



# Partner-specific behavior in social networks: Coordination among actors with heterogeneous preferences



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## ABSTRACT

Conventions guide our daily behavior. If everyone agrees on what the best convention is, coordination is easy. We study coordination games in which individuals have conflicting preferences. Theoretical arguments and experimental tests on conventions in networks start too much from the assumption that actors need to behave the same in their interactions with different others. We propose the actors' ability to vary behavior when interacting with different partners (partner-specific behavior) as a mechanism facilitating coordination in situations where actors have different preferences. Results show that whether partner-specific behavior is disadvantageous or advantageous for coordination depends on the distribution of preferences in the network. Moreover, subjects seem unable to foresee when partner-specific behavior is disadvantageous, since they invest in partner-specific behavior also when this does not pay off.

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## 1. Introduction

People are often in situations in which they benefit from adjusting their behavior to the behavior of others in their social environment. Examples include driving on the same side of the road as other drivers, setting the time for a meeting, and talking in the same language as the person we are talking to (Bojanowski and Buskens, 2011; Harsanyi and Selten, 1988; Schelling, 1960). In these situations, individuals try to anticipate what others will do to determine their own behavior (Lewis, 1969). In other words, individuals aim at *coordinating* their decisions in order to achieve a commonly desired outcome (Blume, 1993). These coordination problems are often resolved by *conventions* guiding our behavior.

The emergence of conventions is often related to the existence of social norms: a pattern of behavior that is customary, expected, and self-enforcing (Ullmann-Margalit, 1977; Young, 1998). In the Netherlands, we speak Dutch by convention. But what happens in groups in which the convention is not so obvious and different individuals prefer different conventions? This paper is concerned with situations in which coordination is not straightforward. It studies how actors handle coordination problems if the actors in a social network have different preferences.

The following example will be used as the illustrative example: a group of employees has to work in pairs to create a product. The

product depends on software components the employees develop in pairs. Within these pairs it is costly if the employees do not use the same operating system (say, *Windows* or *Mac*). We assume, for the sake of illustration, that the chosen operating system is not crucial for integrating the software components developed by different pairs to compose the final group product. All employees have to decide individually whether to use the *Windows* or *Mac* operating system. Assume that some employees prefer to use *Windows*, while others prefer *Mac*. Notwithstanding this *heterogeneity in preferences* between the employees, all pairs of employees are more productive when they create the program on the same operating system, due to the advantages of integrating their efforts (coordination), instead of each working on their own preferred operating system (miscoordination). However, an employee who decides to design the software component on the operating system preferred by the other employee, but not by himself has lower benefits from the coordination, since that employee has to invest in working with the non-preferred operating system.

In the example above, coordination is straightforward between two employees who prefer the same operating system. Coordination is more difficult between two employees who differ in their preferences as it introduces uncertainty as to which employee should deviate from his or her preference in order to coordinate. The situation becomes even more complicated when employees do not develop components with only one colleague at a time, but are involved in a network and are working with multiple colleagues simultaneously. In these situations the structure of the network matters (e.g. Choi and Lee, 2014; Goyal, 2007). If an employee mostly works with colleagues with a different preference, it might

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be better for this employee to adjust his or her behavior in order to gain more benefits from the relationship with colleagues. However, deciding who should deviate from their preference is more difficult when the preferences are equally distributed within the network and actors have about equal numbers of neighbors with one or the other preference. This might lead to opposing groups with coordination within the groups, but miscoordination in interactions between members of different groups (Hernández et al., 2013).

This coordination problem causing segregation is expected to be especially prevalent if employees have to choose the same operating system in collaborations with all their colleagues, but might be less problematic if employees can differentiate the operating system they use in interaction with different colleagues. We introduce such an ability to differentiate behavior, i.e., *partner-specific* behavior, as a possible mechanism that might overcome the coordination problem when actors prefer different conventions. In doing so, we extend existing models that have mostly assumed that employees have to choose the same operating system in all their dyadic collaborations.

We propose that the ability to behave partner-specifically might simplify the coordination problem for employees working with colleagues who have different preferences. However, it also introduces more uncertainty. When two employees are able to work with both operating systems, they might have difficulties agreeing on a specific one. This problem would not arise when both have a preference for the same operating system or are bound to an operating system due to other partners. Thus, choosing behavior that suits your specific partner might increase coordination problems if employees have different preferences and everyone is able to differentiate behavior between different partners. In such situations, the distribution of preferences within the network might be important in determining when the ability to behave partner-specifically facilitates coordination.

This tension leads to the following research questions: *Does being able to differentiate behavior towards different partners facilitate coordination in social networks when actors have heterogeneous preferences regarding the different conventions?* And, assuming that flexibility might be beneficial under some conditions: *Under which conditions do individuals want to choose their behavior partner-specifically?*

One reason that most research so far has neglected this partner-specific behavior is probably, that most applications try to explain emergence of a norm at the group level, while there was less emphasis at dyadic coordination. By relaxing this rather specific assumption on coordination in networks, we broaden the applicability of game-theoretic models to a wider set of coordination problems. In our example, some firms might supply their employees with two computers enabling them to choose their operating system depending on their collaboration, while other firms enforce that each individual employee can only use one operating system, e.g., by providing them with only one computer. Because we often find ourselves in situations where we have the opportunity to choose the behavioral option that suits our specific partner best, it is important to understand the implications of this assumption better (cf. Tsvetkova and Buskens, 2013). Examples include switching languages depending on your conversation partner and choosing a different clothing style when going out with a different person. A second reason that others avoided modeling differentiating behavior in a network context is that if actors can solve the coordination problem within the dyad, the network context might be less relevant to understand behavior in the dyads. We show explicitly that also under our assumption the broader network context is still relevant.

By proposing partner-specific behavior as a possible mechanism that can help overcome coordination problems, we complement

previous *experimental* research assuming actors have to choose the same strategy for all their interaction partners (e.g. Berninghaus et al., 2002; Buskens et al., 2008; Goyal, 2007; Goyal and Vega-Redondo, 2005; van Huyck et al., 1990; Jackson and Watts, 2002). While most of experimental research has been on settings in which the preferred convention is the same for everyone, the most relevant experiments for us are those where this is not the case. Previous experimental research has shown that coordination is increasingly difficult when the degree of heterogeneity in preferences within the network increases. For example, Hernández et al. (2013) show that networks consisting of actors with conflicting preferences segregate into two components, each consisting of actors choosing the behavior they prefer. Helbing et al. (2014) found that there is more coordination in coordination games in which actors' preferences coincide rather than if preference differ between actors. Additionally, research has shown that in games with network formation interactions with actors who have different preferences are mostly avoided (Ellwardt et al., 2016). Neary (2012) shows that when given the opportunity, individuals will change their preference to match the preferences of the majority to reach coordination as coordination is more difficult when individuals have different preferences. The overall message of these studies seems to be that coordination is more difficult when actors have heterogeneous preferences. However, all these studies still assume that actors have to choose the same behavior for all their partners. This limits the applicability of these models and possibly overestimates how difficult it is to coordinate in heterogeneous populations. To our knowledge, there is no experimental research that examines what the consequences are of relaxing this assumption. Tsvetkova and Buskens (2013) are amongst the first to allow for partner-specific behavior, but do not elaborate on its consequences regarding coordination. Our work complements this literature by proposing the ability of actors to behave partner-specifically as a possible solution to overcome the coordination problem.

Although this paper focuses strongly on emergence of conventions modelled in a strategic manner using coordination problems, the substantive problem addressed also relates to understanding, e.g., social influence processes in networks (e.g. Marsden and Friedkin, 1993) and the spread of innovations and social norms in networks (Centola and Macy, 2007), which are often not theorized using arguments involving strategic interdependence. We will say a bit more on such wider implications in the conclusion and discussion section of the paper.

The remainder of this paper is organized as follows. Section 2 introduces the coordination game and deduces hypotheses. In the first part of section 3, we describe the experiment used to test the predictions. In the second part, we elaborate on the operationalizations and present the analytical strategy. In section 4, we present the results. Section 5 concludes and provides directions for future research.

## 2. Formal model and analytical solutions

### 2.1. The game

Actors are connected through a network and play coordination games (Ellison, 1993) with their neighbors in the network. Actors may or may not behave partner-specifically and actors' preferences for outcomes in the game may differ.

Fig. 1 represents a coordination game in which two actors can choose between using a *Windows* or *Mac* operating system and both actors are so-called *Windows-lovers*. Both actors prefer coordination over miscoordination ( $a_i > b_i$ ,  $d_i > c_i$ ,  $i = 1, 2$ ). Furthermore, actors prefer coordination on the equilibrium (*Windows, Windows*)

		Actor 2				Actor 2	
		Windows	Mac	Windows	Mac	Windows	Mac
Actor 1	Windows	$a_1, a_2$	$c_1, b_2$	100, 100	30, 00		
	Mac	$b_1, c_2$	$d_1, d_2$	00, 30	70, 70		

Payoff inequalities:  $a_i > b_i, d_i > c_i, a_i > d_i, i = 1, 2$ .

Fig. 1. Homogeneous two-player coordination game (general and experiment version).

		Actor 2 Mac-lover				Actor 2 Mac-lover	
		Windows	Mac	Windows	Mac	Windows	Mac
Actor 1 Windows-lover	Windows	$a_1, a_2$	$c_1, b_2$	100, 70	30, 30		
	Mac	$b_1, c_2$	$d_1, d_2$	00, 00	70, 100		

Payoff inequalities:  $a_i > b_i, d_i > c_i, i = 1, 2, a_1 > d_1, a_2 < d_2$ .

Fig. 2. Heterogeneous two-player coordination game (general and experiment version).

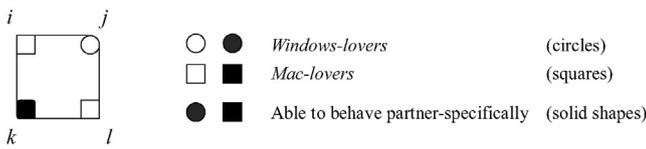


Fig. 3. Example of an interaction network.

over coordination on the equilibrium (*Mac, Mac*) ( $a_i > d_i, i = 1, 2$ ). We construct the payoff matrix for the experiment as follows: actors receive 30 points for playing their preferred strategy and an additional 70 points for coordination. By taking the transpose of Fig. 1, we capture the coordination game in which both actors prefer *Mac* over *Windows*, in this situation we call both actors *Mac-lovers*. In both games, the actors are homogeneous with regard to preferences: both actors prefer either *Windows* or *Mac*. In our game, we allow for heterogeneity in preferences within the population. Fig. 2 represents a game with heterogeneous preferences (see Bojanowski and Buskens, 2011; Hernández et al., 2013)

As in the homogeneous game, actors prefer coordination over miscoordination ( $a_i > b_i, d_i > c_i, i = 1, 2$ ). However, actors no longer prefer coordination on the same equilibrium. Actor 1 prefers coordination on the equilibrium (*Windows, Windows*), whereas actor 2 prefers coordination on the equilibrium (*Mac, Mac*) ( $a_1 > d_1, a_2 < d_2$ ).

Subjects in our experiment played repeated coordination games for 20 periods with payoffs as illustrated in Figs. 1 and 2 among a group of four actors. Actors are arranged on a network. If actors  $i$  and  $j$  are connected in the network, they play the coordination game. This network remains unchanged over the repeated game. Symmetric networks are used: all actors within one network have the same number of neighbors. The actors have global information regarding their own and the preferences of all other actors in the network and regarding the ability of actors to behave partner-specifically or not. Actors receive also information about the behavior of all actors in the network. Fig. 3 represents a possible interaction network: actors  $i$  and  $j$ , actors  $j$  and  $l$ , actors  $i$  and  $k$ , and actors  $k$  and  $l$  are connected in this network. Actors  $i, k$ , and  $l$  are *Mac-lovers* (squares), while actor  $j$  is a *Windows-lover* (circle). Only actor  $k$  is able to behave partner-specifically (solid shape).

To deal with a heterogeneous population, we study the effect of partner-specific behavior on coordination. Following Tsvetkova and Buskens (2013), we define partner-specific behavior as the ability of actors to choose the behavioral option for each partner separately. In other words, an actor can, e.g., choose to play *Windows* when playing with a *Windows-lover* and can choose to

play *Mac* when playing with a *Mac-lover*. We distinguish three versions of the game. (1) Actors cannot behave partner-specifically, i.e. each actor has to choose the same behavior with all neighbors. (2) Actors can behave partner-specifically, i.e. each actor can differentiate behavior in interactions with different neighbors. (3) Actors can buy the ability to behave partner-specifically. This creates an initial choice before the actual coordination game in which each actor chooses whether to buy the ability to behave partner-specifically. When this ability is bought, the actor can differentiate behavior when interacting with different neighbors. Otherwise, the actor chooses the same behavior with all neighbors. Thus, the extent to which actors can behave partner-specifically is exogenously determined in versions 1 and 2 of the game and is endogenous in version 3.

### 2.2. The effect of heterogeneity in preferences on coordination

To derive hypotheses on coordination in different networks, we consider the difficulty of the coordination problem in different networks depending on the network structure and the actors' preferences in the network. For any pair of actors in the games described above (either *Windows* or *Mac-lovers*), the strategy combinations (*Windows, Windows*) and (*Mac, Mac*) are the pure Nash equilibria.<sup>1</sup> If both players are *Windows-lovers*, the equilibrium (*Windows, Windows*) is payoff-dominant, i.e. both players receive a higher payoff if they both play *Windows* than if they both play *Mac* (Harsanyi and Selten, 1988). The equilibrium (*Windows, Windows*) is also risk-dominant in the sense of Harsanyi and Selten, since  $\pi = (a_i - b_i) / (a_i - b_i - c_i + d_i) > 0.5$  (in our numerical example in Fig. 1,  $\pi = 0.71$ ). If both actors are *Mac-lovers*, the equilibrium (*Mac, Mac*) is payoff-dominant and risk-dominant. In games with one *Windows-lover* and one *Mac-lover*, there is neither a payoff-dominant nor a risk-dominant equilibrium. Therefore, at the level of the dyad, there are always two pure equilibria. Based on the either the payoff- or risk-dominance criterion, coordination is straightforward if actors have the same preference, but coordination is less straightforward if the actors have different preferences (Hernández et al., 2013; Neary, 2012).

When two connected actors have different preferred equilibria, we talk about a heterogeneous dyad, while otherwise we have a homogeneous dyad. Coordination in heterogeneous dyads implies a suboptimal outcome for the actor deviating from his preferred

<sup>1</sup> We neglect mixed equilibria, because the mixed equilibrium is Pareto-dominated by both pure equilibria whatever the type of actors in a game are.

behavior. In order to coordinate, one of the actors has to give in. However, it is difficult for both actors to anticipate whether the other actor will deviate from his preferred behavior in order to coordinate. Moreover, coordination will not be obtained when both actors expect the other to give in or expect the other not to give in and choose the preferred behavior of their partner. Research has shown that coordination is more difficult in this type of coordination game, i.e. coordination games in which actors have different preferences, compared to homogeneous coordination games (e.g. Helbing et al., 2014; Sekiyama, 2014). From this we deduce the following hypothesis:

H1.1: *Coordination is more difficult in heterogeneous dyads than in homogeneous dyads.*

A network consisting of four actors in which there are two *Windows-lovers* and two *Mac-lovers* has a higher heterogeneity in preferences than a network consisting of four actors in which there are three *Windows-lovers* and one *Mac-lover*. When actors have different preferences and know the preferences of the other actors in their network, they receive additional information that might make it easier for them to anticipate which strategy the other actors will choose (Goyal and Janssen, 1997). In homogeneous networks, coordination is not problematic at all. In networks with limited heterogeneity, i.e. in which three out of four actors have the same preferences, it is likely that the minority group will adjust their behavior in order to coordinate on the equilibrium preferred by the majority although the minority might give it a try (Fischer, 1982; Hernández et al., 2013). If preferences are equally distributed in the network, actors have no simple heuristic to coordinate on a specific equilibrium, which will inhibit coordination not only at the network level, but also at the dyadic level. Therefore, we state the following hypotheses:

H1.2: *Heterogeneity in preferences at the network level negatively influences coordination at the dyadic level.*

H1.3: *Heterogeneity in preferences at the network level negatively influences coordination at the network level.*

### 2.3. The effect of the number of actors that can behave partner-specifically

Considering the complete network of relations, when nobody is able to behave partner-specifically, all actors choose one behavioral strategy to use with all their neighbors. Given that all our networks are connected, i.e., each actor is connected to every other actor directly or indirectly via the network, there are also only two pure strategy equilibria at the network level such that all neighbors coordinate on the same behavior: everyone chooses *Mac* or everyone chooses *Windows*. More precisely, given the networks we use in the experiment, it is straightforward to check that these are the only pure strategy equilibria in the game, although one can construct networks and preferences with equilibria in which some neighbors do not coordinate. Still, the difficulty of choosing one of the two equilibria depends on the distribution of preferences in the network.

In games where all actors behave partner-specifically, each actor chooses a strategy to use for each neighbor separately. Actor 1 can coordinate with actor 2 on the equilibrium (*Windows, Windows*) and with another actor on the equilibrium (*Mac, Mac*). Thus, there are many more equilibria at the network level, namely two for every dyad, which can all be independently chosen. Still, in dyads with actors with the same preferences, the choice will be relatively easy, but the more heterogeneous dyads there are in the network, the more difficult it will be to have all dyads coordinate in the network.

The third version of the game allows actors to invest in the ability to behave partner-specifically. In this version of the game, the number of actors able to behave partner-specifically is endogenously determined. This creates situations in which some actors

choose one strategy for all their interactions and others choose different strategies in different interactions. From the above, we know that the number of equilibria is larger in networks where all actors behave partner-specifically, compared to networks in which none of the actors behave partner-specifically. The number of equilibria in networks where some actors behave partner-specifically lies in between these extremes, its specific number depending on the number of actors able to behave partner-specifically. The number of equilibria at the network level grows with the number of actors in the network able to behave partner-specifically. Therefore, we expect that coordination in the complete network is more difficult when more actors can behave partner-specifically. And, although the number of equilibria within a dyad does not depend on whether actors can behave partner-specifically, the behavior of actors in one dyad depends on what they do in other dyads as well, especially when they cannot act partner-specifically. Thus, actors are more likely to have clues about the behavior of their partners when fewer partners can behave partner-specifically, which implies that also at the dyadic level coordination is expected to be more likely, the less actors in the dyad and network can behave partner-specifically. Therefore, we pose the following hypotheses:

H2.1: *The number of actors within a dyad able to behave partner-specifically negatively influences coordination at the dyadic level.*

H2.2: *The number of actors within a network able to behave partner-specifically negatively influences coordination at the network level.*

### 2.4. The moderating effects of network-level heterogeneity and partner-specific behavior

In Hypotheses 1.2 and 1.3, we argue that coordination is more difficult in networks in which the preferences are equally distributed, as actors embedded in these networks do not have a heuristic to coordinate on one equilibrium (Hernández et al., 2013). Contrastingly, in networks in which a majority of actors has the same preference, the tendency for everyone to coordinate on this majority preference will be relatively strong. As a consequence, we expect at the dyadic level that the coordination problem in heterogeneous dyads is more easily resolved when these dyads are embedded in networks with a clear majority in terms of preferences (see Hypothesis 3.1 below). Therefore, if everyone has the same preference, partner-specific behavior does not matter much because everyone wants to coordinate on the same equilibrium anyway. However, partner-specific behavior can slow down the resolution towards the majority preference if minority actors try to stick to their own preference in some relations. On the contrary, in networks with equally divided preferences, it can take quite some time before all actors agree on one behavior, and then the coordination problem might be even resolved faster at the dyadic level without per se always choosing the same equilibrium in all relations. Thus, the ability to behave partner-specifically is expected to be less detrimental not only in homogeneous networks, but also in networks with equally divided preferences. This leads to the following hypotheses:

H3.1: *The negative effect of being in a heterogeneous dyad on coordination is smaller in networks with a clear majority of preferences than in networks with equally divided preferences.*

H3.2: *In homogeneous networks and networks with equally divided preferences, coordination at the dyadic level is less inhibited by the number of actors able to behave partner-specifically in the dyad than in networks with a minority and a majority group.*

H3.3: *In homogeneous networks and networks with equally divided preferences, coordination at the network level is less inhibited by the number of actors able to behave partner-specifically in the network than in networks with a minority and a majority group.*

Your type: Red		Your choice		Your type: Yellow		Your choice	
		Red	Yellow			Red	Yellow
Other subject's choice	Red	100	0	Other subject's choice	Red	70	30
	Yellow	30	70		Yellow	0	100

Fig. 4. Overview of points.

### 2.5. The effect of heterogeneity on investments in the ability to behave partner-specifically

In games in which actors have to choose whether or not they want to invest in the ability to behave partner-specifically before they play the coordination game, the number of actors able to behave partner-specifically is endogenously determined. This decision relates to our second research question.

Although we expect a negative relation between the number of actors within the network able to behave partner-specifically and coordination, we argue that actors are still willing to invest in the ability to behave partner-specifically under circumstances in which they suspect that partner-specific behavior might help. Kohlberg and Mertens (1986) show that actors are willing to invest their own profits if this investment guarantees a higher payoff than actors would have received without making the investment. The choice to invest in the game thus reveals the expectations of a specific actor regarding the outcome of the game (Cachon and Camerer, 1996). We expect that actors want to invest in the ability to behave partner-specifically predominantly in games where it may be difficult to coordinate if you cannot behave partner-specifically. We argue that actors are able to anticipate that it is harder to coordinate when the heterogeneity in preferences increases. When an actor expects all his neighbors to play his preferred strategy, that actor would not need the ability to behave partner-specifically. However, if an actor's partners have heterogeneous preferences, actors might foresee coordination problems if they cannot adapt their behavior depending on the preferences of their partners. This uncertainty might be because neighbors in the network themselves have different preferences, but also because neighbors of neighbors have different preferences and thus increases in the heterogeneity of the network. Therefore, we pose the following hypothesis:

H4: *The heterogeneity in preferences in a network has a positive effect on the number of actors that choose to invest in the ability to behave partner-specifically.*

## 3. Data and measurements

### 3.1. Experimental design

Subjects played  $2 \times 2$  coordination games similar to the ones described in the formal models above in groups of four. Subjects received points dependent on the decisions they made. At the end of the experiment, points were exchanged for monetary earnings (1500 points equaled one euro). Points were earned by choosing 'Red' or 'Yellow'. When both subjects in a dyad coordinated on the same behavior, both received 70 points. When both subjects in a dyad made a different decision, both received 0 points. Subjects were also assigned a type designed to reflect their preference. Subjects were assigned either type Red or type Yellow. If subjects were assigned type Yellow and they chose 'Yellow', they received 30 additional points. If subjects were assigned type Yellow and they chose 'Red', they received 0 additional points. By assigning points this way, we induced subjects with a 'preference' for one of the two options. We did not use the *Windows-lover* and *Mac-lover* terminology as used in the illustrative examples to avoid a bias caused by personal preferences of subjects.

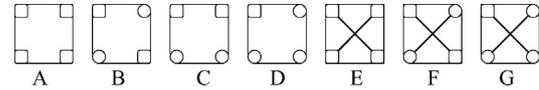


Fig. 5. Overview network structures: circles represent 'Yellow' type; squares 'Red' type.

Thus, as shown in Fig. 4, the representation also used to instruct the subjects, subjects earned 100 points for coordinating while choosing their preferred option. Subjects received 30 points for not coordinating, but still choosing their preferred option. When subjects coordinated using their non-preferred option, they received 70 points. By assigning points in this way, we ensured that subjects prefer coordination over miscoordination (since  $100 > 30$  and  $70 > 0$ ) and prefer to make the decision in line with their type over making the decision not in line with their type ( $100 > 70$  and  $30 > 0$ ).

Subjects played the coordination game on seven different networks. In each network, subjects played 20 periods in the same group of four players. The computer screen showed subjects their network. A link between two subjects indicated that those two subjects were going to interact. In each of the seven different networks, subjects were assigned types Yellow or Red. This assigned type did not change over the 20 periods within one network. The assigned type could change when subjects switched to another network. Subjects were informed about their types and the types of their neighbors at all times. We used different networks to create variance with respect to the heterogeneity in preferences within networks as well as the number of heterogeneous dyads in networks, while keeping the structural positions within networks constant. The seven networks are presented in Fig. 5. Note that we assigned preferences to subjects. Subjects themselves could not change their preference and the assigned preference does not say anything about the actual preferences of subjects.

Three different conditions were included in this experiment. In the first condition, none of the subjects could behave partner-specifically. Each subject had to make the decision between 'Red' and 'Yellow' for all their neighbors at once. Subjects are allowed to change their decision between periods based on the information they received on their points earned and the choices of the other subjects in their network. In the second condition, all subjects could behave partner-specifically. Instead of making one decision for all their neighbors at once, subjects were able to differentiate their decisions between their neighbors. Again, subjects could change their decision between periods based on the information they received on their points and the choices of the other subjects in their network.

In the last condition, subjects could invest in the ability to behave partner-specifically. This created an initial choice in which each subject had to choose, before deciding between 'Red' and 'Yellow' whether they wanted to make this decision for each of their neighbors separately [partner-specific] or for all their neighbors at once [not partner-specific]. Subjects were able to change their decision to invest in the ability to behave partner-specifically between the different networks, but not during the 20 periods in the same network. For each network, a cost of 10 points was imposed for subjects wanting to make the decision for each of their neighbors separately. Subjects needed to pay only once 10 points for this ability to use it 20 periods. After this initial decision, subjects were

asked to choose between 'Red' and 'Yellow' for all their neighbors at once or for each of their neighbors separately, dependent on their initial choice.

Other than the *number of subjects able to behave partner-specifically* there were no differences between the conditions. Each subject played 20 periods on all seven networks in one of the three conditions. Conditions were randomly assigned to the sessions in which the subjects enrolled. Varying the number of subjects able to behave partner-specifically enables us to make a between-subject comparison for the influence of the number of subjects able to behave partner-specifically on coordination.

The experiment was programmed and conducted with z-Tree software (Fischbacher, 2007). Subjects were recruited amongst students at Utrecht University using the Internet recruitment system ORSEE (Greiner, 2004). Seven sessions took place in January 2014 at the Experimental Laboratory for Sociology and Economics (ELSE) at Utrecht University. 168 subjects took part in the experiment. Due to a computer crash in one session we lost information on 24 subjects, bringing the total number of subjects to 144.

Each of the three experimental conditions was tested in two sessions leading to 52 in the first condition, 40 subjects in the second and 52 subjects in the third condition. There were 68 (47.2%) male subjects. The age of the subjects ranged from 18 to 56 with an average age of 24. Furthermore, 40 (27.8%) subjects had followed a course in game theory before participating in the experiment. At the beginning of the experiment subjects received written instructions in English. The instructions were the same for every subject in the same condition (instructions with screenshots are found in Appendix A in Supplementary material).

All subjects played three practice periods before the actual experiment started to get used to the computer interface. A questionnaire was presented to the subjects after the experiment to obtain additional information. Subjects earned a minimum of 16.50 euros and a maximum of 22.00 euros, with an average of 19.50 euros for 120 min of their time. The subjects in the experiment made a total of 31,204 decisions.

### 3.2. Measurements

We start explaining the dependent variables. Coordination at the dyadic level is established when two subjects that are linked in a network made the same decision: either both subjects chose 'Red' or both subjects chose 'Yellow'. We constructed the variable *times coordination at the dyadic level* as a count of the number of times the two subjects in one dyad behaved the same over the 20 periods they were linked in a network.

Coordination at the network level is obtained when all dyads in the network coordinated in the same period. Coordination at the network level does not necessarily imply that all subjects made the same decision. When allowing for partner-specific behavior it could be that a subject embedded in two dyads, coordinated on the equilibrium (Red, Red) with one neighbor and coordinated on the equilibrium (Yellow, Yellow) with the other neighbor. The variable *times coordination at the network level* is a count over 20 periods of the number of periods all dyads in a given network simultaneously coordinated.

The variable for the number of subjects that chose to invest in partner-specific behavior is constructed as the number of subjects who chose the option to make the choice between 'Red' and 'Yellow' for each of their neighbors separately. This choice was only given to the subjects in the third condition of this experiment. We constructed two variables: *number of actors able to behave partner-specifically within the dyad and network*. Values of this variable range from 0, none of the subjects invested in the option to behave partner-specifically, to 2 or 4, all subjects invested in the option to behave partner-specifically.

As a first independent variable, the dummy variable *heterogeneous dyad* indicates whether two subjects in a dyad had the same preference (0) or not (1). This is only an independent variable at the dyadic level. At the network level, we use the index of qualitative variation (IQV) as a measure for the heterogeneity in preferences at the network level. The IQV is a measure of variability based on the ratio of the total number of differences in a distribution to the maximum number of possible differences within the same distribution. The index varies from 0 to 1 (Agresti and Agresti, 1978; Mueller and Schuessler, 1961). *The heterogeneity in preferences* has three values. It is 0 when all subjects in a network are assigned the same preference. When half of the subjects in the network are assigned a preference for Yellow and half of the subjects are assigned a preference for Red, its value is 1. When three subjects in a network have the same preference and one the other preference, the heterogeneity in preferences is 0.75.

In two of the three conditions, the number of subjects able to behave partner-specifically was exogenously determined. In the first condition, none of the subjects was able to behave partner-specifically. The value for the number of subjects able to behave partner-specifically is set to 0 for all dyads and networks in the first condition. In the second condition, all subjects were able to behave partner-specifically. The value for the number of subjects able to behave partner-specifically is set to 2 for all dyads and to 4 for all networks in the second condition. In the third condition, subjects were asked whether they wanted the ability to behave partner-specifically. The value of the variable in this condition ranges from 0 to 2, depending on how many subjects in the dyad decided to invest in the possibility to decide for each of their partners separately. Similarly, the network level variable ranges from 0 to 4. Table 1 provides descriptive statistics of all variables.

### 3.3. Analytical strategy

This study uses dependent variables at two levels: the coordination outcome at the dyadic level, the coordination outcome at the network level, and the number of subjects investing in the ability for partner-specific behavior at the network level. The data have a nested structure with subjects' decisions embedded in subjects, dyads, and networks, while subjects and dyads are embedded in networks. In most multilevel models the lowest level contains the most observations and the highest level contains the least observations, while members of the lowest levels can only be part of one higher level (for example: students are part of one class within one school) (Hox, 2010) and dependent variables are mostly measured at the lowest level. However, in our data, the lowest level is the subject decision level, while our dependent variables are at the dyadic or network level and are accumulations of many subject decisions. Moreover, each subject acts repeatedly in multiple dyads as well as in multiple networks. This implies that the outcomes at multiple dyads as well as multiple networks are influenced by the same subjects. This is due to the set-up of the experiment: the 144 subjects, each making many decisions while being members of a total of 1224 dyads. In addition, these 1224 dyads were clustered within 252 networks. This makes that the dyadic and network-level outcomes are not independent. They are built up from many lower level units, namely the decisions of the subjects who were members of the respective dyads and networks. This implies that our units of analysis are not the lower level units nested in higher level conglomerates, but the higher level units build up from lower level decision. Therefore we use a kind of reversed multi-level models also called *multiple membership models* (see Goldstein, 2013).

In these multiple membership models random effects are added for each member of a network or dyad to account for the fact that

**Table 1**  
Descriptive statistics variables at the dyadic and network level.

	Mean/%	Std.	Min.	Max.	N
<i>Dependent variables</i>					
Periods coordination at the dyadic level	18.07	3.98	0.00	20.00	1224
Periods coordination at the network level	14.90	6.61	0.00	20.00	252
<i>Independent variables</i>					
Heterogeneous dyad dummy	0.44	0.49	0.00	1.00	1224
Heterogeneity in preferences					
IQV = 0.75	28.57	0.00	0.00	0.75	72
IQV = 1	42.86	0.00	0.00	1.00	108
Number of subjects able to behave partner-specifically in the dyad					
Condition 1	(0) 100.00%	0.00	0.00	0.00	442
Condition 2	(2) 100.00%	0.00	2.00	2.00	340
Condition 3	(0) 59.05%				261
	(1) 30.09%	0.68	0.00	2.00	133
	(2) 10.86%				48
Number of subjects able to behave partner-specifically in the network					
Condition 1	(0) 100.00%	0.00	0.00	0.00	91
Condition 2	(4) 100.00%	0.00	4.00	4.00	70
Condition 3	(0) 43.96%				
	(1) 25.27%				
	(2) 14.29%	1.14	0.00	4.00	91
	(3) 15.38%				
	(4) 1.10%				

outcomes are constituted based on decision of the same subjects.<sup>2</sup> By adding a random effect we can control for unmeasured subject characteristics that might influence our dependent variables at the dyadic and network level. For the dyadic outcomes, we also add random effects for the other subjects in the network that are not a member of the focal dyad, because over 20 rounds they might also have a strong influence on the decision of the subjects in the focal dyad. We include equal weights for all four subjects in the network in both the dyadic level as in the network level analyses. At the network level this is straightforward: there are four subjects within a network who all need to coordinate. For the dyadic level, we argue that coordination is also influenced by the subjects not directly embedded in that specific dyad. Although one might argue that the subjects not involved in a dyad have a smaller influence on behavior in the dyad than the subjects directly involved in the dyad, we chose for this relatively parsimonious way of accounting for the interdependence.

## 4. Results

### 4.1. Descriptive results

Fig. 6 provides an overview of the percentages coordination per period, at the dyadic and at the network level. At the dyadic level, 77.37% of all dyads coordinate in the first period. This percentage increases to 95.10% in the last period. At the network level, 51.14% of all networks coordinate in all dyads simultaneously in the first period. This percentage increases to 85.62% in the last period.

### 4.2. Distribution of preferences and coordination

Over all networks, homogeneous dyads coordinate 98.52% of the periods, while this is 79.95% for heterogeneous dyads. Thus, homogeneous dyads coordinate more often than heterogeneous dyads. In the first period, this difference is larger: 94.74% of the homogeneous dyads coordinate compared to 55.37% of the heterogeneous dyads. These descriptive results are in line with Hypothesis 1.1 stating that coordination is more difficult in heterogeneous dyads than in homogenous dyads.

Table 2 provides an overview of the percentages coordination at the dyadic and the network level for each network structure. We report the heterogeneity in preferences, the percentage coordination over all periods, and the percentage coordination in the first period. We can make a distinction between networks in which all subjects have two neighbors (networks A–D) and networks in which all subjects have three neighbors (networks E–G). When looking at the networks in which all subjects have two neighbors we see that coordination occurs most often in network A, where the heterogeneity in preferences is 0. The percentage coordination decreases when the heterogeneity in preferences increases (networks B, C and D). For the networks in which all subjects have three neighbors, we see the same pattern. Coordination occurs most often in network E, where the heterogeneity in preferences is 0 and decreases when the heterogeneity in preferences increases (networks F and G). This pattern is found both at the dyadic and at the network level. Table 2 shows that the differences in the percentages coordination between the different networks are larger at the network level than at the dyadic level. These descriptive results are in line with Hypotheses 1.2 and 1.3 predicting a negative relationship between the heterogeneity in preferences and coordination at the dyadic and the network level.

### 4.3. Partner-specific behavior and coordination

Table 3 provides an overview of the percentages coordination at the dyadic and network level by the number of subjects within a network able to behave partner-specifically. At the dyadic level, approximately 90% of all dyads coordinate, regardless of the number of subjects within the network able to behave partner-specifically. This percentage is slightly higher when one subject within the dyad is able to behave partner-specifically. In those games, approximately 92% of the dyads coordinate. These descriptive statistics are not in line with Hypothesis 2.1 predicting a negative relationship between the number of subjects able to behave partner-specifically in a dyad and coordination at the dyadic level.

At the network level, coordination is obtained in 83.42% of the networks in which none of the four subjects is able to behave partner-specifically. This percentage drops to 64.26% when one subject is able to behave partner-specifically. It stays roughly the

<sup>2</sup> We performed the analyses by running MLwiN-based models in STATA.

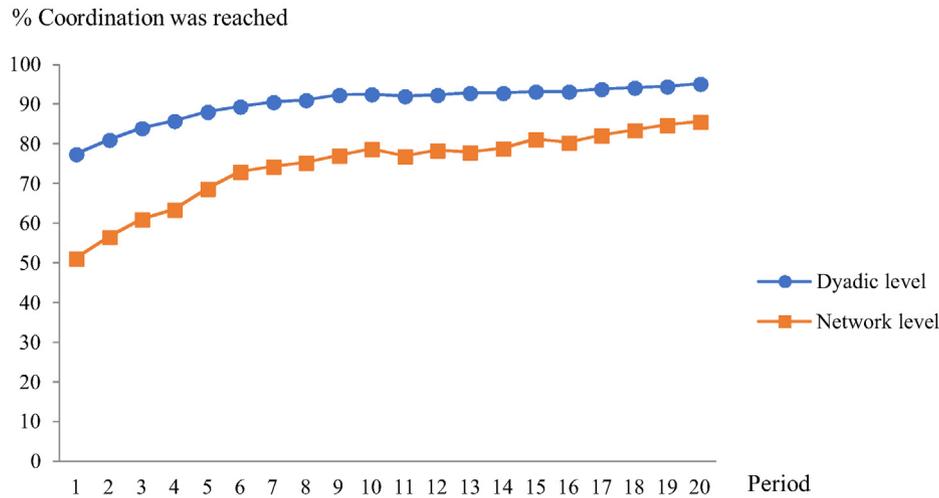


Fig. 6. Percentages coordination for each period over all dyads and over all networks.

Table 2  
Percentages coordination at the network.

Network	Number of neighbors	IQV	Dyadic level		Network level	
			Over all periods	Period 1	Over all periods	Period 1
A	2	0	99.51	98.61	98.47	97.22
B	2	1	79.86	44.44	54.31	5.56
C	2	1	75.97	66.67	40.56	22.22
D	2	0.75	96.28	86.11	88.89	63.89
E	3	0	99.42	97.69	98.19	94.44
F	3	1	81.71	52.31	49.03	0.00
G	3	0.75	96.32	91.20	86.67	69.44
Total			90.33	77.37	74.48	51.14

Table 3  
Percentages coordination at the dyadic- and at the network level for the number of subjects within the dyad or network that is able to behave partner-specifically.

Number of subjects able to behave partner-specifically in a dyad or network	Percentage coordination	
	Dyadic level	Network level
0	90.05	83.42
1	92.22	64.26
2	90.19	39.53
3		70.00
4		64.26

same when more subjects are able to behave partner-specifically. We find an exception in networks where two subjects are able to behave partner-specifically. Coordination is obtained 39.53% of the time in these networks. Although the differences in the percentages coordination at the network level between having one, three or four subjects able to behave partner-specifically are very small, the difference with having no subjects able to behave partner-specifically is quite large. These descriptive results are partly in line with Hypothesis 2.2, which postulates a negative relationship between the number of subjects in a network able to behave partner-specifically and coordination at the network level. However, the extra drop in coordination when two subjects can behave partner-specifically cannot be explained by this.

4.4. Explanatory results: dyadic level

Table 4 presents the multiple membership models estimated to test hypotheses regarding the dyadic level dependent variable. To account for the nesting of dyads (N=1224) in networks (N=252), we add a random effect for networks. To take into account the mul-

multiple membership structure because subjects appear in multiple dyads, we add an extra random effect at the subject level (N=144). As can be seen in Model 0,  $\rho=0.308$  indicating that roughly 30% of the total variance is at the network level. This indicates that it is important to take the multi-level structure into account. The random effect at the subject level seems small, but we cannot ignore the interdependence that might be caused by the same subjects appearing in multiple dyads.

In Model 1, we add the effects for the dyadic and network level predictors. We see that coordination is harder for heterogeneous dyads than for homogeneous dyads ( $b=-3.036$  with  $p<0.001$ ). Heterogeneous dyads coordinate on average 3 periods less over the 20 periods, compared to homogeneous dyads. Therefore, we can confirm Hypothesis 1.1 stating that coordination is more difficult in heterogeneous dyads than in homogeneous dyads. Dyads coordinate slightly though significantly more in IQV=0.75 networks ( $b=0.822$  with  $p<0.05$ ) than dyads in homogeneous networks, which contrasts with Hypothesis 1.2. In line with Hypothesis 1.2, results show that dyads embedded in the IQV=1 networks coordinate significantly less ( $b=-2.134$  with  $p<0.001$ ) than dyads embedded in homogeneous networks. Over the 20 periods, dyads embedded in the IQV=1 networks coordinate on average approximately 2 periods less than dyads embedded in the homogeneous networks. In contrast to Hypothesis 2.1, the number of actors able to behave partner-specifically in the dyad positively influences coordination. Actors embedded in dyads in which one of the two actors can behave partner-specifically, coordinate on average approximately 2 periods more over the 20 periods than actors embedded in dyads in which nobody is able to behave partner-specifically ( $b=1.859$  with  $p<0.001$ ). However, this effect is not linear as actors embedded in dyads in which two actors are able to behave partner-

**Table 4**  
Multiple membership regression on coordination at the dyadic level (1224 dyads in 252 networks, 144 subjects).

	Hyp.	Model 0		Model 1		Model 2	
		Parameter	SE	Parameter	SE	Parameter	SE
<b>Fixed part</b>							
Constant		18.005***	0.174	19.621***	0.260	19.952***	0.280
<i>Independent variables</i>							
Heterogeneous dyad				−3.036***	0.223	−7.567***	0.389
Heterogeneity in preferences network (ref IQV = 0)	H1.1						
IQV = 0.75	H1.2			0.822*	0.363	0.062	0.388
IQV = 1	H1.2			−2.134***	0.360	−0.364	0.401
Number of actors able to behave partner-specifically in the dyad (ref = 0 actors)							
1 actor	H2.1			1.859***	0.347	−0.068	0.441
2 actors	H2.1			0.660*	0.291	−0.173	0.355
Heterogeneous dyad * IQV = 0.75	H3.1					7.091***	0.491
Heterogeneous dyad * 1 actor partner-specifically	H3.2					5.872***	0.604
Heterogeneous dyad * 2 actors partner-specifically	H3.2					4.297***	0.510
Heterogeneous dyad * 1 actor partner-specifically * IQV = 0.75	H3.2					−6.234***	0.986
Heterogeneous dyad * 2 actors partner-specifically * IQV = 0.75	H3.2					−7.501***	0.695
<b>Random part</b>							
Variance (subject level)		0.011	0.013	0.024	0.028	0.012	0.014
Variance (dyadic level)		10.849	0.490	8.675	0.395	6.647	0.306
Variance (network level)		5.224	0.691	2.409	0.418	3.395	0.476
<b>Fit statistics</b>							
Deviance		Parameter	Df	Parameter	Df	Parameter	Df
Difference in deviance		6843.150	3	6116.000	9	5791.260	14
ICC		0.308		727.150	6	324.740	5
<b>Explained variance</b>							
R <sup>2</sup> dyadic level				0.200		0.387	
R <sup>2</sup> network level				0.539		0.350	

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$  (two-sided tests).

specifically coordinate on average approximately 1 period more over the 20 periods ( $b = 0.660$  with  $p < 0.05$ ).

Model 1 fits the data significantly better than Model 0 (difference in deviance test:  $\chi^2(6) = 727.150$ ,  $p < 0.001$ ). In this model, we are able to explain 20.0% of the variance at the dyadic level and 53.9% of the variance at the network level. The small value for the variance at the subject level indicates that unmeasured characteristics of subjects do not seem to have a systematic effect on coordination in dyads. The explained variance is mainly due to the difference between heterogeneous and homogenous dyads and the number of actors able to behave partner-specifically.

In Model 2, we add the cross-level interaction terms. Model 2 provides more precise explanations for the differences found in Model 1. In Model 1 we saw that coordination is harder for heterogeneous dyads than for homogeneous dyads. When we add the interaction with IQV = 0.75 results show that heterogeneous dyads (without actors that can behave partner-specifically) embedded in IQV = 0.75 networks coordinate significantly more, compared to heterogeneous dyads embedded in IQV = 1 networks ( $b = 7.091$  with  $p < 0.001$ ), but still less than homogeneous dyads. The negative effect of heterogeneous dyads increases with heterogeneity (IQV) in preferences at the network level. This provides evidence for Hypothesis 3.1. Homogeneous dyads embedded in homogeneous networks do not coordinate significantly more than homogeneous dyads embedded in IQV = 0.75 networks or in IQV = 1 networks (IQV = 0.75:  $b = 0.062$  with  $p = 0.438$ ; IQV = 1:  $b = -0.364$  with  $p = 0.184$ ). Results show significant evidence for the interaction effect with partner-specific behavior and degree of heterogeneity in preferences. In networks with IQV = 1, heterogeneous dyads in which one or two of the actors are able to behave partner-specifically coordinate significantly more than heterogeneous dyads in which none of the actors are able to behave partner-specifically (1 actor able to behave partner-specifically:  $b = 5.872$  with  $p < 0.001$ ; 2 actors able to behave

partner-specifically:  $b = 4.297$  with  $p < 0.001$ ). However, coordination in heterogeneous dyads is a bit more difficult when both actors are able to behave partner-specifically. In networks with a clear majority (IQV = 0.75), this positive effect of partner-specific behavior disappears again as can be seen from the coefficients  $-6.234$  and  $-7.501$  for the three-way interactions. In addition, we can see in this model in which all types of heterogeneous ties are modelled separately that actors being able to behave partner-specifically does not affect coordination in homogeneous dyads ( $b = -0.068$  with  $p = 0.437$ ;  $b = -0.173$  with  $p = 0.310$ ). Jointly, this shows that partner-specific behavior does not hinder coordination in homogeneous networks, improves coordination in heterogeneous dyads in networks with IQV = 1, but not in networks with IQV = 0.75. Therefore, these effects still do not provide evidence for Hypothesis 2.1 on an overall negative effect of partner-specific behavior on coordination, but they support the arguments behind Hypothesis 3.2 that partner-specific behavior has particular disadvantages in networks with a minority and a majority.

Model 2 fits the data significantly better than Model 1 (difference in deviance test:  $\chi^2(5) = 324.740$ ,  $p < 0.001$ ). In this model we are able to explain 38.7% of the variance at the dyadic level and 35.0% of the variance at the network level.

#### 4.5. Explanatory results: network level

At the network level, we have two dependent variables: (1) coordination at the network level and (2) number of subjects investing to behave partner-specifically. The first dependent variable is used to test hypotheses 1.2, 2.3 and 3.3 (Table 5: Models 1 and 2) and the second dependent variable is used to test hypothesis 4 (Table 5: Model 4). The empty Models 0 and 3 show that there is hardly any variance attributable to the individual level.

In Model 1, we find a significant negative effect of heterogeneity in preferences on coordination at the network level. Coordination

is reached on average approximately 2.1 periods less in networks with  $IQV=0.75$  ( $b=-2.104$  with  $p<0.001$ ) compared to homogeneous networks and on average approximately 9.8 periods less in networks with  $IQV=1$  ( $b=-9.896$  with  $p<0.001$ ).<sup>3</sup> Thus, we find evidence for Hypothesis 1.3. There is also a significant negative effect of the number of subjects able to behave partner-specifically on coordination at the network level ( $b=-0.349$  with  $p<0.05$ ). Coordination at the network level is obtained 1.4 periods less over all 20 periods in networks where all subjects are able to behave partner-specifically, compared to networks in which none of the subjects is able to behave partner-specifically. This is in line with Hypothesis 2.2. In this model, we see that most of the variance is attributed to the network level and only a small amount of the variance to the subject level. This indicates that also at the network level, there does not seem to be a systematic effect of specific subject characteristics on the performance of the group. In this model, we are able to explain 46.6% of the total variance.

In Model 2, we add the interaction effects. In line with results from dyadic level analyses, we find a negative effect of the number of subjects able to behave partner-specifically in networks with  $IQV=0.75$  ( $b=-1.401$  with  $p<0.001$ ). However, coordination is not significantly easier when the number of subjects able to behave partner-specifically in the network increases in networks with  $IQV=1$  ( $b=0.657$  with  $p=0.054$ ). Thus, this qualifies the evidence on Hypothesis 2.2: because the negative effect of the number of actors able to behave partner-specifically is only found for networks with  $IQV=0.75$ . The results provide some evidence for Hypothesis 3.3, because coordination is clearly less inhibited by the ability for partner-specific behavior in homogeneous networks and networks with  $IQV=1$ . Moreover, the negative effect of partner-specific behavior disappears completely in these networks. Model 2 fits the data better than Model 1. In this model, we are able to explain 51.0% of the total variance.

As can be seen in Model 4, we find significant evidence in line with Hypothesis 4 that subjects are more willing to invest in partner-specific behavior in more heterogeneous networks. However, this effect is only found in networks with  $IQV=1$ . In these networks approximately one subject more chose to invest in the ability to behave partner-specifically ( $b=1.460$  with  $p<0.001$ ), compared to subjects embedded in homogeneous networks. We did not find a significant effect in networks with  $IQV=0.75$  ( $b=0.117$  with  $p=0.304$ ). Actors embedded in these networks do not significantly more often choose to behave partner-specifically, compared to actors embedded in homogeneous networks. Therefore, we find some evidence to confirm Hypothesis 4, but the effect does not seem to linear. Apparently, the subjects might realize better than we suspected in our derivation of the hypothesis that partner-specific behavior can also have disadvantages, particularly in networks with  $IQV=0.75$ . The variables in this model explain 46.2% of the variance in the dependent variable. Again, the remaining variance at the subject level is very small.

#### 4.6. Distribution of points and partner-specific behavior

Although we theoretically predicted that partner-specific behavior in most circumstances inhibits coordination, quite some subjects were willing to invest in partner-specific behavior. Therefore, the additional question we should ask is whether people

actually profit from their ability to behave partner-specifically? Descriptive results show that the average number of points earned per interaction is approximately equal in all three conditions (none of the actors is able to behave partner-specifically: 90 points, all actors are able to behave partner-specifically: 91 points and actors can choose to behave partner-specifically: 91 points). In the third condition, we allowed subjects to buy the ability to behave partner-specifically. Subjects who invested in this ability earned on average 83 points per interaction ( $N=13$ ) and subjects who did not buy the ability to behave partner-specifically earned on average 94 points per interaction ( $N=39$ ). Note that all the points we report here, do not yet take into account the cost for choosing to behave partner-specifically, which imply an additional disadvantage for subjects making that choice. These descriptive results indicate that subjects do not benefit in terms of points earned from the ability to behave partner-specifically. Given that we have seen above that the likelihood of coordination depending on partner-specific behavior strongly depends on the heterogeneity in the network, we distinguish between these three types of networks in Table 6. Although partner-specific behavior seemed to provide more an advantage in  $IQV=1$  networks than in  $IQV=0.75$  networks, we see that especially in the most heterogeneous networks, subjects who chose to behave partner-specifically earn less. The finding that subjects being able to differentiate earn less is a striking if only because these subjects have more behavioral options, but cannot utilize these options to improve their outcomes.

Two aspects seem to contribute to this finding. First, in dyads where one actor is able to behave partner-specifically that actor is more likely to deviate from his or her preferred strategy in order to coordinate, thereby earning less than the actor without the ability to differentiate. Apparently, choosing to be able to differentiate signals a stronger willingness to coordinate relatively to sticking to one's own preference, which might reduce bargaining power in a dyadic relation. Second, in dyads where both actors can differentiate their behavior miscoordination is more likely if both actors are prepared to give way to the preferences of the other for achieving coordination, resulting again in fewer earnings for flexible actors.

#### 4.7. Sensitivity analyses

'Coordination' could have been defined in many different ways in this study. We chose to operationalize coordination in an absolute sense: through counting the *number of periods of coordination* over all 20 periods. However, we could also consider whether coordination is obtained in an *earlier* or *later* period in certain games compared to others. To test the robustness of our findings, we constructed a variable indicating the *period in which coordination was obtained for the first time*. To test the hypotheses, we performed a Tobit regression in which we specified the upper limit as 20. A value of 21 on the variable *period of first coordination* indicates that coordination was not obtained within the 20 observed periods (results can be found in Appendix B in Supplementary material). At the dyadic level, the results are insensitive to this alternative operationalization of *coordination*. At the network level, the effect of partner-specific behavior became insignificant. The number of actors able to behave partner-specifically in the network did not influence the period in which coordination was reached for the first time. We should note, however, that we could not combine the Tobit models with the full multi-level structure as applied for the main models, but given that the results are rather robust we are confident that this is not of major influence as well.

Kohlberg and Mertens (1986) suggest that subjects with game theoretical knowledge may be able to coordinate more often than subjects without game theoretical knowledge. At the end of the experiment, subjects filled out a questionnaire in which they were asked: "Have you ever followed a course in game theory?" This ques-

<sup>3</sup> A sensitivity analysis including network dummies rather than the measure for  $IQV$  shows similar results. Actors coordinate approximately 2 periods less in the  $IQV=0.75$  networks and approximately 10 periods less in the  $IQV=1$  networks. Moreover, the model including network dummies does not fit the data significantly better than Model 1 (difference in deviance test:  $\chi^2(4)=1.190$ ,  $p=0.880$ ). Results can be found in Appendix C in Supplementary material.

**Table 5**  
Multiple membership regression on coordination and investments in partner specific behavior at the network level.

	Dependent variable: coordination at the network level= (252 networks, 144 subjects)						Dependent variable: number of subjects investing to behave partner-specifically (91 networks, 52 subjects)					
	Hyp.	Model 0		Model 1		Model 2		Hyp.	Model 3		Model 4	
		Parameter	SE	Parameter	SE	Parameter	SE		Parameter	SE	Parameter	SE
<b>Fixed part</b>												
Constant		14.743***	0.430	20.109***	0.635	19.930***	0.672		1.045***	0.129	0.385*	0.194
<i>Independent variables</i>												
Heterogeneity in preferences network (ref IQV = 0)												
IQV = 0.75	H1.3			−2.104**	0.816	−2.367**	0.784				0.117	0.245
IQV = 1	H1.3			−9.896***	0.734	−10.144***	0.726	H4			1.460***	0.224
Number of actors able to behave partner-specifically in the network	H2.2			−0.349*	0.186	−0.223	0.313					
Heterogeneity in preferences network *												
Number of actors partner-specifically in the network <sup>a</sup> (ref IQV = 0)												
IQV = 0.75	H3.3					−1.401**	0.446					
IQV = 1	H3.3					0.657	0.408					
<b>Random part</b>												
Variance (subject level)		0.055	0.107	0.068	0.098	0.041	0.074		0.009	0.011	0.025	0.026
Variance (network level)		45.177	4.054	24.143	2.207	22.119	2.077		1.325	0.208	0.777	0.142
<b>Model fit</b>												
Deviance		Parameter	Df	Parameter	Df	Parameter	Df		Parameter	Df	Parameter	Df
Difference in deviance		1674.460	3	1516.310	6	1494.670	8		282.900	3	233.740	5
				158.150	4	21.640	2				46.160	2
<b>Explained variance</b>												
R <sup>2</sup>				0.466		0.510					0.414	

<sup>a</sup> Variable number of actors able to behave partner-specifically in the network is centered on its grand mean.

**Table 6**

Average number of points earned per interaction by the ability to behave partner-specifically and IQV for subjects in condition 3 (52 Subjects).

	Average points earned by interaction		
	IQV = 0.00	IQV = 0.75	IQV = 1.00
Subjects able to behave partner-specifically	95	91	74
Subjects not able to behave partner-specifically	100	91	79

tion is used to construct a variable indicating the number of people within a network that followed a course in game theory. When we add this variable to the multiple membership models, we find our results to be insensitive to adding this variable and the variable itself does not have a significant effect neither at the dyadic level ( $b = 0.115$  with  $p = 0.246$ ) nor at the network level ( $b = 0.139$  with  $p = 0.367$ ).

We examined whether it makes sense to assume that the slopes of the predictor variables do not vary across groups. We added random slopes for the network level predictors to our dyadic level model. We incorporated these random effects after we included the fixed effects and before we included the interaction effect. Results show a small variance component for the number of subjects within a network able to behave partner-specifically ( $variance = 0.009$  with  $p = 0.011$ ). The variance for the heterogeneity in preferences at the network level, on the other hand, is quite large ( $variance = 8.289$  with  $p = 0.362$ ). This indicates that the effect of the latter variable seems to have different slopes for the different groups. However, the direction and significance of the predictor variables in the model were not influenced by including this random slope.

Next, we examined whether it made sense to add random effects for all four subjects in the network also to the analyses for at the dyadic level. We ran a model including random effects only for the subjects within the dyad. Also in these models the random effect at the subject level remained relatively small ( $variance = 0.029$ ) and the alternative specification did not change the results.

## 5. Conclusion and discussion

The aim of this study is to better understand the emergence of conventions in situations where individuals have different preferences. Previous experimental research has shown that agreeing on a convention is more difficult in situations where actors have different preferences (Bojanowski and Buskens, 2011; Helbing et al., 2014; Hernández et al., 2013; Sekiyama, 2014). However, most of this research has assumed that people are not able to choose different conventions when interaction with different partners. Societies are changing rapidly and people tend to invest more in flexibility, for example by learning how to work with different software programs. This flexibility might be especially useful when people have to work together with multiple partners that have different preferences. We analyzed decisions of actors in networks on, for example, which operating system they want to use for designing a new program with their different neighbors. We studied heterogeneous populations in which some subjects preferred coordination on one behavior and other subjects preferred coordination on another behavior. As experimental manipulations, we varied the distribution of preferences within the networks and whether subjects were able to differentiate behavior when interacting with different others or whether they could invest in such a flexibility in behavior.

Regarding the preferences of subjects, we hypothesized that it is harder to coordinate in heterogeneous dyads than in homogeneous dyads. We also expected a negative relationship between the heterogeneity in preferences of the network and coordination,

both at the dyadic and at the network level. In networks where the heterogeneity in preferences is at its lowest, all subjects have the same preference and thus it will be easy to coordinate. When the heterogeneity in preferences becomes larger, the distribution of preferences amongst players becomes more equal. This will make it harder for subjects to anticipate which of their interaction partners will give in and deviate from their preferred behavior to coordinate. Hence, coordination is more difficult. Results show coordination is the most difficult in heterogeneous dyads embedded in perfectly heterogeneous networks. Coordination is easier for heterogeneous dyads embedded in networks where there exists a majority and a minority group. Moreover, being able to behave partner-specifically helps coordinating in heterogeneous dyads embedded in perfectly heterogeneous networks. For heterogeneous dyads embedded in networks where there exists a majority and a minority group in terms of preferences, being able to behave partner-specifically hinders coordination.

We predicted a negative relationship between the ability to behave partner-specifically and coordination, due to a larger number of equilibria to coordinate on. Findings show that coordination at the network level is harder when there is a majority of subjects with one preference and a minority with another preference. However, results do not show such a negative effect of the number of subjects within a network able to behave partner-specifically and coordination for homogeneous networks or heterogeneous networks in which the preferences are equally distributed. A possible explanation for this lies in the fact that in homogeneous networks coordination on the preference of everyone is anyway not a problem, while in the case of equally distributed preferences subjects might coordinate on different preferences in different pairs. In networks with a majority, the majority preference is probably most often going to be chosen, but minority subjects who can differentiate behavior might be less inclined to conform with the majority directly.

Given these findings and regarding the research questions: what can we conclude from this study? Does being able to differentiate behavior towards different interaction partners facilitate coordination in situations where actors have different preferences? No, in most situations the ability to behave partner-specifically is not an advantage. In networks where there exists a majority and a minority group in terms of preferences the ability to differentiate behavior actually hinders coordination. However, the ability to behave partner-specifically can overcome the coordination problem for actors in heterogeneous dyads embedded in perfectly heterogeneous networks.

As briefly addressed in the introduction, results of this study have implications for the behavior of individuals in networks where different actors have different preferences. Our finding that coordination is easier in networks where there exists a majority and minority group in terms of preferences relates to the literature on social influence processes (Kandel and Lazear, 1992; Marsden and Friedkin, 1993) and the literature on the diffusion of innovations and social norms in networks (Centola and Macy, 2007). Our finding that coordination is easier in networks where there exists a clear minority and a majority group in terms of preference underlines the importance of the distribution of preferences for the diffusion of behavior. Whereas in perfectly heterogeneous networks, heterogeneous dyads tend to at least try to coordinate on their preferred strategy, the tendency to deviate from this strategy is much stronger in networks with a clear minority and majority group illustrating that conformity is reached more easily if the majority opinion is more obvious. Results of this study add to this literature by showing that the ability to behave partner-specifically hinders coordination in such networks. This implies that actors stick to their preferred strategy longer and are less likely to conform to group norms if the conformity process runs more along

the lines of dyadic interactions than in processes that involve the whole group. This is especially interesting in the light of studies on peer-pressure (e.g. Corten and Knecht, 2013).

Because the experimental set-up of this study limited us to studying small groups with limited variation in structural features of the network, we do not draw direct implications on how structural differences in larger networks might affect the diffusion processes we studied. However, the individual behavior observed in our experiment provides detailed information on how actors decide depended on what their neighbors and what they themselves did in the past. These behavioral rules might be generalized and implemented in agent-based models in which agents play coordination games in larger networks with more structural variations. Such theoretical models provide additional implications on how network structure affects the emergence of conventions given the decision rules actors in our experiment use.

There are two key elements in our experimental design that are interesting to alter in future research. The first element regards the fixed costs of the ability to behave partner-specifically. Results of this study show that when the heterogeneity in preferences within the network is higher, more people invest in the ability to behave partner-specifically. However, we do not know whether this still holds when we vary the costs of the ability to behave partner-specifically. Given that in real-life the costs of, for example, learning another language may also differ between different persons, investigating the effect of varying the costs of the ability to behave partner-specifically forms a particularly interesting direction for future research. The second interesting direction for future research is related to the networks in which subjects interact. The conclusions drawn in this experiment are limited to fewer group members than real-life social networks in which people behave. Moreover, in this study the interaction network is given, while in real-life networks often vary between time points. It is interesting to examine how partner-specific behavior can influence coordination in networks where subjects themselves can contribute to the interaction network and freely choose their interaction partners.

This study is one of the few gathering empirical evidence on the influence of partner-specific behavior in social networks where subjects have heterogeneous preferences. Although there are certainly many aspects within this topic to be addressed in the future, we made an important contribution to unraveling the influence of partner-specific behavior on coordination and providing some fine-grained evidence to the too simplistic intuition that if people would be a bit more flexible about which conventional behavior to choose, this would imply that, at the group level, coordination is more easily realized.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.socnet.2017.05.006>.

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