, thus, $\delta_1 + \delta_2 = 1$) should hold to keep the tie constant. In its turn, any value of $\delta_2/(1-\delta_1)$ may sustain multiple equilibria. If its value is 1 (under normalization), for example, not only an efficient equilibrium but also a standard Nash equilibrium may exist, namely if the Nash contribution level coincides with the reference contribution, so that the impulse is zero. On the other hand, regarding equilibria with negative ties, an equilibrium with $\alpha = -1$ only exist in that event if it entails a corner solution with zero contributions (as in that case the payoff from the public good is zero, and MC < 0 holds for contributing less). Consider next that $\beta > 0$. Then, the anticipated additional public and private payoff effects from influencing the other's contribution will affect the optimal contribution level. Its impact is most easily seen if we assume now that no tie mechanism exists. Equilibria with contributions larger than the Nash outcome, including an efficient equilibrium (if $\beta = 1$), exist in that case, as the benefit from contributing an extra unit becomes $(1+\beta)m$. Of course, in the absence of the tie mechanism, in any equilibrium contributions fall back to the one-shot Nash prediction in the final round (the so-called end-effect). In view of the multiplicity of equilibria and their relationship with parameter values (specifically, β, δ_1, δ_2, and g^{ref}) it becomes particularly interesting to see what kind of behavioral dynamics the experimental data presented below will show, and what the estimated parameter values will look like.

2.3 Implementation for estimation and testing

Let V_{ikt} denote the utility derived from choosing contribution level k ($k \in \{1, \dots, K\}$). To estimate the model we add a random variable $\varepsilon_{ik}/\theta_i$ to account for unobserved factors, where $1/\theta_i$ indicates the importance of the noise term. Consequently, contribution level k will be chosen if $V_{ikt} + \varepsilon_{ik}/\theta_i > V_{ilt} + \varepsilon_{il}/\theta_i$ for all $l \neq k$. Assuming that the ε_{ik} are i.i.d. and double-exponentially distributed, we obtain the multinomial logit model (see e.g. Anderson et

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[28] By assuming that the reference contribution is a fraction of and at most equal to an individual's own contribution vDvW cannot find symmetric equilibria where both ties in a dyad are negative. Evidence of a time-invariant and identical reference contribution level is presented in the next section.

al. 1992), where the probability that individual *i* chooses contribution *k* in period *t*, denoted by π_{ikt}, is given by:

$$\pi_{ikt} = \frac{\exp(\theta_i V_{ikt})}{\sum_{k=1}^{K} \exp(\theta_i V_{ikt})} \tag{7}$$

From this expression it is easily seen that if $\theta_i \to 0$ every contribution level gets chosen with the same probability and, thus, purely random behavior is obtained, while the contribution that maximizes utility is chosen if $\theta_i \to +\infty$. The log-likelihood of observing a certain stream of contribution choices by individual *i* over all (*T*) repetitions or periods of the game can then be written as:

$$\mathrm{LogL}_i = \sum_{t=1}^{T} \sum_{k=1}^{K} d_{ikt} . \ln(\pi_{ikt}) \tag{8}$$

where $d_{ikt} = 1$ when action *k* is chosen in period *t*, and $d_{ikt} = 0$ otherwise.

By using a maximum likelihood estimation procedure (Matlab’s fmincon function), and exploiting additional information regarding α_{ij0} and g_{ijt}^{exp} (see below), all the remaining parameters of our model can be empirically determined. Leaving out the subscript denoting the individual − for convenience, and because our main focus will concern group level estimates − these parameters are: the perceived influence parameter β, the tie persistence parameter δ_1, the tie impulse parameter δ_2, the noise parameter θ, and the reference contribution g^{ref}. Observations are clustered at the individual level when calculating the standard errors for the group level estimates.

3 Experiment and Additional Datasets

In this section we present the design and procedures of our experiment (labeled Dataset 1), followed by a discussion of datasets taken from two other studies (Dataset 2 and Dataset 3) that we will also use for the estimation and testing of our social ties model. As noted in the Introduction, model estimates regarding our experimental data (Dataset 1, see below) have been further used for an elsewhere reported model-based fMRI analysis to look for neurobiological evidence of the tie mechanism. [29] The most relevant findings of this analysis will be referred to in section 5.

3.1 Experimental design and procedures (Dataset 1)

For the estimation of the model we designed a non-standard public good game experiment involving multiple rounds. Apart from asking participants, in each round, to provide their expectation regarding the contribution of their counterpart (g_{ijt}^{exp}) – to enable the estimation of the forward-looking perceived influence parameter β_i (see eq. (5)) –, we use a non-linear public good game with both an interior standard (selfish) Nash outcome and an interior (efficient) Pareto optimal outcome. A conventional one-shot or finitely repeated linear public good game – with a fixed payoff both from the private account and the public account – entails a standard Nash equilibrium with no contribution to the public good, while efficiency requires that the whole endowment is contributed. For the estimation of ties this is problematic, because these corner solutions are compatible with, respectively, any $\alpha \leq 0$ and any $\alpha \geq 1$. Thus, for example, any non-positive social tie would lead to a null contribution in that case whereas, if feasible, subjects with anti-social ($\alpha < 0$) would prefer a lower contribution level than subjects with purely selfish preferences ($\alpha = 0$). Specifically, the following payoff function was used (see eq. (2)): $P_i = 14(g_i + g_j) + 32(12 - g_i) - (12 - g_i)^2 - 160$, where we have dropped the time index t, for convenience. In each round, subjects were endowed with 12 markers to split between a public account and a private account. As the first term on the right-hand side of the payoff function shows, any marker to the public account yielded a marginal per capita return of 14 (monetary units, MU) while markers to the private account yielded a decreasing marginal return as indicated by the second and third terms, which show the payoff of markers in the private account $(12 - g_i)$. Furthermore, a fixed cost of 160 MU was subtracted each round. The standard Nash

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[29] See Bault et al. (2015), who explicitly refer to the at the time available previous version of this paper. The specific analyses presented and discussed in this paper have not been published before.

prediction is a contribution of 3 markers to the public account, while efficiency prescribes a contribution of 10 tokens to the public account. Both contributions are an interior element of the action space $\{0, \dots, 12\}$.

After a separate part in which social value orientation was measured (using a Ring-test as in van Dijk et al. 2002, with no feedback until the end of the experiment[30]), detailed instructions were provided regarding the public good game, followed by a quiz to check understanding.[31] Thereafter, subjects played the game for 29 rounds with a fixed anonymous partner in a computerized experiment. Contribution decisions were made simultaneously with the aid of an on-screen payoff table, which showed the total payoff for each possible contribution combination. Once both subjects had made their decisions, they were asked about their expectation concerning the other's current contribution (without monetary incentives to avoid greater complexity). Subsequently, subjects got feedback regarding the contribution of the other, their payoff for the past round and their total cumulative payoff, both in MU. The exchange rate was 0.6 Eurocent for 1 MU.

Because we wanted to link our estimated parameters also to brain activation data to see whether a neural substrate for the tie mechanism exists, one subject out of each pair was positioned in a brain scanner while the other was seated at a computer in a separate room.[32] Because no difference in behavior was found between the scanned and non-scanned participants, we pooled the data[33]. We will come back to the neural findings below.

The experiment was run at the Amsterdam Medical Center of the University of Amsterdam. Throughout the experiment anonymity was maintained. In total 56 students participated. The whole experiment took between 1.5 and 2 hours per pair, with average earnings amounting to 45 euro.

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[30] In a Ring-test, which measures distributional preferences, multiple choices between two alternatives, each representing a payoff allocation to Self and Other, have to be made. Moreover, each payoff combination (alternative) is taken from a circle. See Liebrand (1984).

[31] Instructions are available upon request.

[32] For the neural analysis we added a further test, before the public good game and (unexpectedly) at the end of round 25, where subjects observed a number of computer allocations of money to themselves and, respectively, a random other subject and their counterpart in the game, to investigate the differential activation in the brain across these tests. Unbeknownst to the participants, computer choices were predetermined such that the chosen allocations were the same between subjects and between the first and the second test. Also, both the sum of the chosen allocations and the sum of the alternative allocations was zero, for self as well as the other. For an analysis of these data, see Fahrenfort et al. (2012).

[33] There was no difference in contributions nor in earnings between the two groups (t-test, $p > 0.9$). There was also no change between rounds 25 and 26 (see previous footnote), either in one's own contribution ($p > 0.5$) or the other's contribution ($p > 0.2$).

3.2 Additional datasets (Dataset 2 and Dataset 3)

In addition to Dataset 1, two other datasets will be used to test our model. Dataset 2 concerns the two-player public good game experiment of van Dijk et al. (2002), while Dataset 3 involves the four-player public good game experiment of Sonnemans et al. (2006). Both experiments were computerized and run at the CREED laboratory in Amsterdam. For a detailed description of the experiments the reader is referred to the original publications.

Dataset 2

In this two-player public good game experiment each subject of a pair got 10 markers, each round, to allocate to a private and a public account. The return on each marker in the public account was constant at 14 cents, while the marginal return on markers in the private account decreased. Moreover, a fixed cost of 110 cents was subtracted. Formally, the payoff function was: $P_i = 14(g_i + g_j) + 28(10 - g_i) - (10 - g_i)^2 - 110$. Due to the differences in the return to markers in the private account and the fixed costs, compared to the experiment of Dataset 1, it is here efficient to contribute all 10 markers to the public account. However, the standard Nash prediction is again to contribute only 3 markers to the public account.

Subjects stayed together in fixed pairs for in total 25 rounds of the game. An on-screen payoff table and a handout showed the payoffs in cents from own and counterpart's contributions. At the end of each round subjects got feedback regarding the contribution of the other, their payoff for the past round, and their total cumulative payoff (earnings in Dutch guilder cents, the relevant currency at the time). The public good game was preceded by a social value orientation test (another such test followed after the game). No information about the subsequent game (or test) was provided and no feedback concerning the test was given until the end of the experiment. In total 52 students participated. The whole experiment took about 2 h, with average earnings amounting to about 51 Dutch guilders (23 euro, without inflation correction).

Dataset 3

In this public good game experiment subjects played in fixed groups of four subjects. The other three group members were identified with a fixed symbol. In every round, each subject got 10 markers to distribute between a private account and a public account. Every marker in the public account earned 7 points, while the marginal return on markers in the private account decreased. Moreover, a fixed cost of 60 points was subtracted from the payoff.

Formally, the payoff function was: $P_i = 7(g_i + \sum_{j=1}^{3} g_j) + 21(10 - g_i) - (10 - g_i)^2 - 60$. Notwithstanding the differences in group size, the returns on markers, and the amount of the fixed costs, the efficient contribution level and the standard Nash prediction are exactly the same as with Dataset 2 (respectively, all 10 markers and 3 markers in the public account). It should be noted that in the social ties model, eq. (2) regarding the utility function now becomes: $U_i = P_i + \sum_{j=1}^{3} \alpha_{ij} P_j$, with α_{ij} as determined by eqs. (3) and (4).

Subjects stayed together in fixed groups of four for in total 32 rounds of the game. Via an on-screen payoff table and handouts the payoffs in points from own and other group members' contributions could be checked. At the end of each round, feedback was given with respect to the contributions of the others, the subject's own payoff for the past round, and the subject's total cumulative payoff so far (in points). The exchange rate was 100 points for 50 Dutch guilder cents. As in the experiment of Dataset 2, a test related to social value orientation preceded the public good game part of the experiment. In this case, however, a different test (a Circle-test instead of a Ring-test) was applied, while another such test was (unexpectedly) applied after round 25.[34] No differences in behavior before and after the break for this second test were found. At the first test, no information about the subsequent public good game was provided, and no feedback on outcomes was given. In total 56 students participated. The whole experiment took about 1.5 h, with average earnings amounting to 25 euro.

To summarize, procedures were very similar for all three studies. Participants engaged in repeated interactions in a non-linear public good game in fixed groups, with either one partner (Dataset 1 and Dataset 2) or three other partners (Dataset 3). Especially in the first two sets, incentives were also very similar. Importantly, in all sets both the Nash and efficient outcome, respectively, required to put 3 and 10 markers in the public account. Only in the experiment of Dataset 1 the latter was an interior outcome, however, and participants were asked to provide their expectation regarding the contribution of their counterpart (allowing us to estimate the forward-looking model). All in all, the three described experimental designs provide a good and challenging opportunity to test the performance of the social ties model and the robustness of our findings within and across samples.

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[34] In contrast to a Ring-test (see footnote 30), in a Circle test only one choice has to be made, by directly picking a point on the circle, which saves a lot of time. See Sonnemans et al. (2006).

4 Results

In this section we first present the estimation results of the social ties model regarding our Dataset 1 (subsection 4.1), followed by the estimation results concerning Dataset 2 and Dataset 3 (subsection 4.2). Then we look at the performance of the estimated model in terms of its behavioral predictions, within as well as out-of sample (subsection 4.3), and, finally, do a comparative analysis involving several other models (subsection 4.4).

4.1 Estimation of the model (Dataset 1)

Figure 1 shows the development of the average contribution to the public good in Dataset 1. The overall average is 6.30 markers, out of an endowment of 12, which corresponds to 52.5%. The average contribution level is very stable over the 29 rounds, ranging from 5.27 in the last round to 7.00 in rounds 18 and 22. The usual end-effect can be observed but is not very large; the average contribution level drops by only 1.07 between round 28 and round 29. Only a minority of 39% (22/56) of the subjects contributed 3 in the final round as predicted by the standard Nash equilibrium (16 % contributed less than 3). The mean contribution of 5.27 in the last round is significantly different from 3 (Wilcoxon signed-rank test: *p* = 0.001).

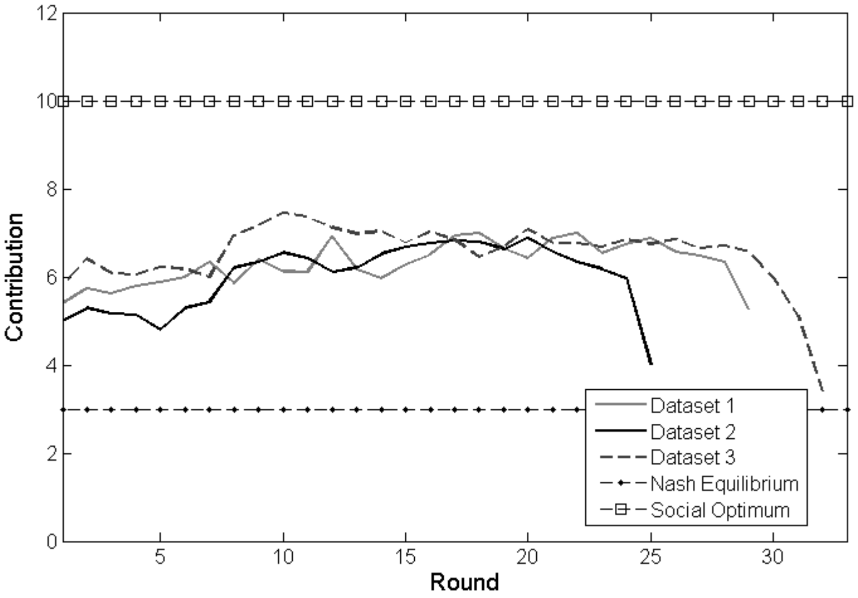

Figure 1. Aggregate contribution behavior

In estimating the model using a maximum likelihood estimation procedure (see eqs. (7) and (8)), we exploit the data on the expected contribution by the interaction partner to determine g_{ijt}^{exp}, and cluster observations at the individual level to calculate standard errors. We first assume that $\alpha_{ij0} = 0$, as there are no antecedents in the relationship, so that subjects start with selfish preferences that may evolve during the interaction. Table 1 shows the group level estimates of the model parameters: β, δ_1, δ_2, and θ.

The left column in Table 1 shows our findings for the myopic model and the right column the results for the forward-looking model. We start with the simple myopic model, with $g^{ref} = 3$ equal to the standard Nash prediction of the contribution. This value concerning the reference point, which figures in the impulse function of eq. (4), is an empirical result based on a comparison of the performance (log-likelihood) of the following five static and dynamic specifications of g^{ref}: the expected contribution by the other, subject's own contribution, a fixed minimal contribution of zero, the Pareto-optimal contribution, and the standard Nash contribution. The Nash contribution (equal to 3) showed the best performance (see Appendix A). The reason may be that the Nash contribution serves as a focal point because it is rather prominent and easy to retrieve in the payoff table that was available to the subjects, but most probably also because it represents the demarcation between antisocial and prosocial actions. Higher contributions generate positive emotional impulses that have a positive impact on the existing social tie while lower contributions generate negative impulses with a negative impact on the tie. Consequently, both positive and negative ties can develop, albeit that the action space for negative ties turns out to be smaller, as there is less room for contributions below the Nash than above. The results show that all the parameter estimates for the myopic model are significant, which implies that the formation of social ties plays a significant role in the contribution decisions. Reciprocity-like effects of impulses matter not only immediately (via $\delta_2 > 0$) but persist in time (via $\delta_1 > 0$) feeding enduring relationships. More precisely, the estimate of $\delta_1 = 0.5$ implies that an impulse counts for about four rounds, as its impact is reduced to around 10% by then. Normalizing the impulse by dividing through 7 – the difference between an efficient contribution and the reference contribution (see section 2) – shows that its weight ($7 \times \delta_2$) is close to 0.5. Since the estimate of δ_1 is also about 0.5 this means that current (normalized) interaction impulses get about the same weight as previous experiences in the tie formation. Interestingly, as these values would add up to 1 our parameter estimates are in line with the (Bayesian) informational interpretation of the tie mechanism offered in section 2. Moreover, these values further imply that the behavioral parameters (δ_1 and δ_2) can sustain an efficient equilibrium because they are compatible with $\alpha_{ij} = 1$ (see below eq. (6) in section 2). In fact, it is easily seen that any contribution level, both below and above the standard Nash, can be supported as an equilibrium, which makes the interaction dynamics important.[35]

Table 1. Group-level estimates (Dataset 1)

	Myopic		Forward-looking	
Parameters	Value	std. err.	value	std. err.
θ	0.0448**	0.0132	0.0461**	0.0158
δ_1	0.5094*	0.2066	0.5052**	0.1830
δ_2	0.0786*	0.0308	0.076**	0.0282
β	-	-	0.0210	0.1371
Log-likelihood	-3737.1358		-3736.8102	
AIC	7480.272		7481.620	
BIC	7496.45		7503.190	

Note: **, significance at 1% level; *, significance at 5% level.

We turn next to the right column in Table 1. Here, we find that forward-looking behavior is not supported by our estimates at the group level. The estimate of the relevant parameter β is insignificant while the remaining parameters are unaffected. Below we will explore at the individual level whether this may be due to the fact that only a minority looks forward (as suggested by the study of Bone et al. (2009), for example).[36] But, first, we want to look at the alternative assumption that we proposed for α_{ij0}, which is to identify it with a subject's social value orientation instead of zero, that is, to take: $\alpha_{ij0} = SVO$. The first column in Table 2 shows the results. Although the performance of this model is even somewhat better as indicated by the statistics below the table, the parameter estimates are very similar. In fact, this similarity is to be expected because the SVO is only affecting significantly the first periods of the interaction, given the observed decay in ties via δ_1. The second column of Table 2 shows the results for the forward-looking model based on individual-level estimation using the following procedure. We first estimate the model at the individual level and use a Likelihood Ratio Test (LRT) to classify subjects as myopic or

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[35] Any permanent unit change in the contribution level leads to a change of 1/7 in the tie value, which in its turn leads to an additional private benefit of contributing of 2 ($1/7 \times 14$) which exactly covers the additional private costs of 2.

[36] Recall in this context also that only a minority contributed 3 in the final round, that is, the contribution level predicted by the standard (selfish) Nash equilibrium.

forward-looking.[37] Based on this classification, we then estimate the corresponding mixture model on the whole sample using maximum likelihood. Each individual contributes to the total likelihood of this mixture model based on the likelihood corresponding to the model selected by the classification. This leaves us with one set of parameters for each group (myopic and forward-looking) and a distribution of individuals across these groups.[38]

Table 2. Group-level estimates (Dataset 1) of the myopic and mixture models with different initial alphas (SVO or 0)

	Myopic, $\alpha_{ij0} = SVO$		Mixture, $\alpha_{ij0} = 0$		Mixture, $\alpha_{ij0} = SVO$	
Parameters	value	std. err.	Value	std. err.	value	std. err.
θ_M	0.0465***	0.0135	0.0420***	0.0147	0.0416***	0.0144
δ_{1M}	0.5646***	0.1995	0.4856	0.3531	0.4694	0.3015
δ_{2M}	0.0695**	0.0309	0.0639*	0.0358	0.0632*	0.0342
θ_{FL}	-	-	0.1081**	0.0481	0.1150**	0.0543
δ_{1FL}	-	-	0.3521	0.3786	0.4103	0.3216
δ_{2FL}	-	-	0.0721*	0.0414	0.0645*	0.0354
β	-	-	0.294**	0.1287	0.2971	0.1818
Forward-looking subjects (out of 56)			19		17	
Log-likelihood	-3727.1607		-3635.9550		-3632.0226	
AIC	7460.3214		7285.9100		7278.0452	
BIC	7476.4993		7323.658533		7315.7937	

Note: ***, significance at 1% level; **, significance at 5% level; *, significance at 10% level.

The results suggest that indeed a minority of about one-third appears to be forward-looking, with as estimated perceived influence parameter $\beta = 0.3$. Although the model shows an improved fit, as indicated by the AIC and BIC, overall there seems to be no big differences in the parameter estimates between the two sub-groups. The third column of the table shows that this especially holds when $\alpha_{ij0} = SVO$ is employed, which again improves the fit a bit. The significance of the estimates appears to be affected mainly by the smaller number of observations within each group.

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[37] We choose this procedure, because the dynamic nature of the social ties model, in particular, the persistence of the impulse effects, stands in the way of using a mixture model analysis at the choice level (as e.g. in Harrison and Rutström 2009).

[38] In addition to the results of Table 2 based on a LRT at the 5% level, we show in Appendix B what happens if instead the BIC, AIC, or a LRT at the 10% level is used as criterion for classification.

Before comparing the performance of our estimated model with other models, we will first estimate the model on the additional datasets, followed by a study of its performance in terms of behavioral predictions within and across the samples.

4.2 Estimation on the additional datasets

Figure 1 shows the development of the average contribution to the public good in Dataset 2 (concerning dyads) and Dataset 3 (groups of four). Dataset 2 exhibits a little bit more cooperation than Dataset 1 as the mean contribution is 6.01 out of an endowment of 10 markers, which corresponds to 60% (versus 52.5% in Dataset 1). Starting from 5.00 in the first round, cooperation slowly builds up to stabilize slightly above 6.50 until the last few rounds where a more noticeable end-effect takes place. Even though Dataset 3 involves four-player groups, instead of dyads, it shows an even higher level of cooperation with an average contribution of 6.52 markers (65% of the endowment). Again, we observe a gradual increase towards stabilization around 7 markers and an important decrease over the last few rounds where the contribution level falls to 3.39. However, as we will see, these overall averages are hiding a substantial heterogeneity at the individual level that we will try to explain with our model.

Because these additional datasets do not contain data regarding the contributions expected from interaction partners required for the forward-looking part of our model, and because of the better group-level performance of the myopic version of the model, we will use the latter for further testing. Table 3 presents the estimation results concerning Dataset 2 and Dataset 3, where we add the results of Dataset 1, for easy comparison.

Table 3. Group-level estimates of the myopic model ($\alpha_{ij0} = 0$)

	Dataset 1		Dataset 2		Dataset 3	
Parameters	Value	std. err.	Value	std. err.	value	std. err.
θ	0.0448***	0.0132	0.0813***	0.0286	0.0319*	0.0167
δ_1	0.5094**	0.2066	0.5489***	0.1845	0.1840	0.3556
δ_2	0.0786**	0.0308	0.0861**	0.0334	0.1460*	0.0841
Log-likelihood	-3737.1358		-1857.1921		-3672.0487	

Note: ***, significance at 1% level; **, significance at 5% level; *, significance at 10% level.

Starting with Dataset 2, the parameter estimates again provide support for the role of the social tie mechanism, with both δ_1 and δ_2 being significantly larger than 0. Moreover, these estimates are close to the ones obtained for Dataset 1. This supports the robustness of our findings since two similar public good environments – with, respectively, a corner and an interior solution for the efficient outcome as the most striking difference − yield very similar estimates. Results are less straightforward for Dataset 3, where the interaction is in groups of four instead of dyads. Although both δ_1 and δ_2 are again positive, pointing at tie formation within the four-player groups, this time the tie-persistence parameter (δ_1) shows a lower value, which means that the history of interaction experiences that impacts a decision is shorter. On the other hand, the tie-proneness parameter (δ_2) now takes the highest value of our three samples, meaning that impulses have a stronger immediate impact on tie formation. This simultaneous decrease in δ_1 and increase in δ_2 suggests that the direct reciprocity effects are more intense in this environment. This may be due to the greater uncertainty about the predictive reward value of interaction partners that subjects are facing in groups of four instead of dyads, as suggested by the (Bayesian) information filtering interpretation of the tie mechanism discussed in section 2. The relatively lower significance levels of the estimates seem to be due to the small number of groups (only 14) in this dataset. The out-of-sample predictive power of the model, to which we turn next, will provide some additional support.

4.3 Behavioral predictions within and out-of sample

Using the estimates of Table 3 for each of the 3 datasets, we forecast individual contribution behavior, within as well as across the different samples, round after round. We do so by calculating the individual's expected contribution in a round, taking as given first-round contributions as well as counterpart's contribution in all subsequent rounds (as we are interested in prediction rather than simulation). Appendix C shows the within-sample predicted (fitted) and actual contributions for each dataset. To assess statistically the performance of the model, Table 4 presents the average root-mean-squared errors (RMSEs) of the predictions within and out-of sample.

Table 4. Average RMSEs of model fit and predictions
using group-level estimates

	Dataset 1	Dataset 2	Dataset 3
Within-sample			
Av RMSE	2.4724	1.8947	2.2643
(Std dev)	(0.7706)	(0.5727)	(0.7813)
Out-of-sample predictions			
Set of parameter estimates used for prediction:			
Dataset 1	-	1.9844 (0.4976)	2.2917 (0.7916)
Dataset 2	2.5113 (1.0465)	-	2.4629 (0.9779)
Dataset 3	2.4894 (0.8353)	2.0309 (0.4829)	-

Note: Standard deviations in parentheses.

The best *within-sample* performance concerns Dataset 2. Even though the performance in the four-player groups case (Dataset 3) is a bit worse, it is still coming out quite close and in fact somewhat better than Dataset 1. It should be taken into account, however, that the endowment of subjects in Dataset 1 is 1.2 times the endowment in Dataset 3 (as well as in Dataset 2).[39] Moreover, both in Dataset 2 and Dataset 3, the efficient outcome coincides with the maximum contribution, which avoids overshooting and may make the efficient outcome more prominent, in contrast with Dataset 1 where the efficient contribution is 10 whereas the maximum contribution is 12. Regarding the *out-of-sample* predictions, Table 4 shows that, overall, the decrease in performance is of low magnitude when compared to the within-sample performance. The largest increase in RMSEs concerns the (groups of four) Dataset 3 for which the measure rises with 9% for the out-of-sample performance of the model estimated on Dataset 2. The raise is limited to 7% or less for the other two datasets.[40]

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[39] For example, if we would normalize by dividing through 1.2 in case of Dataset 1, its average (normalized) RMSE becomes 2.0603 which is now smaller than the one for Dataset 3. The average absolute error equals 1.9323 which is 16% of the endowment.

[40] The within and out-of-sample performance of Dataset 3 becomes worse if the tie-persistence parameter δ_1 is put equal to 0, which supports the importance of this parameter also for this dataset.

To illustrate the dynamics of individual tie estimates and the corresponding (actual and fitted) individual contributions, Figure 2 presents a characteristic subset for each dataset. In all these figures, S stands for subject.

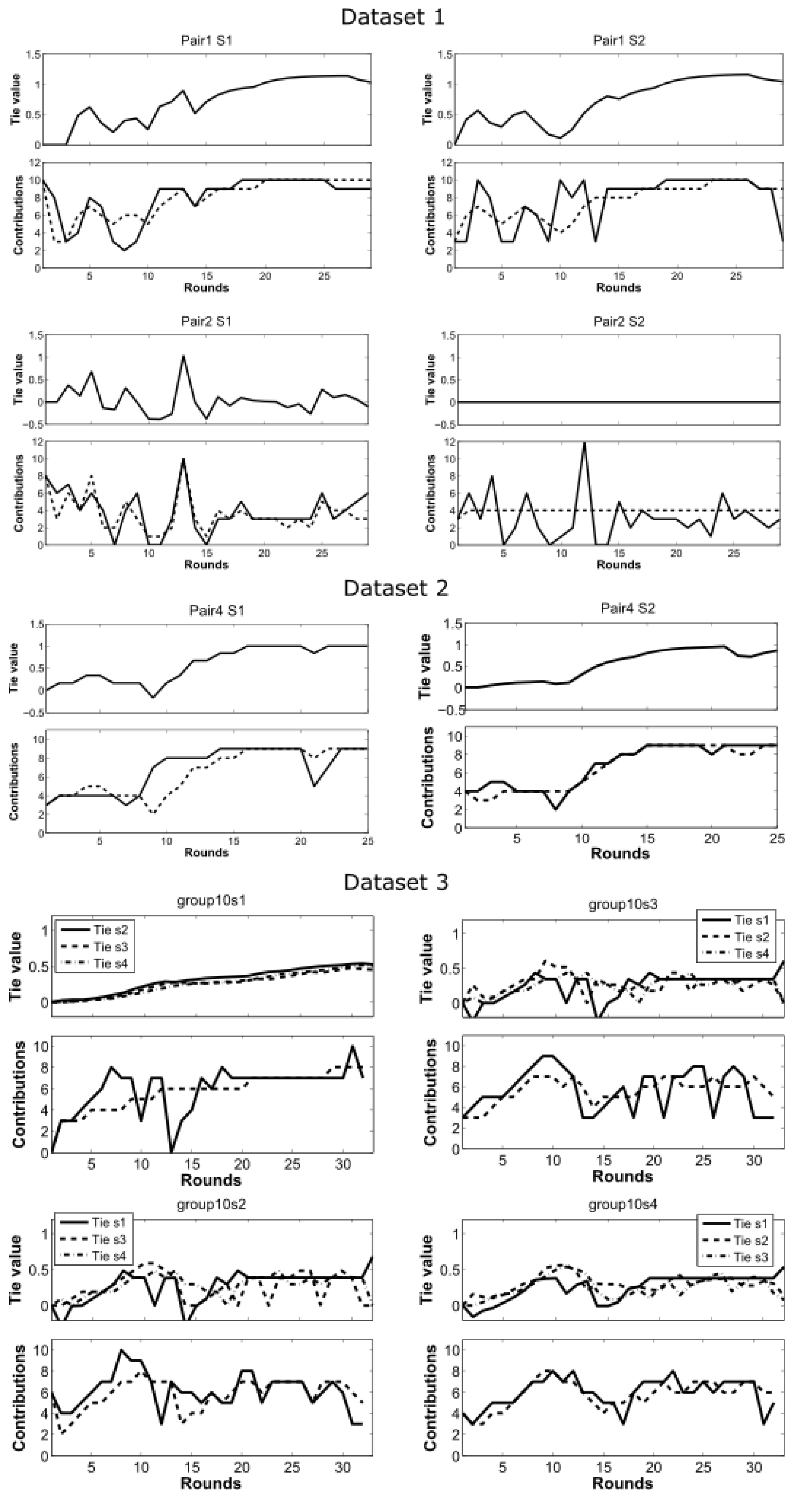

Figure 2. Illustration of the dynamics of individual tie estimates and contributions, with dotted lines showing fitted contributions

The development of the estimated tie values – presented in the top panel for each subject – clearly reveals their gradual adjustment to the past contributions by the respective counterpart (with the exception of Pair2-S2 of Dataset 1). Regarding the fitted contributions, particularly, the actual contributions of pairs exhibiting quite stable behavior for a significant number of rounds are well tracked. Remarkably, this also holds for cases where pairs are exhibiting more complex contribution dynamics (e.g., Pair2-S1 of Dataset 1), albeit not always, in which case a kind of smoothing takes place (e.g., Pair2-S2 of Dataset 1).

4.4 Model comparison

In this subsection we compare our model with several other models that can be used to explain our data.

First of all, because δ_2 is significantly different from zero, which points at reciprocity-like effects, we reject the standard model of selfish preferences.[41] Furthermore, because δ_1 is also significantly different from zero, we rule out the hypothesis that subjects adapt their behavior on the basis of only the most recent interaction experience (last-period's play), as assumed by reciprocity models like tit-for-tat. Longer-term history matters and counterparts' actions continue to significantly influence contribution behavior for a number of periods.

We next compare our model to that of a standard fixed social preferences model, where an individual i attaches a fixed (time independent) weight α_i to counterpart j's utility:

$$U_{it} = P_{it}(g_{it}, g_{jt}) + \alpha_i P_{jt}(g_{jt}, g_{it}) \tag{9}$$

Table 5 presents the parameter estimates of this model, together with the AIC and BIC scores. Compared with the endogenous and dynamic social ties model, see Table 1, the model with a fixed weight performs clearly worse.

Table 5. Fixed social preference model

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[41] Note that if subjects were contributing only for selfish reasons, they would choose the Nash contribution in the last period, since there were no more gains to be expected from cooperation at that point. However, as mentioned above, we find that only a minority does so, and a mean contribution in the last period that is significantly different from 3.

Parameters	Value	std. err.
θ	0.0187	0.0118
α	0.5303***	0.1594
Log-likelihood	-4121.21	
AIC	8246.42	
BIC	8250.47	

Note: ***, significance at 1% level.

As argued in subsection 2.2, the social ties model generates behavior that is similar to inequality aversion if the individual's own contribution is the reference contribution in the impulse. Our results, however, show that this specification can be rejected (see subsection 4.1 and Appendix A). Because subjects' expectations regarding their partner's contribution in each round is available in Dataset 1, we can also more directly specify and investigate an inequality aversion model *à la* Fehr and Schmidt (1999) and Bolton and Ockenfels (2000). An immediate caveat is in order, though, because the authors of these models do not aim to study dynamic issues and the evolution of play. Nevertheless, it seems interesting to explore the performance of this type of model, in particular, because we find that strategic forward-looking behavior does not seem to play a major role in our dataset. Therefore, we estimate the following model:

$$U_{ikt} = P_{ikt} - \alpha_i . \max\{P_{jkt} - P_{ikt}; 0\} - \beta_i . \max\{P_{ikt} - P_{jkt}; 0\} \tag{10}$$

where P_{ikt} is i's expected payoff in period t for a contribution level k, given i's expectation about j's contribution in t, and P_{jkt} is the related expected payoff of j. The parameters $\alpha_i$and β_i, respectively, denote the intensity of disadvantageous inequality aversion and advantageous inequality aversion. Estimation of this model renders the following parameter estimates, if we only constrain them to be non-negative: θ = 0.0170 (0.0118), α = 0.9436 (2.2172) and β = 1.5855 (0.0260), with standard errors in parentheses. Only the advantageous inequality aversion parameter β turns out to be significant. Even if we neglect the insignificant estimate of θ, suggesting a lack of grasp of this model on the data, the results are not encouraging. They not only suggest that disadvantageous inequality aversion is (much) weaker than advantageous inequality aversion (as observed for a large minority of subjects in e.g. Blanco et al. (2011), but also, and more importantly, that individuals would be willing to throw away one dollar to reduce advantageous inequality by one dollar, as β turns out to be larger than 1. Furthermore, if we restrict the parameters, as in Fehr and Schmidt (1999), in the following way: $0 \leq \beta \leq \alpha$ and $\beta < 1$, then both parameter estimates go to 1 and all parameters become insignificant. All in all, these findings are not supportive for the relevance of this model in our case.

5 Further Evidence

Neurobiological evidence. In a companion paper (Bault et al. 2015) we report on an fMRI analysis investigating whether a neural substrate exists for the proposed tie mechanism (eq. (3)). In this model-based analysis we use the myopic model and the estimates of the parameters δ_{i1} and δ_{i2} to get a dynamic estimate of the tie-value α_{it}, which is then linked across the rounds of the game in the experiment to the brain activity of the scanned subjects (one of each pair in our Dataset 1). Our main finding is that the dynamics of the tie value appears to be tracked by the activation of the *posterior superior temporal sulcus* (pSTS), a brain region implicated in inferring the intentions and behavioral relevance of others and the signaling of cooperative partners, friends, and loved ones.[42] We also find that activation of this same region reflects inter-individual differences in the parameters δ_{i1} and δ_{i2}. Furthermore, the pSTS appears to be functionally connected with the *medial prefrontal cortex* (mPFC) that in its turn tracks the contributions decided on by the respective subjects. Together, these results are supportive for the existence of a cortical network dynamics that corresponds with the proposed social tie mechanism.

Other experimental evidence. Several other recent studies suggest the usefulness and relevance of considering other-regarding preferences to be endogenous and dynamic as in our social tie model. Goette et al. (2012) show that there is a qualitative behavioral difference in the interaction between groups formed under the so-called minimal group paradigm and groups that have experienced real social interactions. More specifically, they find that in-group favoritism when making cooperative decisions is stronger when interaction-based social ties are present. They also find differences in punishment behavior in the sense that groups with social ties among their members do not punish more strongly out-group defectors than in-group defectors − whereas groups formed according to the minimal group paradigm do − but punish more strongly when the victim of defection is an in-group member. These

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[42] Our finding extends the result of Fahrenfort et al. (2012) showing a correlation between pSTS activation during the computer imposed money allocation test and liking ratings of the interaction partner at the end of the experiment (see footnote 32). Furthermore, evidence exists suggesting a link between oxytocin and pSTS activity (Gordon et al. 2013, Laursen et al. 2014).

important differences make them conclude that “both conceptually and empirically, economists should take into account that social ties are an important factor in group interactions, within organizations and societies.” (Goette et al. 2012, p114). Closer to our modeling concerns, Malmendier and Schmidt (2012) study gift giving in a three-player setting and find that prior gift giving strongly affects the recipient’s decision in favor of the gift giver even if this comes at the cost of the third player. In their view, “a gift creates a bond between the giver and the recipient of the gift. Suppose that, initially, DM [Decision Maker] is equally concerned about the welfare of all other players. Once the gift is given, the welfare of the gift giver gets a higher weight in DM’s utility function” (Malmendier and Schmidt 2012, p23). For modeling, they refer to the vDvW social ties model, as other models of social preferences are found to fail in explaining their result. They suggest a model, with some similarity to ours, where “by giving or withholding a gift the potential gift giver receives a larger or smaller weight in the utility function of the decision maker” (Malmendier and Schmidt 2012, p32).[43] Building on these results, Liang and Meng (2013) study the impact of social connections (through club membership) on indirect reciprocity. In an indirect investment game where the trustor and the beneficiary of the trustee’s decision are not the same person, they find that a social connection between the trustor and the beneficiary increases the repayment of the trustee, but only when the trustor has been kind enough. They explain this result by the conjunction of two facts: first, a sufficiently trusting decision by the trustor creates a positive tie with the trustee; second, social connections are transitive (“friends of my friends are also my friends”). As a consequence, the trustee is more generous to the beneficiary because he anticipates that it will please the trustor, a person he is now positively caring about. It is easily seen that these findings can be understood with our model, for suppose that $U_i = P_i + \alpha_{ij} U_j$, and i perceives the utility of j as $U_j = P_j + \alpha_{jh} P_h$, then i starts to care about h as well, with $U_i = P_i + \alpha_{ij} P_j + \alpha_{ij} \alpha_{jh} P_h$.[44] Finally, van Winden (2015) shows that our estimates of the

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[43] In their formalization they focus on (beliefs about) chosen strategies, though, whereas the social ties model focuses on realizations (experiences). For experimental evidence that particularly the latter may matter, see Pan and Xiao (2016). Furthermore, because their experimental data concerns a one-shot game, they cannot consider forward-looking behavior of the main player (the second mover), nor can they address the issue of the persistence of reciprocity effects. The same holds for Cox et al. (2008) who suggest a formalization of reciprocity based on an axiom asserting that more generous behavior by a first mover induces more altruistic preferences in a second mover, while adding that this can be interpreted as that the second mover’s preferences are emotional state-dependent. Nevertheless, their approach shows some similarity with ours in that it focuses on the relevance of interaction experiences, rather than beliefs, for social preferences.

[44] Note, however, that this would predict intransitivity in case of enemies, as enemies of enemies become friends according to this model. Furthermore, note that Indirect bonding can only work if people know each other's relationships. Evolutionary scholars suggest that this is only possible up to a group size of a few hundred. According to Jared Diamond, crossing this threshold has important consequences for social conflict

parameters of the tie mechanism (δ_1 and δ_2) can explain the behavior of responders in the ultimatum game and the related power-to-take game, in particular, that rejection and destruction will typically occur if less than 20% is left for the responder.

6 Concluding Discussion

In this paper we have presented substantial support for the proposed social ties mechanism. Individuals develop bonds with others under the influence of positive or negative interaction experiences (impulses). The resulting endogenous other-regarding preferences generate additional utility[45], which is different from standard outcome related utility or procedural utility, that is, utility derived from the judged fairness of a decision-making process. The persistence over time of the reciprocity-like effects of impulses on ties appears to be substantial, with around four rounds in dyads. In particular, if it is taken into account that the experimental setting – e.g., by maintaining anonymity and barring communication – is likely to be of much lower emotional intensity than interactions in the field. Even though the persistence appears to be weaker in larger groups (of four), this finding is of much wider relevance, because various affective mechanisms based on dyads can facilitate and moderate larger-scale cooperation and collective action (van Winden 2015). For instance, above we discussed spillover effects through indirect bonding and generalizations like social value orientation.[46] Dyadic relationships can further be used for targeted interaction to reward or punish free-riders in social dilemmas involving additional individuals (Rand et al. 2009). Moreover, people typically maintain multiple dyadic relationships, in different contexts (like at work and in the neighborhood), which generate multiple affective social ties networks, the interests of which they are likely to take into account when deciding on participation in collective action. Such affective networks will also promote indirect reciprocity – as people start to care about what happens to people they have bonds with – also if norms that are

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management: "increasing numbers of dyads become pairs of unrelated strangers. When strangers fight, few people present will be friends or relatives of both combatants, with self-interest in stopping the fight. Instead, many onlookers will be friends or relatives of only one combatant and will side with that person, escalating the two-person fight into a general brawl." (Diamond 2005, p286.)

[45] There is also further neurobiological support for this. For example, Fareri et al. (2012) find greater brain activation in an important reward related area (the ventral striatum) when someone shares a positive experience with a friend than with a stranger.

[46] See also Pettigrew (1998, 2006) on the importance of bridging friendships in overcoming negative attitudes of in-groups towards out-groups, where similar spill-over effects are mentioned.

considered to be important to relationship partners are violated by others, which helps to maintain social norms. Finally, emotional leadership based on affective dyadic relationships with followers can be exploited by leaders for large-scale collective action, as is well-known from history.

The affective tie mechanism is simple and flexible, and seems honed in evolution for decision making under great uncertainty and potential danger. It can lead to constructive as well as destructive relationships, while its fundamental nature makes it relevant to all social decision making. With respect to economic decision making, this holds not only for public sector issues like the provision of public goods but also private sector related topics such as the functioning of markets and regulation. Regarding the former, for example, it affects our thinking about the rationale for government intervention and the pros and cons of mobility and migration (van Dijk and van Winden 1997), in view of the inherent dynamics of affective social ties networks and their impact on the internalization of external effects. Policies that neglect accompanying crowding-out or crowding-in effects on intrinsic motivation are vulnerable to a preference-based analogue to the Lucas Critique (Lucas 1976, Bowles and Reyes 2012). From a mechanism design or choice architecture perspective, also other less conventional policy issues present themselves, related to the fact that exposure and interaction are key for the tie mechanism to work. For instance, what is the optimal size and optimal (housing) infrastructure of neighborhoods or political units? What is the optimal mix of direct versus indirect forms of political participation, in view of their impact on tie formation? Moreover, to what extent and how can people’s bonding capacity and social value orientation later in life be influenced through early rearing conditions (e.g., Pedersen 2004)?

Regarding private sector governance, several interesting issues present themselves. The existence of a social ties mechanism, with its dependence on affective interaction experiences, naturally directs attention to people’s disposition towards others and their subjective wellbeing. Through the way people interact, exchange mechanisms like markets, and their structure, are likely to affect both (Brandts et al. 2009). For instance, in an atomistic market where agents are price-takers and cannot have a direct impact on their competitors, ties are not expected to develop due to a lack of affective impulses. However, in case of restricted competition, like an oligopoly, ties are likely to matter. While positive ties may generate collusion, negative ones may lead to aggressive (cut-throat) competition. Interestingly, in various forms of experimental markets with restricted competition collusion is often observed, especially if the number of sellers is smaller than four (Potters and Suetens

2013). Moreover, the effectiveness of anti-cartel and insider trading measures can be substantially reduced in case of affective ties, because the benefits can be extended tacitly, with no explicit agreement, and need not require (direct) compensation.[47]

Our findings are further relevant for the debate on the role of emotion expression (Xiao and Houser 2005, Grosskopf and López-Vargas 2014, Dickinson and Masclet 2014) and emotion regulation (Gross 1998, Heilman et al. 2010, Gross et al. 2011, Mesquita and Frijda 2011). Importantly, notice that key to affective social tie formation is a process of emotional 'impression' or 'imprinting', modifying internal preferences, instead of or in addition to emotional expression via external facial, vocal or behavioral responses. Emotional expression can be affected, though, as the emotional response corresponding to an impulse will be modulated by an already existent affective tie. For example, positive ties will attenuate our response to a sudden break of cooperation by our partner. Regarding the heavily debated topic of emotion regulation (see e.g. the special section in *Emotion Review* of January 2011) we would only like to add here that, in fact, this influence of the tie mechanism can be seen as regulating the emotional impact of an impulse, including its expression or 'venting'. The modulation of affective processes by other affective processes does not exclude the involvement of more cognitive networks, however (see section 5).

Our research, finally, also bears upon the debate concerning the impact of impulsivity on social decision-making. Because of its automatic and affective nature, decision-making under time pressure or cognitive load is expected to increase the behavioral importance of the tie mechanism relative to slower and more effortful cognitive (strategic reasoning) processes. And, if our hypothesis is correct that social value orientation is an aggregate measure of experienced ties over time, this would then also hold for an individual's SVO. These predicted effects may shed a new light on recent experimental evidence suggesting a positive impact of impulsivity and cognitive load on pro-social decision-making (e.g., Rand et al. 2012, Cornelissen et al. 2011).

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[47] *The Economist* (October 10th, 2015, p72) gives an interesting example involving a standard recently imposed by an appeals court's decision in the US: "prosecutors must henceforth show that the person providing inside information received a "direct personal benefit". That is a shift from what Mr Bharara's team [the federeal prosecutor with jurisdiction over Wall Steet] had claimed was sufficient: showing that the recipient could profit from the information, and was a friend or family member of the person providing it. The "benefit", in short, came from merely providing something of value to someone the provider valued. (…) a chief executive with access to material, non-published information could pass it along, knowing it could be worth millions of dollars to the recipient, yet possibly avoid prosecution because he was not explicitly compensated."

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Appendix A: Log-likelihood of the myopic model with different reference points

Reference point	Log-likelihood
Expected other’s contribution	-4131.8493
Own contribution	-4164.6669
(Fixed) zero	-3820.6641
(Fixed) Pareto-optimal	-4094.0798
(Fixed) Nash equilibrium contribution	-3737.1358

Appendix B: Mixture-model estimation on Dataset 1 with other classification criteria

Classification Criterion	BIC		AIC		LRT ($p < 0.10$)	
Parameters	M	FL	M	FL	M	FL
θ	0.0417	0.1036	0.0429	0.0841	0.0427	0.091
δ_1	0.4418	0.3998	0.4559	0.3725	0.4334	0.4012
δ_2	0.0659	0.0674	0.0523	0.075	0.0618	0.069
β		0.2931		0.246		0.2791
Log-likelihood	-3633.6412		-3613.9026		-3626.516	
Forward-looking Subjects	20		29		24	

Appendix C: Within-sample predicted versus actual contributions based on the group-level estimates for each dataset (Table 3)

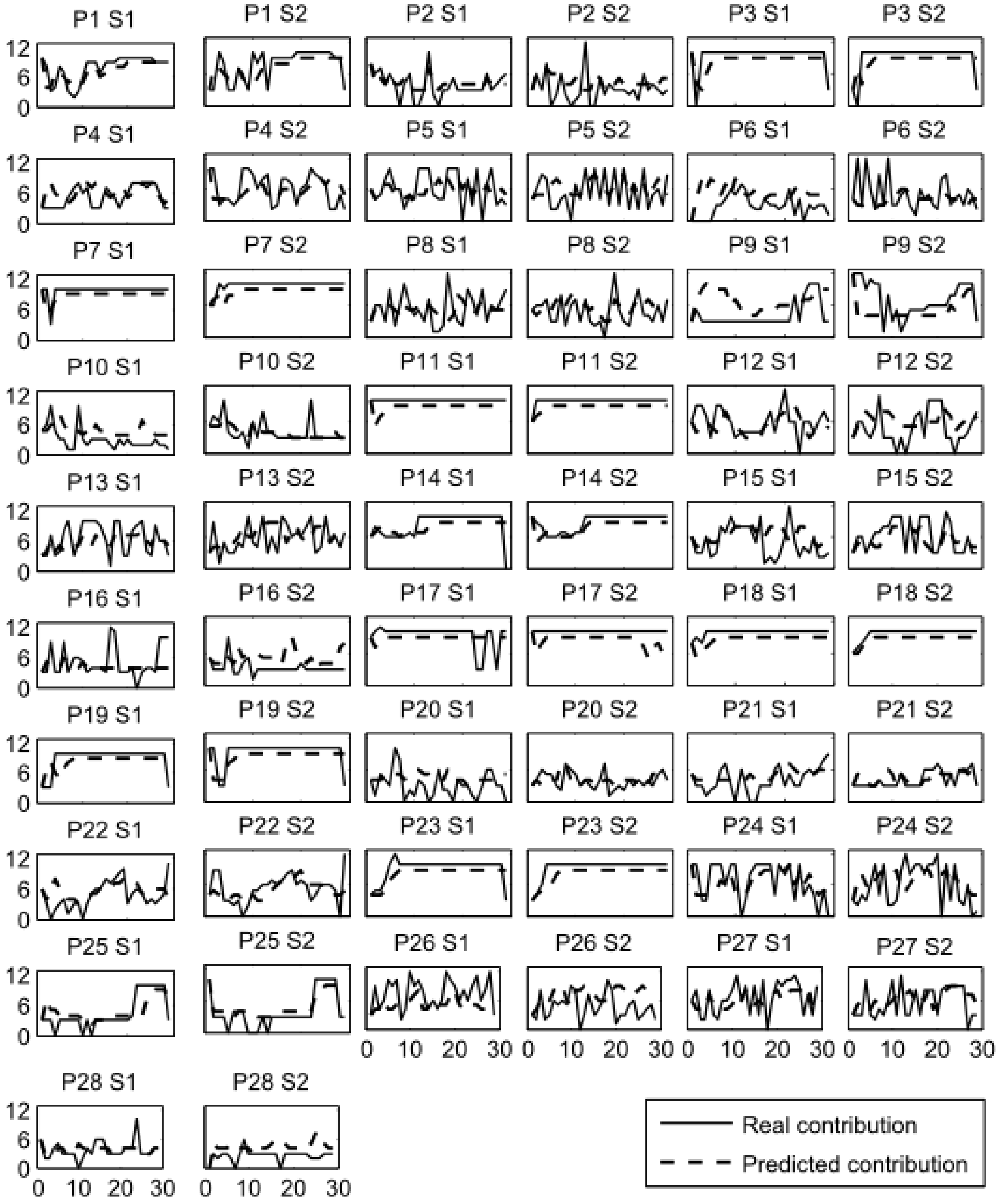

Figure C1. Dataset 1

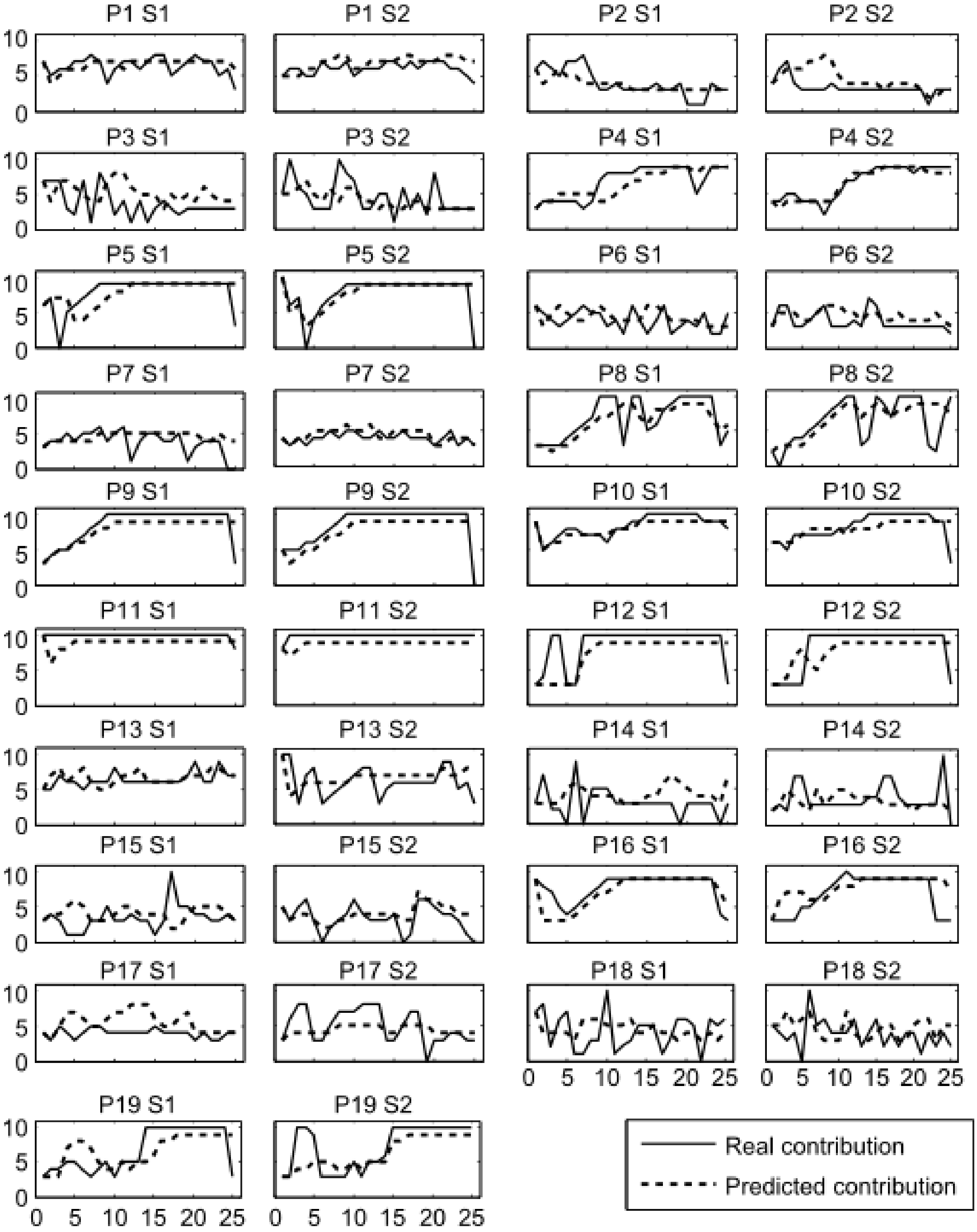

Figure C2. Dataset 2

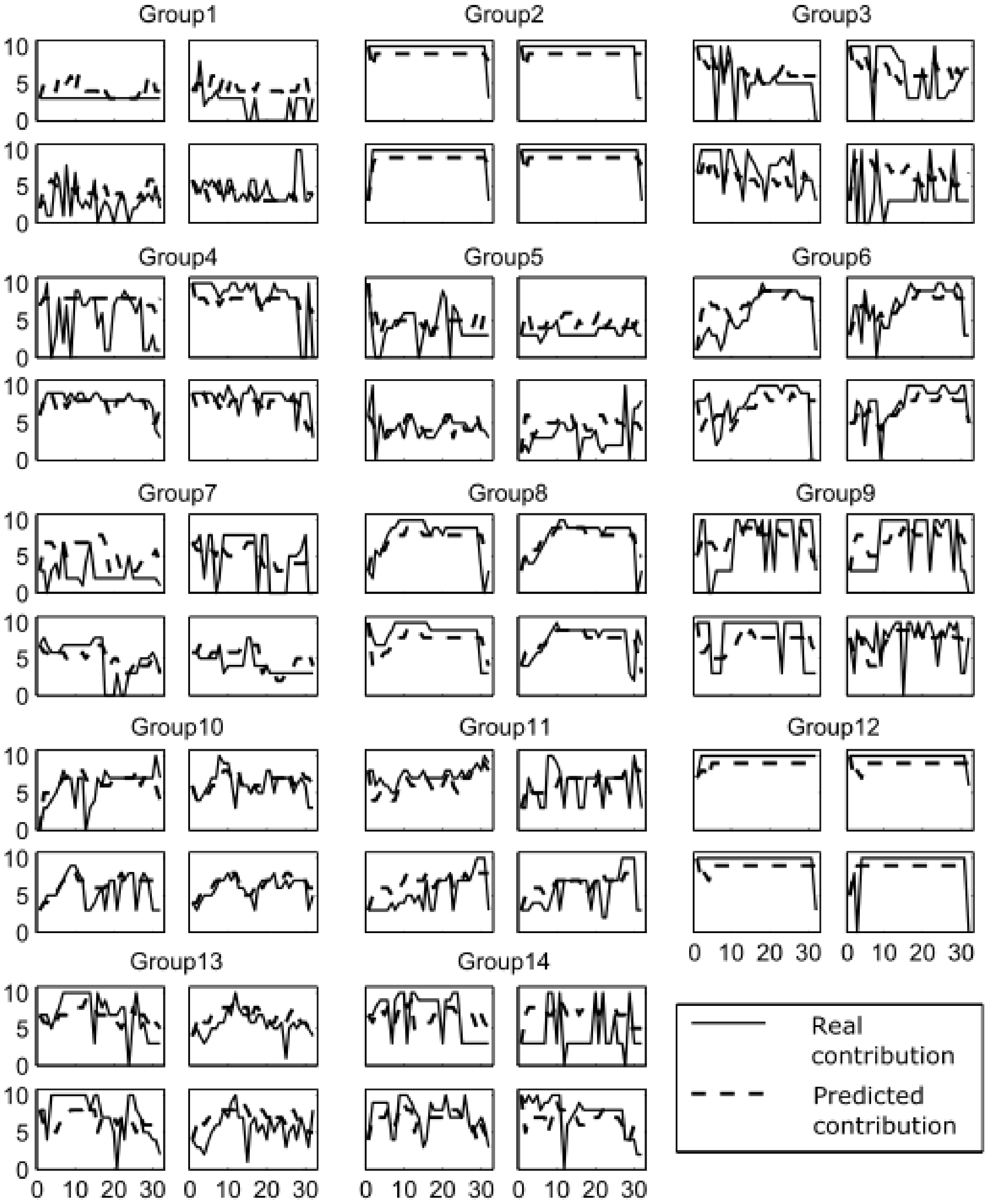

Figure C3. Dataset 3