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Technology adoption in markets with network effects: Theory and experimental evidence ☆

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ABSTRACT

We examine a technology-adoption game with network effects in which coordination on either technology *A* or technology *B* constitutes a Nash equilibrium. Coordination on technology *B* is assumed to be payoff dominant. We define a technology's critical mass as the minimal share of users, which is necessary to make the choice of this technology the best response for any remaining user. We show that the technology with the lower critical mass implies risk dominance and selection by the maximin criterion. We present experimental evidence that both payoff dominance and risk dominance explain participants' choices in the technology-adoption game. The relative riskiness of a technology can be proxied using either technologies' critical masses or stand-alone values absent any network effects.

1. Introduction

In many parts of modern economies (e.g., in information and communications) the payoff associated with a particular technology (or, product) depends positively on the total number of users choosing the same technology. The emergence of positive network effects (i.e., demand-side economies of scale) typically depends on user preferences for compatibility (see Shapiro and Varian, 1998; Farrell and Klemperer, 2007). Technologies may be differentiated, but the importance of differentiation for users' adoption decisions is often negligible when compared with their preference for *compatible* technologies.

A characteristic feature of markets with positive network effects is that users (which can be consumers or firms) typically face several incompatible technologies (standards) when making their purchasing decisions.[1] It

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[1] Examples of rivalry between incompatible technologies include the VCR standards battle between JVC-sponsored VHS and Sony-sponsored Beta (see Cusumano et al., 1992) and the coexistence of different standards in wireless-telephone networks (namely, CDMA, TDMA and GSM) in the United States (see Gandal et al., 2003).

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is well known that simultaneous user choices between incompatible technologies that exhibit pronounced network effects give rise to multiple equilibria (see Farrell and Saloner, 1985; Katz and Shapiro, 1985). Users, therefore, face a coordination problem that involves strategic uncertainty since it is not clear, which equilibrium should be expected.[2]

There are numerous stories of "market failures" in the presence of network effects, when users fail to coordinate on the allegedly superior technology. A prominent example is the persistence of the Qwerty keyboard standard, which has been proscribed as inferior to the rival standard Dvorak (see David, 1985).[3] David argues that network effects can explain the emergence of such "Qwerty worlds", in which users persistently select inferior technologies. In contrast to David, we analyze this issue from the perspective of equilibrium selection. Users make their choices under strategic uncertainty and (because of asymmetries in technologies) face a trade-off between payoff and risk.

Harsanyi and Selten (1988) develop the concept of risk dominance as a criterion for equilibrium selection in games with multiple Nash equilibria. Loosely speaking, it selects the Nash equilibrium in which players choose the less risky strategy. A strategy tends to be less risky if it secures a relatively high payoff, independently of the choices by the other players. Another criterion for equilibrium selection is payoff dominance, which is given when an equilibrium yields to all players a higher payoff than any of the other equilibria. In a coordination game with two Nash equilibria, with one equilibrium being payoff dominant (like Dvorak in the Qwerty situation), the concept of risk dominance may have opposite effects on the prediction of the actual outcome. If the payoff-dominant Nash equilibrium is also risk dominant, the concept of risk dominance is reassuring. If, however, the opposite is true, i.e., one Nash equilibrium is payoff dominant while the other one is risk dominant, then a trade-off emerges, which may imply coordination on the inferior risk-dominant equilibrium or coordination failure (disequilibrium outcomes).

In this paper, we offer experimental evidence on how human subjects resolve the trade-off between risk dominance and payoff dominance in the presence of network effects.[4] We introduce a technology-adoption game, where $N \geqslant 2$ users simultaneously choose one of two technologies, A or B, that both exhibit positive network effects. The utility of adopting one of the technologies is the sum of the stand-alone value plus the network value which is linearly increasing in the number of users of the same technology. We restrict the parameters of the game such that coordination of all users on either technology is a Nash equilibrium and coordination on B is the payoff-dominant equilibrium.[5]

We introduce the concept of a "critical mass," which we define as the minimal share of users necessary to make the choice of a technology the best response for any remaining user.[6,7] Intuitively, a technology with a lower (larger) critical mass is less (more) risky since it requires less (more) users to coordinate, which implies a lower (higher) level of strategic uncertainty. We show that the critical-mass concept is closely related to risk dominance and the maximin criterion. In other words, a technology is chosen by both, risk dominance and the maximin criterion, if and only if the technology has a smaller critical mass.

We present the results of an experiment, where participants play the technology-adoption game for different parameter constellations. In all the versions of the game, coordination on technology A constitutes the risk-dominant equilibrium, while coordination on technology B constitutes the payoff-dominant equilibrium. Our main results are the following: (*i*) Both, payoff dominance and risk dominance, explain participants' choices (giving rise to disequilibrium outcomes), and (*ii*) the relative riskiness of a technology can be proxied by either the difference in technologies' critical masses or the difference in their stand-alone values.[8]

[2] We follow Harsanyi and Selten (1988) and Van Huyck et al. (1990, 1991) who use the term strategic uncertainty to describe the uncertainty that players are facing when they have more than one *equilibrium* strategy. Burton and Sefton (2004) use another approach. They analyze experimentally how strategic uncertainty affects participants' choices among equilibrium strategies. Under strategic uncertainty they understand a player's uncertainty about the other player's choice among all possible strategies including *non-equilibrium* strategies.

[3] Other prominent example includes Microsoft's operating system MS DOS and the videocassette recorder standard VHS, which have been proscribed as inferior vis-à-vis Apple (see, e.g., Shapiro and Varian, 1998) and Beta (see Cusumano et al., 1992), respectively.

[4] We do not know of any experimental evidence on the trade-off between payoff dominance and risk dominance in a setting of competing technologies, each giving rise to positive network effects. Yet, there are several experimental studies on coordination games that are related to our study. Cooper et al. (1990) report coordination failure in experimental coordination games, where participants largely fail to coordinate on the payoff-dominant equilibrium. While the authors do not explicitly analyze the influence of riskiness, it is possible that the trade-off between payoff dominance and risk dominance was responsible for the observed pattern. Van Huyck et al. (1990, 1991) report on coordination-game experiments, where they observe that in the case of a trade-off between payoff dominance and security (the choice of a strategy yielding the highest minimal payoff), disequilibrium outcomes prevail in the first period (which can be considered as a proxy for a one-shot game). Straub (1995) concludes from his experiment on repeated coordination games that coordination failure appears to result from a trade-off between payoff dominance and risk dominance.

[5] In that sense, technology B is the superior one, while technology A is inferior.

[6] It is well known that markets with network effects exhibit a critical-mass effect (see, for instance, Rohlfs, 1974; Economides, 1996; Suleymanova and Wey, 2011).

[7] Liebowitz and Margolis (1996) also point out the importance of the critical mass in their illustrative analysis of consumers' choices between different standards. Besides several differences, our analysis gives theoretical support to their approach based on the risk-dominance criterion.

[8] Note that a Nash equilibrium is either risk dominant or not. In that sense, the risk-dominance concept does not take account of gradual changes of the riskiness of equilibrium play. Interpreting the risk-dominance criterion in terms of the critical mass allows us to transform a binary criterion into a continuous measure. The latter is important for the empirical analysis of our experimental data.

More precisely, we find that an increase in technology B's relative payoff dominance (proxied by the relative difference in technologies' maximal payoffs) increases the probability of a B-choice. We also show that an increase in the relative riskiness of technology B (proxied either by the relative difference in critical masses or stand-alone values) reduces the probability of a B-choice.

Our paper is closely related to Heinemann et al. (2009). They experimentally analyze a critical-mass coordination game, where $N \geqslant 2$ players choose between a safe and a risky strategy. The safe strategy delivers a constant payoff, irrespectively of the other players' choices. The payoff of the risky strategy depends on the choices of the other players such that at least K players have to choose this strategy to deliver a higher payoff than the safe strategy. If less than K players choose the risky strategy, then the payoff is zero. Heinemann et al. introduce the coordination requirement $k:=(K-1)/(N-1)$ to proxy the coordination problem that players face when choosing the risky strategy. Their experiment shows that the number of participants choosing the risky strategy becomes smaller when the coordination requirement increases. A similar relationship is observed regarding an increase of the safe payoff.

Our study is different from Heinemann et al. in that we consider a game where *both* strategies are risky; i.e., payoffs always depend on the choices made by the other players. When both strategies are risky, our critical-mass concept allows us to proxy the strategies' *relative* riskiness. Furthermore, we analyze the influence of the minimal payoffs (given by technologies' stand-alone values) on participants' choices in the experiment.

Schmidt et al. (2003) examines the influence of changes in payoff and risk dominance on participants' choices in experimental coordination games. Their main finding is that only changes in risk dominance help to explain the observed data. We extend their analysis by proposing different proxies for risk dominance based on the technologies' critical masses or their minimal payoffs. Most importantly, we show that both the proxies for risk and payoff dominance explain participants' behavior in our one-shot coordination game.

We proceed as follows. In Section 2 we introduce the technology-adoption game and define the critical-mass concept. Section 3 shows how the concept of critical mass relates to risk dominance and the maximin criterion. Section 4 presents the design of the experiment and Section 5 reports the experimental results. Finally, Section 6 concludes.

2. The technology-adoption game

Suppose that $N \geqslant 2$ identical and discrete users (which can be consumers or firms) simultaneously make their choices between two technologies, A and B. The payoff that a user derives from technology $i = A, B$ positively depends on the total number of users choosing the same technology, $N_i \leqslant N$, and is given by

$$U_i(N_i) = \upsilon_i + \gamma_i(N_i - 1). \tag{1}$$

The parameter $\upsilon_i \geqslant 0$ can be interpreted as the "stand-alone value" that a user derives from technology i absent any network effects. The term $\gamma_i(N_i - 1)$ measures positive network effects if $N_i > 1$ users choose the same technology i.[9] The coefficient $\gamma_i \geqslant 0$ measures the (constant) slope of the network-effects function of technology i. Users always find it optimal to adopt one of the technologies, so that $N_A + N_B = N$ holds.

The game is parameterized such that it has two strong Nash equilibria in pure strategies, in which either all users choose technology A (A-equilibrium) or all users choose technology B (B-equilibrium).[10] The B-equilibrium is supposed to be payoff dominant. We summarize the corresponding parameter restrictions as follows.

Assumption 1. We invoke the following parameter restrictions:

(i) $\upsilon_j < \upsilon_i + \gamma_i(N-1)$, for $i, j = A, B$ and $i \neq j$.
(ii) $\upsilon_B + \gamma_B(N-1) > \upsilon_A + \gamma_A(N-1)$.

The proof of the next proposition shows that part (i) of Assumption 1 ensures that there are exactly two (strong) Nash equilibria in pure strategies (A-equilibrium and B-equilibrium), so that users face a coordination game. Part (ii) implies that the B-equilibrium is payoff dominant.[11]

Proposition 1. *The technology-adoption game has exactly two (strong) Nash equilibria in pure strategies, the A-and the B-equilibrium.*

Proof. An equilibrium, in which users coordinate on technology i, is a strong equilibrium if $U_i(N) > U_j(1)$ holds, which is equivalent to part (i) of Assumption 1. There cannot exist another equilibrium in pure strategies in which both technologies are chosen. Assume, on the contrary, that there exists such an equilibrium where $N_A < N$ users choose technology A and $N_B < N$ users choose technology B, with $N_A + N_B = N$. Then it must hold that $U_A(N_A) \geqslant U_B(N_B + 1)$ and $U_B(N_B) \geqslant U_A(N_A + 1)$. From Eq. (1) it follows that $U_A(N_A + 1) > U_A(N_A)$, which together with the former inequalities implies $U_B(N_B) \geqslant U_A(N_A + 1) > U_A(N_A) \geqslant U_B(N_B + 1)$. It follows that $U_B(N_B) > U_B(N_B + 1)$. Obviously, this is not consistent with (1). Hence, the condition $-\gamma_A(N-1) < \upsilon_A - \upsilon_B < \gamma_B(N-1)$ assures that there are only two Nash equilibria in pure strategies; namely, the A-equilibrium and the B-equilibrium. □

Proposition 1 states the problem of multiple equilibria, which is a characteristic feature of markets with network effects. Let us now introduce the critical-mass concept. We define the *critical mass*, m_i, of technology i as the minimal share of users choosing technology i that is necessary to make the choice of this technology the best reply for any remaining user. The following lemma

[9] We assume that users do not create network effects for themselves.

[10] A Nash equilibrium (in pure strategies) is *strong* if each player has a unique (pure-strategy) best response to his rivals' equilibrium strategies (see Harsanyi, 1973).

[11] See also Kim (1996), who derives similar results for a symmetric coordination game, in which $N \geqslant 2$ players make binary choices.

provides the formal derivation of the critical mass and states its properties.[12]

Lemma 1. *The critical mass of technology i is given by*

$$m_i = \frac{\upsilon_j - \upsilon_i + \gamma_j(N-1)}{(\gamma_A + \gamma_B)(N-1)}, \tag{2}$$

with i, j = A, B and i ≠ j. It holds that $m_A = 1 - m_B$ *and* $m_i \in (0, 1)$*. Moreover,* $\partial m_i/\partial \upsilon_i < 0$, $\partial m_i/\partial \gamma_i < 0$, $\partial m_i/\partial \upsilon_j > 0$, *and* $\partial m_i/\partial \gamma_j > 0$.

Proof. Consider the decision problem of a single user. Assume that $\widetilde{N}$ other users choose technology *i*. If choosing technology *i* constitutes the best response for a user under the assumption that all other, $N - \widetilde{N} - 1$, users choose technology $j \neq i$, then it also constitutes the best response in all other cases (when less than $N - \widetilde{N} - 1$ users choose technology *j*). Hence, it must hold that $U_i(\widetilde{N}+1) \geqslant U_j(N - \widetilde{N})$ or

$$\upsilon_i + \gamma_i \widetilde{N} \geqslant \upsilon_j + \gamma_j(N - \widetilde{N} - 1). \tag{3}$$

The minimal value of $\widetilde{N}$, which satisfies Inequality (3), $\widetilde{N}_{\min}$, is given by[13]

$$\widetilde{N}_{\min} = \frac{\upsilon_j - \upsilon_i + \gamma_j(N-1)}{\gamma_A + \gamma_B}.$$

Given part (i) of Assumption 1 it holds that

$$0 < \widetilde{N}_{\min} < N - 1. \tag{4}$$

Thus, m_i is given by

$$m_i = \frac{\widetilde{N}_{\min}}{N-1} = \frac{\upsilon_j - \upsilon_i + \gamma_j(N-1)}{(\gamma_A + \gamma_B)(N-1)}. \tag{5}$$

Adding the critical masses of technologies *A* and *B*, we get $m_A + m_B = 1$. From (4) and (5) it follows that $m_i \in (0,1)$. The signs of the derivatives $\partial m_i/\partial \upsilon_i < 0$, $\partial m_i/\partial \gamma_i < 0$ and $\partial m_i/\partial \upsilon_j > 0$ are straightforward, while

$$\frac{\partial m_i}{\partial \gamma_j} = -\frac{\upsilon_j - [\upsilon_i + \gamma_i(N-1)]}{(\gamma_A + \gamma_B)^2(N-1)} > 0 \tag{6}$$

follows from part *(i)* of Assumption 1. □

The critical mass of technology *i* decreases when the parameters υ_i and γ_i of the payoff function increase, while it increases in the parameters υ_j and γ_j of the other technology. When technology *i*'s stand-alone value and/or the slope of its network-effects function increases, less users are needed to make the choice of this technology the best reply for the remaining users. Hence, technology *i*'s critical mass decreases. When, in contrast, those parameters increase for the rival technology *j*, technology *i*'s critical mass increases. Note also that since $m_A = 1 - m_B$ holds (as stated in Lemma 1), an increase of one technology's critical mass implies a decrease of the other technology's critical mass by the same amount.

We finally observe that part (ii) of Assumption 1 implies that technology *B*'s critical mass is restricted from above; or, precisely, that $m_B < \gamma_B/(\gamma_A + \gamma_B)$ holds.

The critical mass is an intuitive proxy of a technology's riskiness. When the critical mass of a technology decreases, the choice of this technology becomes less risky in the sense that fewer users are needed to make the choice of this technology the best reply for any remaining user. Conversely, a large critical mass means that a relatively large portion of users is needed to induce others to follow for sure. This implies a large degree of strategic uncertainty.

The problem of multiple Nash equilibria in games has inspired a large literature, one strand mainly dealing with improving the theoretical prediction of equilibrium play and another strand using experimental methods to explore participants' actual behavior. In a coordination game, the Nash-equilibrium concept does not yield a unique prediction for participants' behavior. The lack of theoretical precision is mirrored in experimental studies, which often conclude that Nash-equilibrium predictions perform poorly in games with multiple equilibria.[14]

We next show the close relationship between the critical-mass concept, risk dominance, and the maximin criterion.

3. Risk dominance and the maximin criterion

3.1. Risk dominance

To find the risk-dominant equilibrium, we apply the tracing procedure proposed by Harsanyi and Selten (1988).[15,16] The tracing procedure describes a process of converging expectations from the priors to the expectations implying one of the Nash equilibria that is called the risk-dominant equilibrium. This procedure starts from the priors for every user $l = 1, 2, \ldots, N$, which characterize the prior expectations of all other users about the probabilities with which user *l* chooses his pure strategies (technology *A* and

[12] The critical mass is closely related to the stability index which is used in Selten (1995) to derive a measure of risk dominance for equilibrium selection in more general games with more than two strong Nash equilibria in pure strategies.

[13] If $\widetilde{N}_{\min}$ is not an integer, we take instead the next integer which fulfills (3).

[14] See Van Huyck et al. (1990, 1991) for contributions, which highlight disequilibrium outcomes in the first periods of experimental coordination games (which can be considered as a proxy for a one-shot game).

[15] Risk dominance criterion is a selection criterion among Nash equilibria. It picks the equilibrium which is chosen by the tracing procedure. In the case of 2×2 games the risk-dominant equilibrium satisfies three axioms: invariance with respect to isomorphism, best-reply invariance, and payoff monotonicity.

[16] The tracing procedure extends the Bayesian approach from one-person to n -player decision problems. The Bayesian approach is motivated by the uncertainty about the choices of the other players. At the beginning of the tracing procedure every player expects all other players to act according to some priors (prior distributions over a player's pure strategies). However, these expectations are not self fulfilling and, hence, have to be adjusted. In each step of the tracing procedure the role of the prior expectations decreases. In each step every player plays a best response given his expectations. The tracing procedure consists in finding a feasible path from the prior expectations to the expectations, which correspond to one of the Nash equilibria. That equilibrium is called risk-dominant equilibrium. Expectations at the end of the tracing procedure are fulfilled.

technology B).[17] To find the priors we follow the three assumptions proposed by Harsanyi and Selten. *First*, a user l expects that either all other users choose technology B (with probability q_l) or all other users choose technology A (with a counter probability $1 - q_l$). *Second*, a user plays a best response to his expectations. *Third*, it is assumed that expectations q_l are independently-distributed random variables and each of them has a uniform distribution over the unit interval. The tracing procedure consists in finding a feasible path from the equilibrium in the starting point given by the priors to the equilibrium in the end point given by the original game. The equilibrium in the end point constitutes the risk-dominant equilibrium. The next proposition defines the risk-dominant equilibrium in the technology-adoption game.[18]

Proposition 2. *In the technology-adoption game, the equilibrium in which all users adopt technology i is risk dominant if and only if technology i has a lower critical mass than the rival technology j, with i, j = A, B and $i \neq j$. If $m_A = m_B$, then there exists no risk-dominant equilibrium.*

Proof. We start with users' priors. Using the first assumption of Harsanyi and Selten, we can derive the value of q_l such that user l is indifferent between the technologies (we denote that value by $\tilde{q}$):[19]

$$\tilde{q} := \frac{\upsilon_A - \upsilon_B + \gamma_A(N-1)}{(\gamma_A + \gamma_B)(N-1)}. \tag{7}$$

Following Harsanyi and Selten's second assumption, we derive from (7) user l's best response to his beliefs: play A if $q_l < \tilde{q}$ and play B if $q_l > \tilde{q}$. The third assumption states that q_l is uniformly distributed over the interval [0, 1]. Hence, the probability that $q_l < \tilde{q}$ is $\tilde{q}$ and the probability that $q_l > \tilde{q}$ is $1 - \tilde{q}$, which holds for any l. Then, user l chooses A with probability $\tilde{q}$ and chooses B with counter probability $1 - \tilde{q}$. This constitutes the prior adopted by all other users about user l's choices at the beginning of the tracing procedure. Given such a prior, the expected payoff of any user from choosing technology A is

$$\upsilon_A + \gamma_A(N-1)\tilde{q}. \tag{8}$$

Similarly, the expected payoff from choosing technology B is

$$\upsilon_B + \gamma_B(N-1)(1-\tilde{q}). \tag{9}$$

Combining (8) and (9) we obtain that a user chooses B if and only if

$$\upsilon_B + \gamma_B(N-1)(1-\tilde{q}) > \upsilon_A + \gamma_A(N-1)\tilde{q}$$

holds, which is equivalent to

$$2(\upsilon_A - \upsilon_B) + (N-1)(\gamma_A - \gamma_B) < 0. \tag{10}$$

Comparing Condition (10) with the formula for m_i stated in Lemma 1, it is obvious that Condition (10) holds if and only if $m_B < 1/2$. From Condition (10) it follows immediately that a user chooses A if and only if

$$2(\upsilon_A - \upsilon_B) + (N-1)(\gamma_A - \gamma_B) > 0. \tag{11}$$

If $m_B = 1/2$, then a user is indifferent between choosing A or B. Conditions (10) and (11) characterize the equilibrium based on the priors: If (10) holds, then all users choose technology B, but they choose technology A if (11) holds. For the special case of our game we do not need to continue the tracing procedure any further and can make use of Lemma 4.17.7 in Harsanyi and Selten (1988, p. 183). This Lemma states that the equilibrium of a game based on the priors is the outcome selected by the tracing procedure, if the following conditions hold. *First*, the equilibrium must be a strong equilibrium point, when each user behaves according to his prior beliefs, which is guaranteed for the B-equilibrium by Condition (10) and for the A-equilibrium by Condition (11). *Second*, the equilibrium must also be an equilibrium of the original game, which holds according to Proposition 1. Hence, we obtain the result that technology i is risk dominant if and only if $m_i < m_j$. □

According to Proposition 2 the technology with the lower critical mass is risk dominant. This result is intuitive as a larger critical mass implies that relatively more users are needed to make the adoption of the technology surely profitable, which leads to a higher degree of strategic uncertainty. If technology B has a larger critical mass than technology A, risk dominance requires to select technology A, which is the payoff-inferior equilibrium.[20]

3.2. Maximin criterion

The maximin criterion selects the technology, which delivers the maximal payoff in the worst outcome. In the technology-adoption game the worst outcome for a player is to be the only user of a technology. In that case, the payoff is given by the stand-alone value of that technology.

In the following corollary we show how the maximin criterion relates to the critical-mass concept.

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[17] At the beginning of the tracing procedure every player assigns a certain probability to the hypothesis that a given player will actually use his pure strategy. The combination of these probabilities for a given player constitutes the expected (prior) probability distribution over the pure strategies of that player or, prior. Any player forms such priors for all other players. Harsanyi and Selten (1988) assume that all other players associate the same prior probability distribution with a given player.

[18] Carlsson and van Damme (1993) implicitly derive the condition of risk dominance for the stag-hunt game. In that game $N \geqslant 2$ identical players make binary choices between two options, one of which delivers a secure payoff while the other delivers a risky payoff that is increasing in the share of players choosing the risky option.

[19] Note that $\tilde{q}$ is the same for all the users.

[20] The critical-mass concept is also related to the theory of global games (see Morris and Shin, 2003) and cognitive hierarchy models. The theory of global games introduces uncertainty into the game, which allows to derive a unique equilibrium prediction. Within our setting, it can be shown that the theory of global games also chooses the technology with the lower critical mass (the analysis of the global-game variant of our technology-adoption game is presented in Keser et al., 2009, which is an older version of this paper). In a cognitive hierarchy model, a type-k player anchors his beliefs in a nonstrategic 0-type and adjusts them by thought experiments with iterated best responses, where a type-1 player chooses a best response to type-0, type-2 to type-1, and so on. In our technology-adoption game, half of type-0 players choose either A or B, while type-1 players choose A as the best response whenever the critical mass of technology A is smaller than the critical mass of technology B. Accordingly, all higher types then also choose A (see Camerer et al., 2004, for a similar observation for the stag-hunt game).

Corollary 1. *Whenever technology A has a lower critical mass, it is chosen by the maximin criterion.*

Proof. Equilibrium B is payoff dominant, hence,

$$\upsilon_A - \upsilon_B + (N-1)(\gamma_A - \gamma_B) < 0 \quad (12)$$

must hold. If equilibrium A has a lower critical mass, then according to Lemma 1 it is true that

$$\upsilon_A - \upsilon_B > -[\upsilon_A - \upsilon_B + (N-1)(\gamma_A - \gamma_B)]. \quad (13)$$

Note that the RHS of Eq. (13) is positive due to (12), hence, $\upsilon_A > \upsilon_B$. □

Corollary 1 states that when there is a conflict between payoff dominance and risk dominance (such that technology A is risk dominant and technology B is payoff dominant), the risk-dominant technology is chosen by the maximin criterion. In that case the risk-dominant technology not only has a lower critical mass but also a larger stand-alone value. This result seems to be quite intuitive. The payoff-dominant technology delivers a higher payoff in the case of successful coordination. In contrast, the risk-dominant technology delivers a higher expected payoff when strategic uncertainty is taken into account. In other words, the risk-dominant technology has to deliver higher payoff in the case of mis-coordination, i.e., when not all users choose the same technology. Note next that there are two parameters, which determine a technology's payoff: its stand-alone value and the slope of its network-effects function. If coordination fails, the slope of the network-effects function becomes less important for a user's payoff. At the same time, the role of the stand-alone value increases, since it does not depend on choices made by the other users. This implies that the risk-dominant technology is also chosen by the maximin criterion because it must have a larger stand-alone value.

Our results allow the following interpretation: A technology's stand-alone value and its critical mass can serve as a proxy for its relative riskiness (or, conversely, relative safety). If, ceteris paribus, a technology's stand-alone value (critical mass) increases (decreases), then a technology becomes less risky.

We next analyze how participants resolve the trade-off between payoff dominance and risk dominance in an experiment, where they play a one-shot technology-adoption game. We focus on parameter constellations, which guarantee that technology A has a lower critical mass (larger stand-alone value) and technology B yields a higher maximal payoff (the payoff in case of a successful coordination). By increasing (decreasing) the stand-alone value of technology A (or, B) or, equivalently, by decreasing (increasing) its critical mass, while keeping the difference in technologies' maximal payoffs fixed, we are able to analyze the influence of the technologies' relative riskiness on participants' choices. To analyze the influence of payoff dominance we vary differences in the technologies' maximal payoffs while keeping their critical masses constant.

4. Design of the experiment

The experiment consists of 16 decision situations. Every decision situation is based on a particular specification of the technology-adoption game. In every decision situation, each of the 17 participants chooses between two alternatives, A and B.[21] The payoffs in each decision situation were presented in a table (see Appendix B for the tables of the 16 decision situations).[22] The payoffs were given in fictitious units.

In a coordination game with two alternatives labeled A and B, A might, according to common habit (e.g., A-quality *versus* B-quality), be considered as preferable to B and thus constitute a focal choice in the technology-adoption experiment. To avoid attributing such saliency to one of the alternatives, we re-labeled the alternatives as either X or Z. Furthermore, we did not want to use consistently the same label for the payoff-dominant (or, respectively, the risk-dominant) alternative in all the decision situations. This could induce some of the participants to stick to the choice of the payoff-dominant (or, risk-dominant) alternative in the whole experiment, if such a choice has been made in the initial decision situations or if the participant simply has a preference for a label. By changing the alternatives' labels, we aimed to induce among the participants more careful choices when assessing the payoffs delivered by the alternatives. In Appendix B, in each of the tables describing a specific decision situation, we state in brackets the respective label actually used for each of the two alternatives in the experiment.

In Table 1 below we present the parameters characterizing each of the 16 decision situations. The parameters include the maximal payoff from choosing alternative i, $U_i^{\max} := U_i(17)$, the difference in the maximal payoffs of the two alternatives, $d^{\max} := U_B^{\max} - U_A^{\max}$, the minimal payoff from choosing alternative i (stand-alone value), $U_i^{\min} := U_i(1)$, the difference in the minimal payoffs of the two alternatives, $d^{\min} := U_A^{\min} - U_B^{\min}$, and the critical mass of alternative i multiplied with 16 (i.e., $N-1$).

The decision situations can be grouped into four blocks of four decision situations, each. Within each block, we keep $U_A^{\max}$ and $U_B^{\max}$ constant. Hence, $d^{\max}$, which can be used as a proxy for the relative payoff dominance of alternative B, does not change within a block. We vary the relative payoff dominance of alternative B across blocks, though. More concretely, we reduce $d^{\max}$ from 75 in the

[21] The choice of a group size of 17 participants is motivated by the necessity (i) to have sufficient variation in the critical mass of the payoff-dominant alternative, with $(N-1)m_B$ being an integer, (ii) to exclude negative payoffs associated with alternative B, and (iii) to have sufficient variation in the payoffs of alternative A, such that both alternatives yield sufficiently risky payoffs (depending strongly on the other participants' choices). If, for instance, we used the group size of $N = 7$, then $(N-1)m_B$ could only take two possible values, $6m_B \in \{4, 5\}$, providing too little variation. In contrast, in our experiment $(N-1)m_B$ takes four different values. The same variation could also be achieved if using the group size $N = 11$. However, we also had to consider values of the critical mass, which are not very far away from 0.5. Otherwise, we (i) could get negative payoffs associated with alternative B (when N_B is small) or (ii) get a very flat payoff function for alternative A. The group size $N = 17$ allowed to have sufficient variation in alternative B's critical mass in a region not too close to 1.

[22] In the tables we rounded the payoffs to the closest integer, where necessary.

Table 1
Parameters of technology adoption game in different decision situations.

	Block 1				Block 2				Block 3				Block 4			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
U_B^{max}	325	325	325	325	300	300	300	300	280	280	280	280	310	310	310	310
U_A^{max}	250	250	250	250	245	245	245	245	229	229	229	229	264	264	264	264
d^{max}	75	75	75	75	55	55	55	55	51	51	51	51	46	46	46	46
U_B^{min}	5	5	5	5	60	60	60	60	133	104	64	4	164	134	92	30
U_A^{min}	134	178	214	243	156	189	216	238	205	205	205	205	232	232	232	232
d^{min}	129	173	209	238	96	129	156	178	72	101	141	201	68	98	140	202
$16m_B$	9	10	11	12	9	10	11	12	9	10	11	12	9	10	11	12
$16m_A$	7	6	5	4	7	6	5	4	7	6	5	4	7	6	5	4

first block to 46 in the fourth block. Within each block we have four decision situations, which vary with respect to the critical mass of alternative *B* and the difference in the alternatives' minimal payoffs. We increase the critical mass of alternative *B* (multiplied by 16) from 9 up to 12. Similarly, the difference in the alternatives' minimal payoffs increases within each block. Thus, using either the critical mass or d^{min} as a proxy, the relative riskiness of alternative *B* increases within each block.[23]

We hypothesize that for a given relative payoff dominance of alternative *B* (proxied by d^{max}) the probability of a *B*-choice is the lower, the higher the critical mass of alternative *B*. We expect the same relationship to hold with regard to the difference in the alternatives' stand-alone values. Moreover, we hypothesize that for a given relative riskiness of alternative *B* (proxied by either m_B or d^{min}) the probability of a *B*-choice is the higher, the higher the relative payoff dominance of alternative *B*.

We ran two sessions of a paper-and-pencil experiment at the Georg-August-Universität Göttingen in February, 2009. In both experimental sessions together, we had 153 participants, all of them being economics students.[24] We excluded from the analysis the decisions of five participants, whose answers were incomplete. In the following, we analyze the decisions of the remaining 148 participants. Each session of an experiment was conducted at the end of a lecture. Students were free to leave the auditorium or to stay and to participate in the experiment.

The experimental instructions were read aloud to guarantee that all of the participants know that the conditions of the experiment are common knowledge.[25] After the instructions were read, the participants could ask questions, which were answered in private.[26]

In each of the two sessions, each participant had to provide answers to all of the 16 decision situations.[27,28] In every session, there were several groups of 17 participants. All participants of a given session were sitting in the same room. In each session only the answers of one group, whose members were randomly chosen from the total number of participants of the session, were considered for the final payment.[29] We analyzed the answers of all members of the selected group in a preselected decision situation (decision situation 2).[30] The analysis took place at the end of the session after all the session's participants had handed in their answers.[31] However, not all members of the randomly chosen group were paid. Out of the 17 selected participants only one was

[23] The increase in alternative *B*'s critical mass (also, the increase in alternatives' minimal payoffs) is achieved through either increasing the stand-alone value of alternative *A* (in blocks 1 and 2) or decreasing the stand-alone value of alternative *B* (in blocks 3 and 4).

[24] The number of participants was almost equal in the two sessions.

[25] See Appendix A for the instructions.

[26] We did not run any training session before the experiment, which is an obvious limitation of a paper-and-pencil experiment. However, we presented an example of a technology-adoption game, which showed how the individual payoff of a participant depends on his own choice and the choices of the other participants.

[27] We implemented a within-subject design with multiple observations for each participant.

[28] The decision situations were presented to participants in an order, which was different from the one given in Appendix B. The decision situations were presented to all the participants in the same order. We did not want to impact participants' choices by ordering the decision situations in a way, in which the influence of either the critical mass or payoff dominance on their choices would be likely. The former could happen if the decision situations of one block were placed according to alternative *B*'s critical mass from the smallest to the largest. Hence, we did not place the decision situations of one block next to each other. To exclude the influence of payoff dominance, we avoided placing the decision situations with the same critical mass of alternative *B* (but various differences in alternatives' maximal payoffs) next to each other. In Appendix B in each table describing a specific decision situation, we provide in brackets the number, under which that decision situation appeared in the experiment's decision sheets.

[29] The randomization was organized as follows: At the beginning of the session every participant got a set of decision sheets together with a participation number on a separate piece of paper. The same number was also noted on the participant's decision sheets. At the end of the session the instructors collected the filled-in decision sheets, while the participation numbers were kept by the participants. The instructors then invited one of the participants in the room to randomly draw 17 sets of decision sheets out of the pile of all collected decision sheets. The 17 participants, whose decision sheets were drawn, were identified with their numbers.

[30] The number of the decision situation which was selected for the payment was announced to the participants after they handed in their decision sheets to the instructors.

[31] Due to natural limitations of a paper-and-pencil experiment we did not present the participants' payoffs after each decision situation. As mentioned above, we did that only at the very end of the session for only one randomly chosen group and considered its answers in only one decision situation. This, however, allowed us to avoid the problem of possible learning by the participants during the experiment.

Table 2
Choices depending on the relative payoff dominance of alternative *B*.

	$16m_B = 9$				$16m_B = 10$				$16m_B = 11$				$16m_B = 12$			
	1	5	9	13	2	6	10	14	3	7	11	15	4	8	12	16
d^{max}	75	55	51	46	75	55	51	46	75	55	51	46	75	55	51	46
N_B	75	70	68	63	65	76	68	59	64	67	61	62	71	66	61	61
N_A	73	78	80	85	83	72	80	89	84	81	87	86	77	82	87	87

Table 3
Choices depending on the relative riskiness of alternative *B*.

	$d^{max} = 75$				$d^{max} = 55$				$d^{max} = 51$				$d^{max} = 46$			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$16m_B$	9	10	11	12	9	10	11	12	9	10	11	12	9	10	11	12
N_B	75	65	64	71	70	76	67	66	68	68	61	61	63	59	62	61
N_A	73	83	84	77	78	72	81	82	80	80	87	87	85	89	86	87

randomly chosen for actual payment in cash.[32] We used a conversion rate of 50 €-Cent for one fictitious unit. In the first session, the randomly chosen participant was paid € 83.00 and in the second session, the payment was € 114.00.

5. Experimental results

As one may expect from experiments conducted by Van Huyck et al. (1990, 1991), disequilibrium outcomes prevail in our data. Table 2 presents the total number of *A*- and *B*-choices in the 16 decision situations (N_A, N_B). The highest share that an alternative achieved in a situation is 60% which is the share of alternative *A* in the decision situation 14. We observe that in most decision situations the number of *B*-choices is smaller than the number of *A*-choices.[33] Only in decision situations 1 and 6 the number of *B*-choices is larger. Over all decision situations, the average share of *B*-choices is 45%, while the average share of *A*-choices is 55%.

Our next observation is that an increase in alternative *B*'s relative payoff dominance tends to increase the number of *B*-choices. In Table 2 we present the 16 decision situations in four blocks of four, but in an ordering that is different from Table 1. In Table 2, we keep in each block the critical mass constant, while within each block d^{max} decreases and takes the values 75, 55, 51, and 46. Table 2 reveals that in each block the number of *B*-choices tends to fall from the left to the right. In blocks 1 and 4 the number of *B*-choices decreases monotonically when d^{max} becomes smaller, whereas blocks 2 and 3 exhibit some irregularities.

In Table 3 we have re-arranged the columns of Table 2 such that again, like in Table 1, each block represents a different value of d^{max}, while within each block $16m_B$ increases from 9, to 10, to 11, and finally, to 12. Inspection of Table 3 yields that in every block the number of *B* -choices almost monotonically decreases as the critical mass of alternative *B* increases.

We next present the results of a regression analysis, where we analyze the joint influence of payoff dominance and riskiness on participants' choices.

Result 1. Participants' choices depend both on the relative payoff dominance of alternative *B*, proxied by the relative difference in maximal payoffs, and its riskiness, proxied by the relative difference in critical masses.

Table 4 presents the results of a Logit regression-1 with the probability of a *B*-choice as the dependant variable. In that regression we proxy the relative payoff dominance of alternative *B* by the ratio of the difference in maximal payoffs to alternative *B*'s maximal payoff, d^{max}/U_B^{max}.[34] Similarly, we proxy the relative riskiness of alternative *B* by the ratio of the difference in critical masses to alternative *B*'s critical mass, $(m_B - m_A)/m_B$.

Table 4 shows that both, the relative payoff dominance of alternative *B* and its relative riskiness, influence participants' choices. The regression results imply that the probability of a *B*-choice increases when the relative payoff dominance of alternative *B* increases. The respective coefficient is significant at the 1% significance level. Our proxy for the riskiness of alternative *B* is negatively correlated

Table 4
Logit regression-1 explaining the probability of a B-choice.

Explanatory variable	Coefficient (standard error)
Constant	-1.1^{**} (0.55)
d^{max}/U_B^{max}	5.72^{***} (2.2)
$(m_B - m_A)/m_B$	-0.75^{*} (0.39)
Wald χ^2, *p*-value	0.0055
Number of observations (number of groups)	2368 (148)

* Significance level is: 10%.
** Significance level is: 5%.
*** Significance level is: 1%.

[32] The answers of the 17 randomly chosen participants in decision situation 2 were noted on the blackboard. Using those numbers, the instructors calculated the payoff (in fictitious units) of the one participant randomly chosen for cash payment (after a participating student has been invited to randomly draw for payment one out of the 17 sets of decision sheets.) The payoff in fictitious units was then converted into €.

[33] Below we discuss possible labeling effects.

[34] The same proxy for payoff dominance is also used in Schmidt et al. (2003).

with the probability of a B-choice. The respective coefficient is significant at the 10% significance level.

We considered several specifications of a Logit regression with explanatory variables based on the alternatives' maximal payoffs and critical masses.[35] All those Logit regressions share two features. The coefficient measuring the influence of alternative B's relative payoff dominance (riskiness) on the probability of a B-choice is positive (negative). Moreover, the former coefficient is almost always more significant than the latter coefficient (in six out of nine regressions, while in three of them the opposite holds). We chose Logit regression-1 for the following reasons: (i) That regression outperforms all others in terms of the significance levels of the individual coefficients and their joint significance based on the Wald χ^2 test. (ii) Logit regression-1 seems to be very intuitive. One can argue that relative differences better mirror the advantage of one alternative over the other than absolute differences. Also, a "normalization" with regard to the payoff-dominant alternative B can be due to the fact that participants evaluate the alternatives relative to the payoff-dominant alternative, which appears to be most attractive at a first sight.

We also considered a Probit regression-1 with the same explanatory variables as in Logit regression-1. That regression delivers even more significant results such that the coefficient measuring the influence of alternative B 's relative risk dominance on the probability of a B-choice is significant at the 5% significance level. The coefficient capturing the influence of alternative B's relative payoff dominance is significant at the 1% significance level. The signs of the coefficients do not change.

We finally controlled for possible labeling effects. For this we introduced a dummy variable which takes the value "1" in a decision situation, where alternative B is labeled as X, and the value "0," where alternative B is labeled as Z. Our results are summarized in Logit regression-1(l) presented in Appendix C. They show that there is some positive labeling effect such that, ceteris paribus, alternative B is more likely to be chosen when it is labeled as X rather than Z: The respective coefficient is significant at the 5% significance level. Both, the coefficient capturing the influence of alternative B's payoff dominance and the one capturing its riskiness, remain significant and do not change the sign. We conclude that the above identified relations between the probability of a B-choice, the relative payoff dominance, and the riskiness of alternative B are robust.

Result 2. Participants' choices depend both on the relative payoff dominance of alternative B, proxied by the relative difference in maximal payoffs, and its riskiness, proxied by the relative difference in minimal payoffs.

In Table 5 we present Logit regression-2 explaining the probability of choosing alternative B. It is similar to Logit regression-1 but replaces the relative difference in critical masses by the relative difference in minimal payoffs as a proxy for riskiness of alternative B. Table 5 shows that both the relative difference in maximal payoffs as well as the relative difference in minimal payoffs explain participants' choices of alternative B. Again, the larger the relative difference in the maximal payoffs, the more participants choose alternative B. The respective coefficient is significant at the 1% significance level. We also see that an increase in the relative difference in the minimal payoffs of the two alternatives reduces the probability of a B-choice. The respective coefficient is significant at the 5% significance level.

Table 5
Logit regression-2 explaining the probability of a B-choice.

Explanatory variable	Coefficient (standard error)
Constant	-2.26^{***} (0.63)
$d^{\max}/U_B^{\max}$	10.9^{***} (3.18)
$d^{\min}/U_B^{\min}$	-0.01^{**} (0.01)
Wald χ^2, p-value	0.0026
Number of observations (number of groups)	2368 (148)

** Significance level is: 5%.
*** Significance level is: 1%.

We examined several specifications of a Logit regression with explanatory variables based on the alternatives' maximal and minimal payoffs.[36] All of those regressions have two common features. *First*, the coefficient measuring the influence of alternative B's relative payoff dominance (riskiness) is positive (negative). *Second*, the coefficient on payoff dominance is more significant than the one on riskiness. This is the case in six out of nine regressions, while in three of them the significance levels of the two coefficients are the same. Logit regression-2 outperforms all of the other regressions in terms of the significance levels of the individual coefficients and their joint significance based on the Wald χ^2 test. Furthermore, the results of Logit regression-2 are quite intuitive. Both explanatory variables relate the difference in maximal (minimal) payoffs of the two alternatives to the maximal (minimal) payoff of the payoff-dominant alternative B, which may seem to be more attractive at a first sight.

We also considered a Probit regression-2 with the same explanatory variables as in Logit regression-2. The significance levels of all the coefficients and their signs do not change. The Probit regression even outperforms in terms of the joint significance of the coefficients.

We finally controlled for possible labeling effects. Our results show that the effect of labeling is positive such that, ceteris paribus, alternative B is more likely to be chosen when it is labeled as X rather than Z (see Logit regression-2(l) in Appendix C). The respective parameter estimate is significant at the 10% significance level. Compared to Logit regression-2, the coefficients measuring the influence of alternative B's payoff dominance and its riskiness on participants' choices do not change the sign and remain robust. We conclude that the above identified relations between the probability of a B-choice, and the

[35] The other specifications of the Logit regression not presented in the paper and the Probit regression (discussed below) are available from the authors on request.

[36] The other specifications of the Logit regression not presented in the paper and the Probit regression (discussed below) are available from the authors on request.

relative payoff dominance and riskiness of alternative *B* are robust.

When we compare Table 5 to Table 4 (where we used the relative difference in the alternatives' critical masses as an explanatory variable), we see that the "maximin" specification performs better in terms of the significance level of the parameter estimates. We speculate that it is easier for participants to apply the maximin criterion than to calculate a critical mass, since the maximin criterion only requires to compare safe payoffs (i.e., the minimal payoffs of each alternative). In other words, the critical mass seems to be a more sophisticated concept for participants than the maximin criterion. We also observe that in both regressions the proxy for alternative *B*'s payoff dominance is more significant than the proxy for alternative *B*'s riskiness (based on either alternatives' minimal payoffs or critical masses). One may speculate that in the technology-adoption experiment the alternatives' maximal payoffs are more decisive for participants' choices than the relative riskiness of the alternatives.

We can now summarize our experimental results as follows: We find that both payoff dominance and riskiness explain the aggregate choices of participants in the technology-adoption experiment. We also show that, to proxy the alternative's riskiness, either the alternatives' critical masses or minimal payoffs can be used. Payoff dominance or risk dominance, separately, would choose one of the two alternatives with probability one. Our results suggest that participants resolve the trade-off between payoff dominance and risk dominance differently, so that in the aggregate changes in the relative riskiness and the relative payoff dominance of alternatives affect participants' choices only at the margin.

Our results complement those of Heinemann et al. (2009). Those authors found that both, the coordination requirement k (which is similar to our critical mass) and the payoff of the safe option, negatively influence the probability of choosing the risky option. There are, however, important differences between their experiment and ours. *First*, in their experiment the coordination requirement k was stated explicitly in each decision situation. In our experiment the participants had to infer the value of the critical mass from the presented payoff tables (see Appendix B). This can explain why in our experiment minimal payoffs provide a better explanation of participants' choices than critical masses do. *Second*, in their experiment, the decision situations were displayed to the participants (on the computer screen) in a sequence ordered by the increasing safe payoff. Our experiment, in contrast, placed all decision situations in the set of decision sheets in an order such that the participants were not explicitly framed to follow threshold strategies.[37]

[37] Heinemann et al. (2009) report that a vast majority of participants used threshold strategies for any given coordination requirement. This implies that a participant chooses the risky strategy if the safe payoff is low and the safe strategy if the safe payoff is high. Moreover, a participant never switches back to the risky strategy for rising safe payoffs. We do not observe such a strict pattern in our data.

6. Conclusion

In a technology-adoption game in which $N \geqslant 2$ identical users simultaneously choose between two technologies that exhibit positive network effects a coordination problem arises. The game has two strong Nash equilibria in pure strategies, where users coordinate on one of the technologies. One of these equilibria is assumed to be payoff dominant. We introduced the heuristic concept of a critical mass, defined as the minimal share of users adopting a technology necessary to make the choice of this technology the best response for any remaining user. We show that the technology with the lower critical mass is risk dominant in the sense of Harsanyi and Selten (1988) and is chosen by the maximin criterion. Our critical-mass heuristic is, thus, theoretically instructive.

In the experimental part we analyze participants' choices in a technology-adoption game which implies a trade-off between risk dominance and payoff dominance, such that the payoff-dominant alternative has a larger critical mass. The results show that participants' choices depend both on *relative* payoff dominance and *relative*riskiness of the alternatives. We proxy the alternative's relative payoff dominance by the difference in maximal payoffs relative to the maximal payoff of the payoff-dominant alternative. With regard to relative riskiness we find that the difference in critical masses or stand-alone values of the alternatives (both relative to the payoff-dominant alternative) do explain the outcomes of our experiment. Our results reveal that an alternative is more likely to be chosen when its relative payoff dominance (riskiness) increases (decreases).

Our results have important implications for firms' strategies and industrial policy. For instance, in order to reduce a technology's (or, product's) relative riskiness, activities to promote user adoption might become advisable, which are otherwise unprofitable or socially not desirable. Such activities could include price discrimination (similar to "introductory" offers) or "biased" innovation (e.g., by focusing exclusively on the quality of the stand-alone value).

There are many possible directions for further experimental research. It would be insightful to run an experiment with different group sizes. We know from previous research that group size is an important factor determining successful coordination. With a larger group size the role of riskiness on participants' choices may become more significant. It is also interesting to analyze the technology-adoption game in a repeated setting. Our concept of the critical mass promises to be instructive in the repeated setting too. An alternative with a low critical mass is likely to have an advantage in the beginning. However, as the game proceeds, one may expect that participants' ability to coordinate their choices improves, which should reduce the importance of riskiness for participants' choices.

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Appendix A

In this appendix we present the English translation of the instructions to our experiment which were handed out in German.

Every decision situation will be presented in a table. In this table you see how your individual payoff in fictitious units depends on your choice and the choices of the other participants of your group. On the next page we give you an example.

Example: Assume that your payoff in a given decision situation depends on your individual choice (alternative *X* or *Z*) and the choices of the other participants of your group as presented in the following table:

Number of others who choose *Z*		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others choose *X*		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	*X*	20	25	30	50	60	65	70	90	120	125	130	140	160	165	172	180	190
	Z	170	150	145	130	125	120	115	90	80	75	70	65	60	55	50	45	40

Instructions. Please do not communicate with any of the other participants! If you have questions please raise your hand so that we can answer your question in private!.

You are participating in a decision experiment, in which you can earn money. With 16 other randomly chosen participants, whose identity will not be known to you, you build a group. How much you earn depends on your own decisions and those of the other participants of your group. Every participant makes his (her) decisions independently of the others.

The experiment consists of 16 different decision situations. In every decision situation, each participant chooses among two alternatives, *X* and *Z*. A participant's payoff in a particular decision situation depends on his (her) own choice and on the number of other participants in the group who make the same choice. The payoff to a participant is the higher, the more other participants of the group have chosen the same alternative as the participant himself (herself). The payoff in each decision situation is independent of the decisions made in any of the other situations and is given in fictitious monetary units.

The fictitious monetary units will be converted into € for one randomly chosen experiment participant, such that one monetary unit will be worth 50 €-Cent. Before this experiment, we have chosen one of the 16 decision situations; the number of this decision situation is kept in a sealed envelope. At the end of the experiment, we shall randomly draw a group of 17 participants, whose decisions in selected decision situation will be analyzed. Out of this group we shall then randomly select one participant for cash payment. Please notice that in the upper left corner of this page as well as on the attached sheet you find your individual participation number. We ask you to keep the attached sheet, with which we can identify you for the potential cash payment.

According to this table your payment is:

- 20, if you choose *X* and none of the other participants chooses *X*, i.e., all 16 other participants choose *Z*,
- 170, if you choose *Z* and none of the other participants chooses *X*, i.e., all 16 other participants choose *Z*,
- 30, if you choose *X*, two of the other participants choose *X* and 14 of the other participants choose *Z*,
- 145, if you choose *Z*, two of the other participants choose *X* and 14 of the other participants choose *Z*,
- 165, if you choose *X*, 13 of the other participants choose *X* and three of the others choose *Z*,
- 55, if you choose *Z*, 13 of the other participants choose *X* and 3 of the others choose *Z*,
- 190, if you choose *X*, all 16 other participants choose *X* and none of the others chooses *Z*,
- 40, if you choose *Z*, all 16 other participants choose *X* and none of the others chooses *Z*.

We ask you now to analyze the following 16 decision situations and mark you respective choice, alternative *X* or *Z*. For marking your choice you find a box under each decision situation.

When all the participants are ready with their choices, we will collect the decision sheets and draw the person who will be paid in cash.

Appendix B

In this appendix we present the decision situations, in which the participants had to make their choices. On the top of each table representing a decision situation we also provide the underlying utility functions (which we did not present to the participants), $U_A(N_A)$ and $U_B(N_B)$, from which we calculated the (rounded) payoffs stated in the tables.

The decision situations were placed in the experiment's decision sheets in an order different from the one given below. In brackets, next to the number of each decision situation, we provide the number under which that decision situation appeared in the decision sheets in the experiment. We presented two decision situations on a single sheet of paper. In the decision sheets we also re-labeled the alternatives such that an alternative could be either labeled as "Z" or "X". In brackets next to each alternative, we provide its label in the specific decision situation in the experiment. Moreover, in the experiment's decision sheets (differently, again, to the presentation below) in every table presenting a given decision situation, the first and the fourth row referred to alternative Z, while the second and the third row to alternative X.

Decision situation 1[6]: $U_A(N_A) = 134.44 + 7.22(N_A - 1)$ and $U_B(N_B) = 5 + 20(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	134	142	149	156	163	171	178	185	192	199	207	214	221	228	236	243	250
	B[X]	325	305	285	265	245	225	205	185	165	145	125	105	85	65	45	25	5

Decision situation 2[8]: $U_A(N_A) = 178 + 4.5(N_A - 1)$ and $U_B(N_B) = 5 + 20(N_B - 1)$

Number of others who choose B[Z]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[X]	178	183	187	192	196	201	205	210	214	219	223	228	232	237	241	246	250
	B[Z]	325	305	285	265	245	225	205	185	165	145	125	105	85	65	45	25	5

Decision situation 3[2]: $U_A(N_A) = 213.64 + 2.27(N_A - 1)$ and $U_B(N_B) = 5 + 20(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	214	216	218	220	223	225	227	230	232	234	236	239	241	243	245	248	250
	B[X]	325	305	285	265	245	225	205	185	165	145	125	105	85	65	45	25	5

Decision situation 4[13]: $U_A(N_A) = 243.33 + 0.42(N_A - 1)$ and $U_B(N_B) = 5 + 20(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	243	244	244	245	245	245	246	246	247	247	247	248	248	249	249	250	250
	B[X]	325	305	285	265	245	225	205	185	165	145	125	105	85	65	45	25	5

Decision situation 5[4]: $U_A(N_A) = 156.11 + 5.56(N_A - 1)$ and $U_B(N_B) = 60 + 15(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	156	162	167	173	178	184	189	195	201	206	212	217	223	228	234	239	245
	B[X]	300	285	270	255	240	225	210	195	180	165	150	135	120	105	90	75	60

(continued on next page)

Decision situation 6[7]: $U_A(N_A) = 189 + 3.5(N_A - 1)$ and $U_B(N_B) = 60 + 15(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	189	193	196	200	203	207	210	214	217	221	224	228	231	235	238	242	245
	B[X]	300	285	270	255	240	225	210	195	180	165	150	135	120	105	90	75	60

Decision situation 7[11]: $U_A(N_A) = 215.9 + 1.8(N_A - 1)$ and $U_B(N_B) = 60 + 15(N_B - 1)$

Number of others who choose B[Z]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[X]	216	218	220	221	223	225	227	229	230	232	234	236	238	240	241	243	245
	B[Z]	300	285	270	255	240	225	210	195	180	165	150	135	120	105	90	75	60

Decision situation 8[12]: $U_A(N_A) = 238.3 + 0.42(N_A - 1)$ and $U_B(N_B) = 60 + 15(N_B - 1)$

Number of others who choose B[X]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[Z]	238	239	239	240	240	240	241	241	242	242	242	243	243	244	244	245	245
	B[X]	300	285	270	255	240	225	210	195	180	165	150	135	120	105	90	75	60

Decision situation 9[3]: $U_A(N_A) = 205 + 1.5(N_A - 1)$ and $U_B(N_B) = 132.57 + 9.2(N_B - 1)$

Number of others who choose B[Z]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[X]	205	207	208	210	211	213	214	216	217	219	220	222	223	225	226	228	229
	B[Z]	280	271	262	252	243	234	225	216	206	197	188	179	169	160	151	142	133

Decision situation 10[9]: $U_A(N_A) = 205 + 1.5(N_A - 1)$ and $U_B(N_B) = 104 + 11(N_B - 1)$

Number of others who choose B[Z]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[X]	205	207	208	210	211	213	214	216	217	219	220	222	223	225	226	228	229
	B[Z]	280	269	258	247	236	225	214	203	192	181	170	159	148	137	126	115	104

Decision situation 11[14]: $U_A(N_A) = 205 + 1.5(N_A - 1)$ and $U_B(N_B) = 64 + 13.5(N_B - 1)$

Number of others who choose B[Z]		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A[X]	205	207	208	210	211	213	214	216	217	219	220	222	223	225	226	228	229
	B[Z]	280	267	253	240	226	213	199	186	172	159	145	132	118	105	91	78	64

Decision situation 12[16]: $U_A(N_A) = 205 + 1.5(N_A - 1)$ and $U_B(N_B) = 4 + 17.25(N_B - 1)$

Number of others who choose B[Z]	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice A[X]	205	207	208	210	211	213	214	216	217	219	220	222	223	225	226	228	229
B[Z]	280	263	246	228	211	194	177	159	142	125	108	90	73	56	39	21	4

Decision situation 13[1]: $U_A(N_A) = 232 + 2(N_A - 1)$ and $U_B(N_B) = 164 + 9.1(N_B - 1)$

Number of others who choose B[Z]	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice A[X]	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
B[Z]	310	301	292	283	273	264	255	246	237	228	219	209	200	191	182	173	164

Decision situation 14[5]: $U_A(N_A) = 232 + 2(N_A - 1)$ and $U_B(N_B) = 134 + 10.97(N_B - 1)$

Number of others who choose B[Z]	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice A[X]	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
B[Z]	310	299	288	277	266	255	244	233	222	211	200	189	178	167	156	145	134

Decision situation 15[10]: $U_A(N_A) = 232 + 2(N_A - 1)$ and $U_B(N_B) = 93 + 13.58(N_B - 1)$

Number of others who choose B[X]	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[Z]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice A[Z]	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
B[X]	310	296	283	269	256	242	228	215	201	188	174	160	147	133	120	106	92

Decision situation 16[15]: $U_A(N_A) = 232 + 2(N_A - 1)$ and $U_B(N_B) = 30 + 17.5(N_B - 1)$

Number of others who choose B[Z]	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A[X]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice A[X]	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
B[Z]	310	293	275	258	240	223	205	188	170	153	135	118	100	83	65	48	30

Appendix C

In this appendix we provide the modifications of the Logit regression-1 and −2, which include a dummy variable measuring the influence of alternative *B*'s label on the probability of a *B*-choice. That variable takes the value "1" if, in the specific decision situation, alternative *B* is labeled as *X*, and takes the value "0" if alternative *B* is labeled as *Z*.

In both tables the significance levels are: ***1%, ** 5%, *10%. The coefficients which are not marked with an asterisk are insignificant at the 10% significance level.

Explanatory variable	Coefficient (standard error)
Logit regression-1(l) explaining the probability of a B-choice	
Constant	−0.88 (0.56)
$d^{\max}/U_B^{\max}$	3.9 (2.37)
$(m_B - m_A)/m_B$	−0.79** (0.39)
Dummy	0.29** (0.14)
Wald χ^2, p-value	0.0023
Number of observations (number of groups)	2368 (148)
Logit regression-2(l) explaining the probability of a B-choice	
Constant	−2.01** (0.65)
$d^{\max}/U_B^{\max}$	8.97*** (3.4)
$d^{\min}/U_B^{\min}$	−0.01** (0.01)
Dummy	0.24* (0.14)
Wald χ^2, p-value	0.0022
Number of observations (number of groups)	2368 (148)

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