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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 technology A and technology B constitute a Nash equilibrium. Coordination on technology B is assumed to be payoff-dominant. We define a technology's critical mass as the minimum share of users necessary to make the choice of this technology a best response for any remaining user. We show that the technology with a lower critical mass is risk-dominant and is chosen by the maximin criterion. We present experimental evidence that both payoff dominance and risk dominance explain participants' choices. The relative riskiness of a technology can be proxied using technologies' critical masses or stand-alone values.

JEL-Classification: C72, C91, D81

Keywords: Network Effects, Critical Mass, Coordination, Riskiness.

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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 its importance 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 (so-called "standards") when making their purchasing decisions.[1] It 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 which involves so-called strategic uncertainty as 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. To mention one prominent example, the Qwerty keyboard standard has been proscribed as inferior to the rival standard Dvorak (see David, 1985).[3] David argues that network effects play an important role for understanding the emergence of so-called "Qwerty worlds," in which users persistently select inferior technologies.

[1] Examples of rivalry between incompatible technologies include the VCR standards battle between VHS sponsored by JVC and Beta sponsored by Sony (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 and Salant, 2003).

[2] We follow Harsanyi and Selten (1988) and Van Huyck et al. (1990, 1991) who use the term strategic uncertainty to describe uncertainty players are facing when they have more than one *equilibrium* strategy. See Burton and Sefton (2004) for another approach. They analyze experimentally how strategic uncertainty affects participants' choices of their 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 examples include 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.

Harsanyi and Selten (1988) develop the concept of risk dominance as a refinement criterion in games with multiple Nash equilibria. In short, that theory selects the Nash equilibrium in which players choose less risky strategies. Intuitively, a strategy tends to be less risky if it secures a relatively high payoff independently of the choices of the other players. In a coordination game with two Nash equilibria -one being payoff-dominant- the concept of risk dominance may help to predict actual outcomes. If a payoff-dominant Nash equilibrium is also risk-dominant, then 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 failure (when players coordinate on the inferior risk-dominant equilibrium) or disequilibrium outcomes (when players fail to coordinate).

In this paper we offer experimental evidence on how the players resolve the trade-off between risk dominance and payoff dominance in the presence of network effects.[4] We introduce a technology adoption game where $N \geq 2$ users choose simultaneously 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 parameters of the game in a way that coordination of all users on either technology is a Nash equilibrium, while coordination on B is the payoff-dominant equilibrium.[5]

We introduce the concept of a "critical mass," which we define as the minimum share of

[4] There is no 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 which are related to our study. Cooper et al. (1990) report coordination failure in their experiments on coordination games as participants largely fail to coordinate on the payoff-dominant equilibrium. While the authors do not analyze explicitly 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 from their coordination game experiments that in case of a trade-off between payoff dominance and security (which chooses 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.

users necessary to make the choice of a technology a best response for any remaining user.[6,7] Intuitively, a technology with a lower (larger) critical mass is less (more) risky as it requires less users to coordinate implying a lower level of strategic uncertainty. We show that the critical mass concept is closely related to the risk dominance refinement and the maximin criterion; i.e., a technology is chosen by both the risk dominance and the maximin criterion if and only if the technology has the 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), *ii)* the relative riskiness of a technology can be proxied by using the difference in critical masses or the difference in stand-alone values.[8]

More precisely, we find that *i)* an increase in B's relative payoff dominance (proxied by the relative difference in maximal payoffs) increases the number of B-choices, and *ii)* an increase in the relative riskiness of technology B (proxied either by the relative difference in critical masses or stand-alone values) reduces the number of B-choices.

Our paper is closely related to Heinemann et al. (2009). They analyze experimentally a critical mass coordination game where $N \geq 2$ 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 it to deliver a higher payoff than the safe payoff. If less than K players choose the risky strategy, then the payoff is zero. Heinemann et al. introduce the coordination

[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.

requirement $k := (K-1)/(N-1)$ to proxy the coordination problem players are facing when choosing the risky strategy. The results of the experimental analysis reveal that the number of participants choosing the risky strategy becomes smaller when the coordination requirement increases. A similar relationship is shown regarding an increase of the safe payoff.

Given Heinemann et al., our main contribution is to consider a game where *both* strategies are risky; i.e., payoffs always depend on the choices of the other players. When both strategies are risky, then our critical mass concept allows to proxy the strategies' *relative* riskiness. Finally, we analyze the influence of the minimum payoffs (given by technologies' stand-alone values) on participants' choices in the experiment.

Schmidt et al. (2003) is an experimental study which examined the influence of changes in payoff and risk dominance on participants' choices in a coordination game. Their main finding is that only changes in risk dominance helped to explain the observed data. We contribute to their analysis by proposing different proxies for risk dominance based on the technologies' critical masses and/or their minimal payoffs.[9] Most importantly, we show that both the proxies for risk and payoff dominance are explaining participants' behavior in our one-shot coordination game.

We proceed as follows. In Section 2 we introduce the technology adoption game and we define the critical mass concept. Section 3 shows how the concept of the critical mass relates to the risk dominance refinement 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 $N \geq 2$ identical and discrete users (which can be consumers or firms) make simultaneously their choices between two technologies, A and B. The payoff a user derives from technology $i = A, B$ depends positively on the total number of users choosing the same technology, $N_i \leq N$, and is given by

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

The parameter $\upsilon_i \geq 0$ can be interpreted as the "stand-alone value" a user derives from technology i absent any network effects. The term $\gamma_i(N_i - 1)$ measures positive network effects if

[9] Our proxy for payoff dominance is same as in their analysis.

$N_i > 1$ users choose the same technology i.[10] The coefficient $\gamma_i \geq 0$ 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).[11] 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 two (strong) Nash equilibria in pure strategies (A- and B-equilibrium), so that users face a coordination game. Part *ii)* implies that the B-equilibrium is payoff-dominant.[12]

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 to 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 $U_A(N_A) \geq U_B(N_B+1)$ and $U_B(N_B) \geq U_A(N_A+1)$. From Equation (1) it follows that $U_A(N_A+1) > U_A(N_A)$, which together with the former inequalities implies $U_B(N_B) \geq U_A(N_A+1) > U_A(N_A) \geq U_B(N_B+1)$. From this 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. *Q.E.D.*

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

[11] 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).

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

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 necessary to make the choice of this technology a best reply for any remaining user. The following lemma provides the formal derivation of the critical mass and states its properties.

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 $i \neq j$. 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 a 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 a best response in all other cases (when less than $N - \widetilde{N} - 1$ users choose technology j). Hence, it must hold that $U_i(\widetilde{N} + 1) \geq U_j(N - \widetilde{N})$ or

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

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

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

Adding up 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

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

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

follows from part *i)* of Assumption 1. *Q.E.D.*

The critical mass of technology i decreases when parameters υ_i and γ_i of the payoff function increase, while it increases in 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, then less users are needed to make the choice of this technology a best reply for the remaining users. Hence, technology i's critical mass decreases. When, in contrast, those parameters increase for the rival technology j, then technology i's critical mass increases.

Two more remarks are notable. *First*, as stated in Lemma 1, $m_A = 1 - m_B$ holds, so that an increase of one technology's critical mass implies a decrease of the other technology's critical mass by the same amount. *Second*, 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 notion of the critical mass is an intuitive proxy of a technology's riskiness. When the critical mass decreases, then its choice becomes less risky in the sense that fewer adopters are needed to make the choice of this technology a best reply for any remaining user. Conversely, a large critical mass implies that a relatively large portion of users is needed to induce others to follow for sure; with the implication that a large degree of strategic uncertainty exists.

The problem of multiple Nash equilibria in games has inspired a large literature; one mainly dealing with improving the theoretical prediction of equilibrium play and another strand of works using experimental methods to explore players' behavior. In a coordination game, the Nash equilibrium concept does not yield a unique prediction for players' 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, the risk dominance refinement, and the maximin criterion.

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

3 Risk Dominance and the Maximin Criterion

Risk dominance. To find the risk-dominant equilibrium, we apply the tracing procedure as 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; the so-called risk-dominant equilibrium. This procedure starts from the priors for every user $l = 1, 2, ..., N$, which characterize the prior expectations of all other users about the probabilities with which user l chooses his pure strategies (technology A and 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. And *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 then 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

[15] The risk dominance criterion is a refinement of the Nash equilibrium concept. 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 then in finding a feasible path from the prior expectations to the expectations, which correspond to one of the Nash equilibria. That equilibrium is then called risk-dominant equilibrium. Expectations at the end of the tracing procedure are fulfilled as the risk-dominant equilibrium is a Nash equilibrium.

[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.

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 first derive users' priors. Using the first assumption of Harsanyi and Selten (1988), we can derive the value of q_l such that user l is indifferent between the technologies (we denote that value by $\widetilde{q}$):[19]

$$\widetilde{q} := \frac{v_A - v_B + \gamma_A(N-1)}{(\gamma_A + \gamma_B)(N-1)}. \tag{7}$$

Following Harsanyi and Selten's second assumption, we derive from (7) user l's best response to his beliefs: play A if $q_l < \widetilde{q}$ and play B if $q_l > \widetilde{q}$. The third assumption states that q_l is uniformly distributed over the interval $[0, 1]$. Hence, the probability that $q_l < \widetilde{q}$ is $\widetilde{q}$ and the probability that $q_l > \widetilde{q}$ is $1 - \widetilde{q}$, which holds for any user l. Then, user l choose A with probability $\widetilde{q}$ and chooses B with counter probability $1 - \widetilde{q}$. That constitutes the prior adopted by all the 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

$$v_A + \gamma_A(N-1)\widetilde{q}. \tag{8}$$

Similarly, the expected payoff from choosing technology B is

$$v_B + \gamma_B(N-1)(1-\widetilde{q}). \tag{9}$$

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

$$v_B + \gamma_B(N-1)(1-\widetilde{q}) > v_A + \gamma_A(N-1)\widetilde{q}$$

holds, which is equivalent to

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

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

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

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 is immediate that a user chooses A if and only if

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

If $m_B = 1/2$, then a user is indifferent between choosing A or B from a risk dominance perspective. Conditions (10) and (11) characterize the equilibrium based on the priors: If (10) holds, then all users choose technology B, and they choose technology A if (11) holds. For the special case of our game we do not need to continue the tracing procedure further and can make use of Lemma 4.17.7 in Harsanyi and Selten (1988, p. 183). This Lemma states that the equilibrium of the 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 $m_i < m_j$, for $i, j = A, B$ and $i \neq j$. *Q.E.D.*

According to Proposition 2 the technology with a 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 leading to a higher degree of strategic uncertainty. If technology B has a larger critical mass than technology A, then the risk dominance criterion requires to select technology A which is the payoff-inferior equilibrium.[20]

Maximin criterion. The maximin criterion selects the technology which delivers the max-

[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 a lower critical mass. 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, then half of type-0 players choose either A or B, while type 1 players choose A as a 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).

imal 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, v_i $(i = A, B)$.

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

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

Proof. Equilibrium B is payoff-dominant, hence,

$$v_A - v_B + (N-1)(\gamma_A - \gamma_B) < 0 \tag{12}$$

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

$$v_A - v_B > -\left[v_A - v_B + (N-1)(\gamma_A - \gamma_B)\right]. \tag{13}$$

Note that the RHS of Equation (13) is positive due to (12), hence, $v_A > v_B$. *Q.E.D.*

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 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, a risk-dominant technology has to deliver higher payoff in 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, then 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 as it does not depend on choices of 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 those 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 (B) or, equivalently, by decreasing (increasing) its critical mass while keeping the other parameters of the technologies fixed, we are able to analyze the influence of the technologies' relative riskiness on participants's 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.[21,22] The payoffs in each decision situation were presented in a table (see Appendix B for the tables of the 16 decision situations).[23] The payoffs were given in fictitious units.

[21] The choice of a group with 17 participants is motivated by the necessity *i)* to have sufficient variation in the critical mass of the payoff-dominant alternative while $(N-1)m_B$ is given by 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 (which depend 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: $6m_B \in \{4, 5\}$, which gives 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 the 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 the region not too close to 1.

[22] To avoid that alternative A may be seen as focal by participants we re-labeled the alternatives in the decision situations presented to participants. An alternative could be labelled as either X or Y, differently in different decision situations.

[23] In the tables we rounded the payoffs to the closest integer, if 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
$16 \cdot m_B$	9	10	11	12	9	10	11	12	9	10	11	12	9	10	11	12
$16 \cdot m_A$	7	6	5	4	7	6	5	4	7	6	5	4	7	6	5	4

In Table 1 we present the parameters characterizing each decision situation; namely: the maximal payoff from choosing alternative $i = A, B$, denoted by $U_i^{\max}$ with $U_i^{\max} := U_i(N)$, the difference in the maximal payoffs of the two alternatives given by $d^{\max}$, with $d^{\max} := U_B(17) - U_A(17)$, the minimal payoff from choosing alternative i (stand-alone value), denoted by $U_i^{\min}$, where $U_i^{\min} := U_i(1) = v_i$, the difference in the minimal payoffs of the two alternatives given by $d^{\min} := U_A(1) - U_B(1)$, and the critical mass of alternative i multiplied with 16 (i.e., $N - 1$).

The decision situations can be grouped into four blocks. In each block we keep $U_A^{\max}$ and $U_B^{\max}$ constant. Hence, $d^{\max}$ does not change within a block. Across blocks, we vary the relative payoff dominance of alternative B. Precisely, we reduce $d^{\max}$ from 75 in the 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 alternatives' minimal payoffs. We increase the critical mass of alternative B (multiplied by 16) from 9 up to 12, so that within each block the relative riskiness of alternative B increases. Moreover, the difference in alternatives' minimal payoffs increases within each block.[24]

[24] 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).

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

We ran two sessions of a paper-and-pencil experiment at the Georg-August University of Göttingen in February, 2009. In both experimental sessions together there were 153 participants, all of them were economics students.[25] We excluded from the analysis the questionnaires 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 the participants know that the conditions of the experiment are common knowledge.[26] After the instructions were read the participants could ask questions which were answered individually.[27]

In each of the two sessions all the participants had to provide their answers in all the 16 decision situations.[28,29] In every session there were several groups of 17 participants. All the participants of a given session were sitting in the same room. In each session only the answers

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

[26] See Appendix A for the Instructions.

[27] 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.

[28] We implemented a within-subject design with repeated observations for each participant.

[29] The decision situations were presented to participants in an order different from the one in which they are given in Appendix B. The decision situations were presented to all the participants in the same order. We did not want to effect 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 would be the case 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.

of one group whose members were randomly chosen from the total number of participants of the session were considered for the final payment.[30] We analyzed that group's answers in a preselected decision situation (decision situation 2).[31] The analysis took place at the end of the session after all the session's participants had handed in their answers.[32]However, not all the members of a randomly chosen group were paid. Out of those 17 participants only one was randomly chosen for the final payment.[33] We used the conversion rate: 1 fictitious unit equals 50 Euro-Cent. In the first session the randomly chosen participant got 83.00 Euro and in the second the payment was 114.00 Euro.

5 Experimental Results

As one may expect from experiments conducted by van Huyck et al. (1990, 1991) disequilibrium outcomes prevail. Table 2 presents the total number of A-choices and B-choices in the 16 decision situations. The highest share an alternative achieved 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. Only in the decision situations 1 and 6 the number of

[30] The randomization was organized as follows. At the beginning of the session every participant got a questionnaire together with a number on a separate piece of paper. The same number was also noted on the participant's questionnaire. At the end of the session the instructors collected the filled in questionnaires, while the numbers were kept by the participants. The instructors then invited one participant to pull 17 questionnaires out of the pile of the collected questionnaires. The 17 participants whose questionnaires were pulled out were identified with their numbers.

[31] The number of the decision situation which was selected for the payment was told to the participants only after they handed in their questionnaires to the instructors.

[32] Due to natural limitations of a paper-and-pencil experiment we did not presented the participants' payoffs after each decision situation. As mentioned above, we did that only at the 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.

[33] 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 participant randomly chosen for the payment. (The questionnaire of that participant was randomly pulled out from the 17 chosen questionnaires by one invited participant.) The payoff in fictitious units was then converted into Euro.

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
$16 \cdot m_B$	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

B-choices is larger. 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 keep in each block the critical mass constant, while within each block $d^{\max}$ decreases and takes the values 75, 55, 51, and 46. From Table 2 we observe 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 each block represents a different value of $d^{\max}$, while within each block the critical mass increases from 9, to 10, to 11, and finally, to 12. From Table 3 we observe that in every block the number of B-choices almost monotonically decreases as the critical mass of alternative B increases from 9 up to 12. We conclude that the number of B-choices (A-choices) tends to decrease (increase) as m_B increases.

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

Result 1. *Payoff dominance of alternative B proxied by the relative difference in maximal payoffs and its riskiness proxied by the relative difference in critical masses jointly explain participants' choices.*

Table 4 presents the results of a Logit regression-1 with the probability of a B-choice as a dependant variable.[34] We considered several specifications for the explanatory variables.[35] We finally decided to proxy the relative payoff dominance of alternative B by the ratio of the difference in maximal payoffs to alternative B' maximal payoff; i.e., $d^{\max}/U_B^{\max}$.[36] Similarly, we proxy the relative riskiness of alternative B with the ratio of the difference in critical masses to alternative B's critical mass; i.e., $[m_B - m_A]/m_B$. Those specifications yield the most significant results. Intuitively, the reason may be twofold. *First*, relative differences better mirror the advantage of one alternative over the other than absolute differences. *Second*, 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 first sight.

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 number of B-choices increases when the relative payoff dominance of alternative B increases. The respective parameter estimate is significant at the 1% significance level. Our proxy for the riskiness of alternative B is negatively correlated with the number of B-choices. The respective parameter estimate is significant at the 10%-significance level.

Result 2. *Payoff dominance of alternative B proxied by the relative difference in maximal payoffs and its riskiness proxied by the relative difference in minimal payoffs jointly explain*

[34] Probit regression delivers even more significant results such that the coefficient capturing the influence of risk dominance is significant at the 5% significance level. The results of a probit regression are available from the authors on request.

[35] Those specifications are available from the authors on request.

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

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)

Note: Significance levels are: ***1%, **5%, *10%.

participants' choices.

In Table 5 we present the parameters of the Logit regression-2 explaining the probability of choosing alternative B.[37] Table 5 shows that both the relative difference in maximal payoffs as well as the relative difference in minimal payoffs of the alternatives explain participants' choices of alternative B. Again, the larger the relative difference in the maximal payoffs, the more participants choose alternative B. The respective parameter estimate is significant at the 1% significance level. We also see that an increase of the relative difference in the minimal payoffs reduces the number of B- choices. The respective parameter estimate is significant at the 5% significance level. When we compare Table 5 with Table 4 (where we used the relative difference in 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 the maximin criterion is easier to apply than to calculate a critical mass as it 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 can summarize our experimental results now as follows. *First*, both payoff dominance and riskiness together explain the aggregate choices of participants. *Second*, to proxy the alternative's riskiness both alternatives' critical masses and minimal payoffs can be used. The payoff dominance and risk dominance refinements choose one of the two alternatives with probability

[37] Probit regression delivers quite similar results. Those results are available from the authors on request.

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)

Note: Significance levels are: ***1%, **5%.

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 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 strategy influence negatively the number of choices of 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 better explain participants' choices than critical masses. *Second*, in their experiment decision situations were displayed on a screen ordered by the coordination requirement. Our experiment instead placed all decision situations in the questionnaire in the order such that participants were not explicitly framed to follow threshold strategies.[38]

We finally note that our results stand in contrast to Schmidt et al. (2003) who showed within their setting that participants' choices were affected by changes in the proxy for risk dominance, but not in the proxy for payoff dominance.

[38] Heinemann et al. (2009) report that a vast majority of participants used threshold strategies for any given coordination requirement. The latter implies that a participant chooses the risky strategy for low safe payoffs and the safe strategy for high safe payoffs. 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 $N \geq 2$ identical users choose simultaneously between two technologies that exhibit positive network effects a coordination problem arises. That game has two strong Nash equilibria in pure strategies where users coordinate on one of the technologies. One of those equilibria is assumed to be payoff-dominant. We introduced the heuristic concept of a critical mass which we defined as the minimum share of users adopting a technology necessary to make the choice of this technology a best response for any remaining user. We showed that the technology with a 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, therefore, theoretically instructive as it provides a new way to interpret risk dominance.

In the experimental part we analyzed 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 data shows that participants' choices depend on *relative* payoff dominance and *relative* riskiness. We proxy the alternative's relative payoff dominance by the difference in maximal payoffs relative to the payoff of the payoff-dominant alternative. With regard to relative riskiness we found that the difference in critical masses or stand-alone values (both relative to the payoff-dominant alternative) do both 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).

There are many possible directions for further experimental research. *First*, it would be insightful to run an experiment with different group sizes. It is known from the 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. *Second*, it is interesting to analyze the technology adoption game in a repeated setting. Our concept of the critical mass seems to be instructive in the repeated setting too. An alternative with a low critical mass is likely to have an advantage in the beginning. As the game proceeds, one may expect that participants' ability to coordinate their choices increases, which should reduce the importance of riskiness for participants' choices.

Appendix A

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

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

You are participating in a decision experiment in which you can earn money. With 16 other randomly chosen participants which will not be known to you, you build up a group. How much you earn depends on your own decisions and decisions 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 every experiment participant makes the choice between two alternatives, X and Y. The participant's payoff in a particular decision situation depends on the own choice and the number of other participants of the group who have made the same choice. The payoff is higher the more other participants of your group have chosen the same alternative. The payments in all the 16 decision situations are independent of each other and are given in fictitious monetary units.

The fictitious monetary units will be converted into Euro for one randomly chosen experiment participant such that one monetary unit will be worth 50 Euro-Cent. Before the Experiment we have chosen one of the 16 decision situations, the number of this decision situation is kept in an envelope. At the end of the experiment first a group of 17 participants will be randomly picked up, whose decisions in this decision situation will be analyzed. From this group then one participant will be randomly chosen for the cash payment. Please notice that in the left upper 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 possible cash payment.

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 other participants of your group. We next give you an example.

Example:

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

Number of others who choose Y		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who 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
	Y	170	150	145	130	125	120	115	90	80	75	70	65	60	55	50	45	40

According to this table your payment is:

- 20, when you choose X and none of the other participants chooses X, what means that all the other 16 participants choose Y,
- 170, when you choose Y and none of the other participants chooses X, what means that all the other 16 participants choose Y,
- 30, when you choose X, two of the other participants choose X and 14 of the other participants choose Y,
- 145, when you choose Y, two of the other participants choose X and 14 of the other participants choose Y,
- 165, when you choose X, 13 of the other participants choose X and three of the others choose Y,
- 55, when you choose Y, 13 of the other participants choose X and 3 of the others choose Y,
- 190, when you choose X, all the other 16 participants choose X and none of the others chooses Y,

- 40, when you choose Y, all the other participants choose X and none of the others chooses Y.

We ask you now to analyze the following decision situations and mark your choices, alternative X or Y. For this you find a box under every decision situation.

When all the experiment participants are ready with their choices, we will collect the questionnaires and establish the person who will be paid in cash.

Appendix B

In this Appendix we present decision situations in which the participants had to make their choices. On the top of each decision situation table we also provide the underlying utility functions (which we did not present to 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 a random order in the questionnaire. We presented two decision situations on a single sheet of paper. In the questionnaire we also re-labeled the alternatives such that an alternative could be either labelled as "X" or "Y".

Decision Situation 1: $U_A = 134.44 + 7.22(N_A - 1)$ and $U_B = 5 + 20(N_B - 1)$																		
Number of others who choose B		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A	134	142	149	156	163	171	178	185	192	199	207	214	221	228	236	243	250
	B	325	305	285	265	245	225	205	185	165	145	125	105	85	65	45	25	5

Decision Situation 2: $U_A = 178 + 4.5(N_A - 1)$ and $U_B = 5 + 20(N_B - 1)$

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

Decision Situation 3: $U_A = 213.64 + 2.27(N_A - 1)$ and $U_B = 5 + 20(N_B - 1)$

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

Decision Situation 4: $U_A = 243.33 + 0.42(N_A - 1)$ and $U_B = 5 + 20(N_B - 1)$

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

Decision Situation 5: $U_A = 156.11 + 5.56(N_A - 1)$ and $U_B = 60 + 15(N_B - 1)$

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

Decision Situation 6: $U_A = 189 + 3.5(N_A - 1)$ and $U_B = 60 + 15(N_B - 1)$

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

Decision Situation 7: $U_A = 215.9 + 1.8(N_A - 1)$ and $U_B = 60 + 15(N_B - 1)$

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

Decision Situation 8: $U_A = 238.3 + 0.42(N_A - 1)$ and $U_B = 60 + 15(N_B - 1)$

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

Decision Situation 9: $U_A = 205 + 1.5(N_A - 1)$ and $U_B = 132.57 + 9.2(N_B - 1)$

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

Decision Situation 10: $U_A = 205 + 1.5(N_A - 1)$ and $U_B = 104 + 11(N_B - 1)$

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

Decision Situation 11: $U_A = 205 + 1.5(N_A - 1)$ and $U_B = 64 + 13.5(N_B - 1)$

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

Decision Situation 12: $U_A = 205 + 1.5(N_A - 1)$ and $U_B = 4 + 17.25(N_B - 1)$

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

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

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

Decision Situation 14: $U_A = 232 + 2(N_A - 1)$ and $U_B = 134 + 10.97(N_B - 1)$																		
Number of others who choose B		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
	B	310	299	288	277	266	255	244	233	222	211	200	189	178	167	156	145	134

Decision Situation 15: $U_A = 232 + 2(N_A - 1)$ and $U_B = 93 + 13.58(N_B - 1)$																		
Number of others who choose B		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
	B	310	296	283	269	256	242	228	215	201	188	174	160	147	133	120	106	92

Decision Situation 16: $U_A = 232 + 2(N_A - 1)$ and $U_B = 30 + 17.5(N_B - 1)$																		
Number of others who choose B		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Number of others who choose A		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Your choice	A	232	234	236	238	240	242	244	246	248	250	252	254	256	258	260	262	264
	B	310	293	275	258	240	223	205	188	170	153	135	118	100	83	65	48	30

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