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Experimental evidence

#785

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
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Editors

Editorial Office

Ruhr Economic Papers #785

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-913-1

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Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche National-bibliografie; detailed bibliographic data are available on the Internet at http://dnb.dnb.de

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/86788913
ISSN 1864-4872 (online)
ISBN 978-3-86788-913-1

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Abstract

We conduct a framed laboratory experiment to gain in-depth insights on factors that drive collective research and development efforts among firms located along the automotive value chain. In particular, we employ a public goods experiment and analyze the influence of sequential decision-making on the willingness to engage in cooperation and on economic welfare. By using a linear value chain setting with three suppliers and one OEM, we analyze vertical R&D cooperation. Our results reveal that contributions increase in situations with sequential decision-making and that sequential decisions increase the overall welfare, even in case of unequally distributed R&D budgets.

JEL Classification: C92, D79, O31

Keywords: Public goods experiment; collective innovation; automobile industry; value chain; innovation barriers; sequential decision making

December 2018

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1 Introduction

In recent years, firms in the automotive value chain face several challenges stemming from market competitors as well as cost and innovation pressure that is passed on through the value chain (see e.g. McKinsey 2013). The development and implementation of new technological solutions among partners through cooperation – in our case located at different stages of the automotive industry value chain – is a way overcome innovation barriers and therefore to cope with these challenges (see e.g. Antonioli et al. 2017). However, research and development (R&D) cooperation along the value chain is fraught with problems that possibly lead to a suboptimal level of cooperation.

This insight is in line with observations made in a publicly financed research project on innovation cooperation along a part of the automobile value added chain, from which practical input in our experimental analysis originates (see Rothgang et al. 2017). The project is part of a larger firm effort to develop new **m**assive **l**ightweight **f**orging components (MLF-project). These components (such as gear wheels, wheel hubs, or ball bearings), for which lightweight designs can be developed, have not yet been part of the efforts to reduce the weight of the automobile. In order to create an innovative final product, cooperation along the value chain has to be intensified. To cope with this challenge, a common initiative has been established.

Findings from the MLF-project show that challenges related to market development and technological progress increase the pressure to cooperate in innovation activities.[1] However, multiple factors impede the actors' engagement in collective R&D. One core obstacle to innovation is the public good aspect of innovation cooperation[2]: the overall benefit of joint innovation efforts for all actors is larger than the individual benefit for each firm. At the same time, the initiation and development of cooperation seems to be driven by a sequential decision mechanism with some firms (in our case mainly steel producers and massive forging firms) taking the lead. As the public good aspect of innovation influences the structural characteristics and dynamics of innovation cooperation and network development in a more general way (e.g. Cantner and Graf 2011: 386 f.), it seems plausible that our specific observation corresponds to a wider variety of cases: How these dynamics work is only partly understood.

In our analysis, we take up these experiences and focus on the following questions: (i) Does a sequential development of cooperation render a possibility to partly solve the public good problem in innovation

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[1] Our experiences are substantiated by observations from expert interviews with R&D representatives from different parts of the massive steel value chain (e.g. in the production of transmission parts and transmissions and wheel hubs).

[2] More precisely, we look at a club good as sub-case of public goods: Individual firms can possibly be excluded from the benefits of knowledge creation in innovation. At the same time, the final benefit from lightweight parts (lower fuel consumption, better handling of the automobile) accrue to all firms in the total value chain.

cooperation along the value chain? (ii) How do these factors influence the welfare generated by common R&D cooperation efforts? The existing literature on public good games that analyses similar decision situations is undecided: While some studies partly find a positive effect (Shang and Croson 2009; Masclet and Willinger 2005, Steiger and Zultan 2014), others conclude that there is no effect (Figuieres et al. 2012), or a negative effect (Gächter et al. 2008).

To shed light on this issue, we focus on vertical innovation cooperation between multiple firms along the automotive industry value chain. The typical structure of automotive value chains is characterized by an OEM (Original Equipment Manufacturer) at the top and a large number of suppliers grouped in different tiers. The latter group encompasses component manufactures (often Small and Medium Sized Enterprises - SMEs) as well as big multinational enterprises (e.g. Bosch, ZF Friedrichshafen) which assemble entire systems that are just in time supplied at the assembly lines of the OEM. During the last decades, an increasing part of value creation and knowledge generation was shifted from the OEMs to specialized suppliers, especially the systems suppliers (Chanaron and Rennard 2007). In our case, especially the metal forging firms and steel producers take an important position in R&D activities as they possess much of the relevant information. Also, their competitiveness is endangered when they fail to bring innovative solutions to the value chain.

In this paper, we represent the different kinds of collective effort by the actors' willingness to engage in joint R&D activities. However, it is important to note that while joint R&D projects take place along value chains also many other kinds of R&D related cooperations can be observed. Thus, our analysis is not merely restricted to formalized R&D cooperation but takes into account a broader range of activities towards common information collection and knowledge transfer, which are characterized by costs for the firms involved and public goods characteristics of the cooperation. Possible activities that we could observe were: (i) financing of R&D projects of research institutes, (ii) common activities to develop a pool of innovation ideas, and (iii) dissemination of knowledge to the customers (OEMs, systems suppliers) about possibilities of new materials and new machine tools, but also the discussion of technical problems in working groups.

Against this backdrop, we are curious to understand what factors foster firms to invest larger parts of their R&D and innovation budget in collective innovation efforts. We employ an experimental laboratory setting in which each actor can be rewarded or sanctioned based on preceding investment decisions in order to test how four distinct treatments (simultaneous – sequential decision; same – varying endowment) affect the "willingness to pay" of all actors involved. To the best of our knowledge, we are the first to use the tools of experimental economics to investigate the behavior in R&D cooperation under certain plausible constellations in the automotive industry. We focus on the pure effects caused by differences in the sequence of choice, avoiding any confounding factors that occur in the field.

We proceed as follows. Section 2 provides a literature review and derives our hypotheses. Section 3 briefly outlines the framing of our study and presents the experimental setup. In Section 4 we present the findings from our experiments. Section 5 concludes with some critical reflections and suggestions for future research.

2 Economic Background and Hypotheses

A firm's ability to access and generate new knowledge is decisive for its innovativeness and economic performance. The same argument holds true for industry value chains. Knowledge transfer among partners through cooperation can be crucial for the competitiveness of the entire value chain. This is the case when innovation barriers can be overcome through cooperation and knowledge exchange as well as the common use of knowledge. This is only one of several possible barriers for innovation which can occur both firm-internal and in the interaction between market actors (Hadjimanolis 2003). However, experience from the MLF-project shows that knowledge flows may be mitigated or even impeded in many ways on each step along the value chain (Rothgang et al. 2017).

In the most basic sense, each actor can simply refuse contributing its own resources/knowledge to the collaborative project, even though he would benefit from the joint R&D efforts of all other partners actively involved. The reason for this is straightforward. Knowledge and research results generated in collective R&D projects – or more general joint innovation efforts – have the character of a club good. Firms in the value chain cannot be excluded from using this knowledge even though they did not contribute to the knowledge production process. At the same time the value of this knowledge does not decay if everyone uses it. Such situations lead to a free-rider problem that results in a suboptimal level of common research or – more general – innovation activity (Baumol 1952).

The actual situation we are studying can be conceptualized appropriately by the public good theory (Olson 1967; Hardin 1968). Public good games without punishment are among the first which were analyzed in laboratory experiments. Early work dates back to the seventies and eighties of the last century (Bohm 1972, 1984; Dawes et al. 1977). According to public good theory nobody makes a contribution to the public good due to possible free riding behavior of actors involved. The common result documented in the public good literature suggests that contributions to a public good are low (for an overview, see Ledyard 1995). However, Di Cagno et al. (2016) analyze conditions under which contributions are higher than theoretically predicted. Many people are conditionally cooperative (a phenomenon also known as reciprocity), i.e. they contribute to the public good if others do the same. About 50% of all actors act as conditional cooperators (Fischbacher et al. 2001). For instance, group members tend to sanction selfish behavior and reward altruistic behavior (Offerman 2002; Andreoni et al. 2003). Own behavior is thus depended on the risk for being sanctioned and on the chances for being rewarded.

From a multitude of studies on public good games, a substantial amount of results has been collected. In this section, we look at specific aspects that are important for our analysis. These are: (i) the effect of sanctions (especially punishment) on the results of public goods games, (ii) the result from different initial endowments on the outcomes, and finally (iii) how sequential decision making and the resulting additional information in decision making influence both the outcome of the pubic good game and the related welfare effect. While the first two aspects are important for forming the assumptions that underlie our experiment, the last one shows how we derive our hypotheses.

The effect of sanctions and rewards have been scrutinized in several experimental designs. Sefton at al. (2007) employ and specify a public good experiment to study effects of sanctions and reward institutions on cooperation and economic efficiency. In their setting sanctions cause costs to both the sanctioning and the sanctioned actor. Their results show that the two institutions differ from each other. Initially, actors tend to choose to use rewards more frequently than sanctions. However, the rate of decay in the level of rewards was faster than that for sanctions. Actors appeared to "give up" more quickly on the use of rewards. For the case of treatments that allowed for sanctions the actors were better able to keep the level of overall group contributions even though sanctions generate costs. The conclusion is that sanctions help to start cooperation in the first place. In the following phase it may be sufficient to keep up convincingly the threat of conducting a sanction. Carpenter et al. (2012) argue that experiments typically assume a situation in which monitoring and punishment takes place in a complete network, i.e. all actors can observe and punish each other. In reality, groups are often formed in a specific architecture.

The effects of punishment in public goods games were analyzed before form various angles (for an overview, see: Chaudhuri 2011). The experiments find that the possibility of punishment increases the willingness to cooperate. However, there are many different ways how punishment is implemented, which influence the results of the experiments. On the one hand, the number of rounds matters. In a one round experiment, Walker and Halloran (2004) find no significant effect either of punishment or of rewards. By comparing experiments with ten and fifty treatment periods, Gächter et al. (2008) find that the average contribution increases with the number of periods. On the other hand, cost-effectiveness of punishment plays an important role. Nikiforakis and Norman (2008) show that the effect of punishing on the outcome depends on the effectiveness of the punishing mechanism. The larger the effectivity of punishing[3], the more

[3] Measured as the relation of effect on recipient's income compared to cost to the punisher.

substantial is the effect on the overall outcome. As Egas and Riedl (2008) show, environments with low cost and a high impact of punishment succeed in increasing the contribution to the public good.

Against the backdrop of these findings, we decided to introduce a punishment regime similar to Egas and Riedl (2008) with 20 repetitions and a ratio between cost for the OEM and decrease in income for the punished firm of 1:3, which should lead to an effective punishment regime. This situation reflects the situation along the automobile value chain with a substantial leverage of OEMs (and – in some cases – also systems suppliers).

Others have analyzed the impact of equal or unequal endowments on the outcome of public good games. The results of the experiments are rather mixed. While Warr (1982; 1983) assumes and Chan et al. (1999) show that income distribution should not influence the overall contribution, other papers find that inequality leads to a reduction in the contribution (Cherry et al. 2005; Aquino et al. 1992). In our analysis, we compare the results obtained in a setting with equal distribution of the R&D budget with an unequal distribution of the R&D budget in order to obtain results for a setting, which is closer to the real-world situation which is characterized by large differences in actual R&D budgets.

Several studies analyze whether transparency increases the level of cooperation. In other words, each actor can directly observe the public good contributions of all other actors. Papers in this strand of literature either focus on factors affecting performance within teams (e.g. Winter 2004) or at the common development of public goods (e.g. Chen et al. 2008). The effect of increased transparency on the contribution to a common good depends on reciprocal motivations that are observed (see e.g. Coats and Neilson 2005). In our case, transparency is systematically linked with sequentially, i.e. the following actor gets informed of the contributions of previous actors depending on the individual constellation. As past studies show, there is conditional cooperation as participants answer to high contributions by also giving high amounts (Fischbacher and Gächter 2010). This shows that when such conditional cooperation is observed, higher contributions can be expected if the peers of observed individuals also contribute high sums. For a prisoner's dilemma situation, Clark and Sefton (2001) show that in individual situations conditional cooperation can be observed. At the same time, the overall cooperation level in their experiment is not higher than in a simultaneous setting without transparency. Others have observed that information about previous contributions increases individual contributions (e.g. Shang and Croson 2009). Related studies partly find a positive effect (Masclet and Willinger 2005; Steiger and Zultan 2014), partly no effect (Figuieres et al. 2012) or even a negative effect (Gächter et al. 2008). Steiger and Zultan (2014) observe in particular that partly transparent networks are as good as fully transparent networks.

In a setup where successive actors have information on the contribution of prior actors, Masclet and Willinger (2005) identify a leadership effect in the sense that prior actors try to influence successive actors to give more through a higher contribution. At the same time, individuals who observe defection by other actors could also withhold their contributions, which may lead to negative reciprocity (Steiger and Zultan 2014). This, in turn, is reflected in our experiment by varying sequences of decisions made by the suppliers. In a setting that compares the leadership effect in situations with an equal vs. unequal distribution of assets, Levati et al. (2007) find that leadership influences the outcome in the case of an equal distribution and in an unequal distribution in the case of information about the distribution of the assets. Although different from our analysis in respect to the implementation of leadership, this latter paper is closest to our assumption. In their paper, Levati et al. (2007) implement leadership as leading by example by one actor, not as we do as a sequential decision choice. Also, there is no punishment mechanism.

If we assume that a leadership effect exists, a successive design experiment should have a positive effect on the overall outcome. In addition, the framing of our experiment as common R&D effort should enforce the leader effect and contribute to a positive effect as it relates to a positive connotation. This leads us to the following set of hypotheses:

> *H1: The successive experiment leads to an increase in the average contribution due to a higher information basis and therefore potential leadership effects.*
>
> *H2: Higher contributions of one or more actors are associated with higher contributions of all other members along the value-added chain.*

In economic literature, welfare effects of the shape of innovation processes is analyzed especially in the context of studies on barriers for innovation. That barriers to innovation (e.g. a lack of available information) lead to decreased economic welfare has been discussed by various studies on innovation activities. Such market failures are regarded as obstacles to reaching superordinate levels of economic welfare (Hadjimanolis 2003).

However, the rich fundus of literature on innovation obstacles does not primarily address the assessment of these welfare losses, but rather looks at the different possible obstacles for innovation (e.g. the overview of barrier research by Hueske and Guenther (2015), and the accounts of different kinds of barriers by D'Este et al. (2012) and Pellegrino and Savona (2017). At the same time, there are accounts that state that it is not at all clear from the beginning that eliminating innovation barriers (e.g. by increasing information availability) leads to a better innovation performance and therefore to increased welfare. The reason is that information availability simply shapes firm-internal decision making which could result in both better or worse innovation performance (for an example see Tang and Yeo 2003).

Welfare losses typically result from a lack of investment in R&D. In our cases, this relates to a lack of contribution to the collaborative R&D project. Due to the public good character of the technological knowledge created during the research project, it is fair to assume that contributions are collectively sub-optimal. This leads us to our final hypothesis:

H3: The successive experiment leads to a higher level of economic welfare.

3 Experimental Design

Experiments are a well-established method, especially in microeconomics and social-psychology. A major advantage of the experimental approach is that we can observe behavior in a highly controlled environment while changing variables of interest, i.e. the observation of events under controlled conditions (Guala 2005). Control not only concerns variables that are influenced by the experimenter. We also have full control of background conditions that might affect the results (e.g. communication, anonymity, and incentives). Therefore, experiments are typically applied for testing economic theories, observing regularities in human behavior, forming a basis for policy advice. The methodology is – similar to simulation – situated between qualitative and quantitative approaches (Roth 1995).

The laboratory allows us to realize decision situations that closely follow theoretical models. Observed decisions can be contrasted with theoretical predictions. Thus, experiments are about the examination of causal links rather than to describe relations (Diekmann 2008). A major advantage is the high level of internal validity due to the controlled environment. A potential shortcoming is the questionable external validity, mainly driven by the disregard of context influence and questions concerning time and causality ("cause and effect").

The framing of our experiment is inspired by observations from the MLF-project and, thus, oriented towards characteristics of cooperation along the automobile value chain. Experiences from this project show that core innovation processes along the value chain exhibit the following characteristics (for further details, see: Rothgang et al. 2017):

(1) Cooperation has characteristics of a public good as firms from multiple steps of the value chain work together and create re-combinatorial technological knowledge in precompetitive research in order to bring forging innovations into the automobile.

(2) OEMs that are located at the end of the value chain have a special relevance for the innovation process, as they are system integrators and have the possibility to create pressure/incentives for the other firms in the value chain to push innovation which can be modeled as punishment. This activity is usually also related to cost (resources for monitoring the activities and influencing firm-internal decision processes).

In practice, the OEMs usually will not punish their component suppliers literally but they are able to exert pressure through their market power, e.g. by including requirements into contracts with forging firms or by regulating access to their relevant firm decision makers to innovative/cooperative suppliers.

(3) One pronounced characteristic of the value chain is that participating firms have at their disposition rather different budgets to perform R&D and contribute to the common goals. This is especially the case for forging firms, part of which do have an own development department. In addition, along the value chain, the possibilities to contribute to the common activities do differ.

(4) As communication is difficult along the value chain, one special measure that has been introduced was increasing the transparency on inputs to innovation along the value chain. This has been done by steel producers and forging firms. Therefore, the question arises whether such increased transparency may be one measure to increase the contribution to the public good.

These general characteristics of the common research activities are fully considered in our experiment. To answer the research questions raised above, we conducted an experimental study based on an extended public goods game[4]: In our experiment, actors faced the decision to invest in a joint R&D project or to keep (part of) their endowment/budget for themselves.[5] Participants faced decisions in groups of four with a fixed group compilation within every round and with fixed roles: supplier 1, supplier 2, supplier 3 or OEM. In each of the 20 rounds, the actors received a personal budget. The monetary values were displayed in Experimental Currency Units (ECU) and one ECU was equal to 0.06 Eurocent. In two treatments this budget was fixed at ECU 1,000 (**_C**: Certain) per actor and in the other two treatments a budget of ECU 250, ECU 750, ECU 1,250, or ECU 1,750 was randomly assigned in every single round to each actor (**_R**: Random).[6]

Beside the budget we varied the decision sequence and the flow of information within the groups. In sequence 1 (**Seq_1**) suppliers 1 to 3 decided simultaneously. And in sequence 2 (**Seq_2**) supplier 1 choose first, then supplier 2 is told about the contribution of supplier 1 and can decide about his contribution. Then supplier 3 is informed about the decision of supplier 2 and so on. In all treatments the OEM was advised about the contributions of all suppliers and got the opportunity to punish. Punishment came at a cost for both the penalized supplier and the OEM. It reduced the payoff of the supplier and of the OEM. For instance, a punishment of 3 reduced the Supplier’s payoff by 3 and the OEM’s payoff by 1.

[4] Public goods games have also been used in environmental economic experiments, see Sturm and Weimann (2006) for an overview.

[5] It was not possible to transfer (part of) the endowment in the next round.

[6] Note that the expected value of the initial budget is the same (ECU 1,000) in all treatments and the total budget per group was fixed at ECU 4,000.

Each player had to decide how much of his endowment he wanted to invest in a collaborative research project. For the collaborative project total payoffs equaled the sum of all investments times two. This reflects the observation from the MLF-project, that common precompetitive innovation efforts lead to a higher total return compared to individual R&D as the results (e.g. in our case knowledge about material characteristics and design features) can be used by multiple firms. For example, we could see that firms producing ball bearings can profit from research results of projects that focus on gear wheels. In our experiment, the profits of the joint R&D project were divided equally between all group members. Table 1 summarizes our four treatments and Figure 1and Figure 2 provide screenshots of the actors' decision screens.

Table 1: Treatments

Treatment	Abbr.	Sequence	Endowment
Sequence 1 Certain	**Seq_1_C**	Supplier 1 & Supplier 2 & Supplier 3 >>> OEM	Certain
Sequence 1 Random	**Seq_1_R**	Supplier 1 & Supplier 2 & Supplier 3 >>> OEM	Random
Sequence 2 Certain	**Seq_2_C**	Supplier 1 > Supplier 2 > Supplier 3 >>> OEM	Certain
Sequence 2 Random	**Seq_2_R**	Supplier 1 > Supplier 2 > Supplier 3 >>> OEM	Random

Note:">" represents the information flow

Figure 1: Screenshot Supplier 2 (Treatment: Sequence 2 Certain)

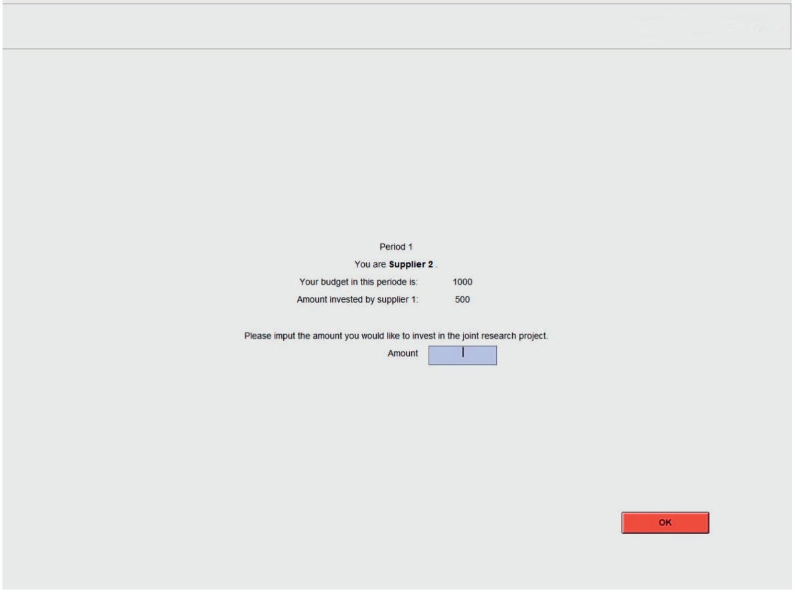
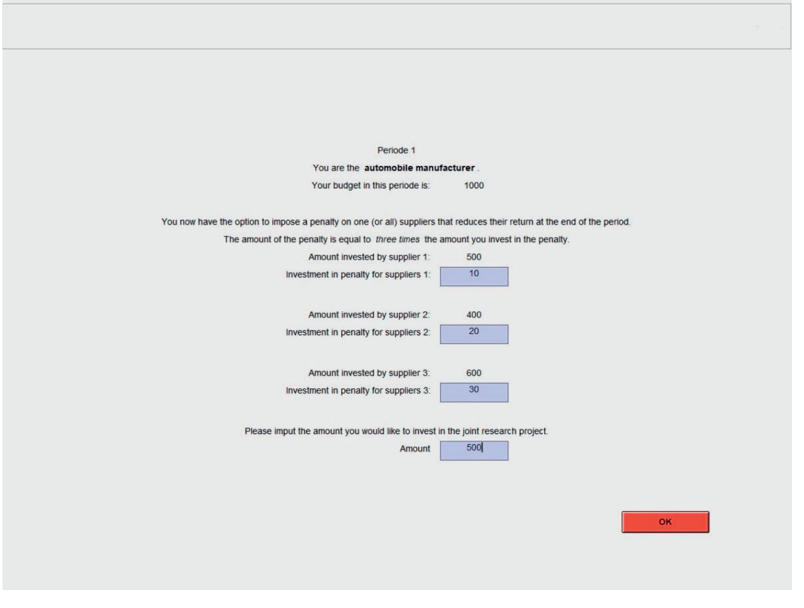


Figure 2: Screenshot OEM (all Treatments)



Actors were randomly assigned to a role as they drew a ball from an urn while entering the laboratory. We tried to balance the distribution of male and female actors across roles and groups by using two different urns.[7] After taking a seat, the participants read the experimental instructions.[8] Before the actual experiment started, all participants took part in a test of understanding, which every actor could solve. All remaining questions were answered in private.

Eight sessions – two for each treatment in random order – were conducted at the Essen Laboratory for Experimental Economics (elfe) in Essen, Germany. We implemented a between-subjects design and each participant only participated in one session. A total of 192 economic and natural science students[9] took part in our experiment. They earned 19.40 Euro on average from a session that lasted about 75 minutes. The experiment was programmed using z-Tree (Fischbacher 2007).

Table 2 summarizes the number of subjects, the number of independent observations (N), the share of female subjects and the average age in the different treatments. Although the share of female subjects slightly differs between the treatments we do not observe significant differences between treatments ($p \geq 0.414$, Fisher's exact test). The same applies to the participants' age, which is never significantly different ($p \geq 0.507$, two-sided Mann-Whitney-*U* test).

Table 2: Subject pool

Treatment	Subjects	N	Female	Age (SD)
Sequence 1 Certain	48	12	0.563	23.333 (2.838)
Sequence 1 Random	48	12	0.521	22.979 (3.028)
Sequence 2 Certain	48	12	0.542	23.125 (3.324)
Sequence 2 Random	48	12	0.458	23.083 (3.370)

Note: N is the number of independent observations; SD is the standard deviation.

[7] However, we had to deviate from this procedure to some degree in our sessions if participants did not show up.

[8] Instruction are available from the authors upon request.

[9] We focused on this specific subject pool because we belief that students with a major in economics or natural science have the highest probability to face R&D related decisions in their later careers.

4 Results

In the following, we analyze subjects' behavior in our four different treatments.[10] We focus on the effect of changes in the decision sequence on the level of contribution to the joint research project.[11] We briefly compare the average punishment between the treatments as well and analyze welfare consequences of a decision sequence variation. Where practicable, we compare the behaviour of suppliers and OEMs within their respective peer group only.

Share of endowment: suppliers and OEMs

In a first step, we analyze the behavior of the whole group (suppliers and the OEMs). Figure 3 shows the average share of endowment, which is invested in the joint R&D project, separated by treatment for all 20 periods.

We observe a rising contribution in the beginning and end-game-effects in all four treatments, but the level differs between them. The highest average contributions are found in **Seq_2_C** (79.1% on average) followed by **Seq_2_R** (71.7%). Lower average contributions were made by group members in **Seq_1_C** (68.4%), while the lowest average could be observed in **Seq_1_R** (59.9%). By looking at the average contribution over all periods, we find significant differences between **Seq_1_R** and **Seq_2_R** ($p = 0.038$, two-sided Mann-Whitney-U test). All other observable differences are insignificant ($p \geq 0.166$).

Share of endowment: suppliers only

Next, we focus solely on the suppliers because they differ from the OEMs with regards to two important factors: they cannot punish other group members and they are always observed by (at least) the OEM. Figure 4 presents the average share of endowment, which is invested in the joint R&D project by the suppliers, separated by treatment in all periods.

We see a lower level of variation compared to OEMs (see below), which might indicate, that suppliers act more stable. The level of contribution is always above 50.0% (minimum: 54.0%, period 19, treatment **Seq_1_R**) in all periods.

[10] For our treatments we use abbreviation for ease of reading. "Sequence 1 Certain": **Seq_1_C**, "Sequence 1 Random": **Seq_1_R**, "Sequence 2 Certain": **Seq_2_C** and "Sequence 2 Random": **Seq_2_R**, see Table 1 for details.

[11] A systematic analysis of the effect of an endowment variation reveals: Comparing **Seq_1_C** with **Seq_1_R** leads to the result that **Seq_1_C** dominates **Seq_1_R**. The effect is not statistically significant ($p = 0.299$, two-sided Mann-Whitney-U test) when aggregated over all periods. In case of **Seq_2_C** and **Seq_2_R**, **Seq_2_C** dominates **Seq_2_R** statistically significantly ($p = 0.013$) when aggregated over all periods.

Figure 3: Share of endowment, OEMs and suppliers, all treatments

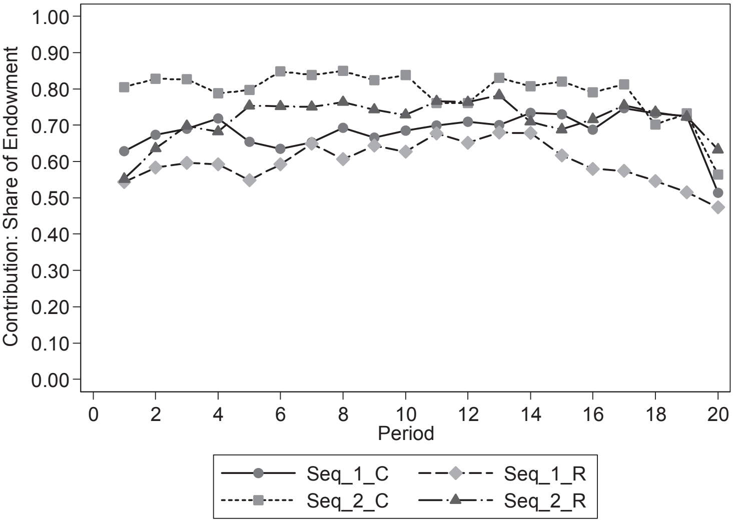
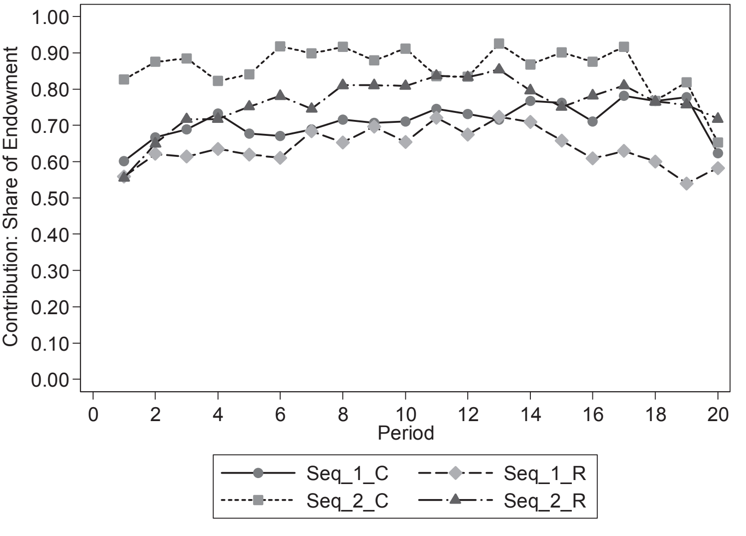
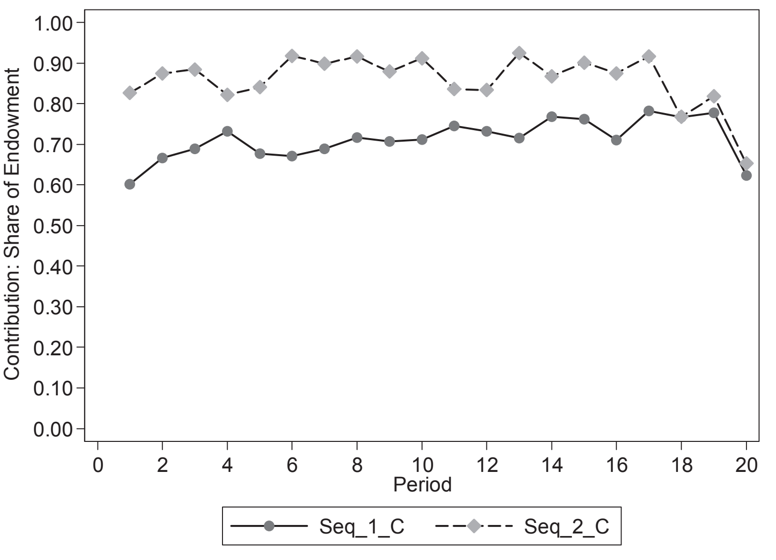


Figure 4: Share of endowment, suppliers only, all treatments



In what follows, we focus on the decision sequence and the flow of information and how they affect the level of contribution by the suppliers. To analyze the effects, we separately compare the two different sequences in both endowment types (**_C**: certain and **_R**: random). In other words, we hold the endowment mode fixed and vary the sequence. In Figure 5 both sequences are compared under the condition that all team member receive the same initial endowment in each round (**Seq_1_C** compared to **Seq_2_C**).

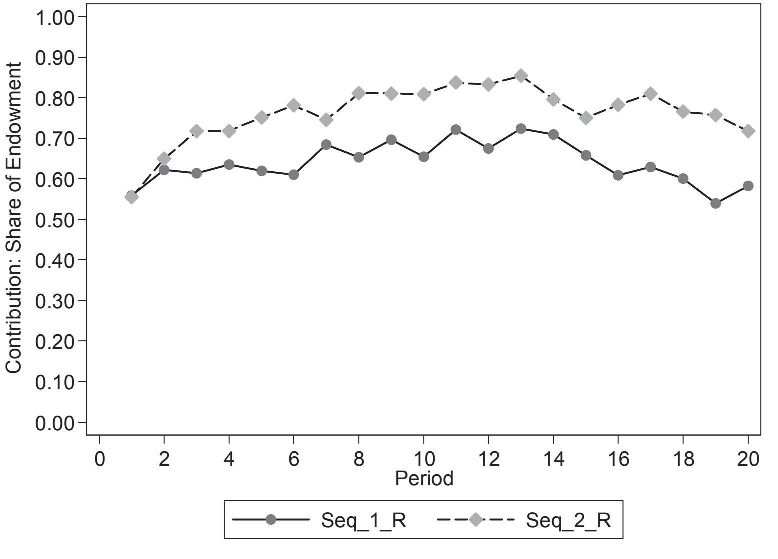
Figure 5: Share of endowment, suppliers only, certain budget



At a first glance **Seq_2_C** dominates in case of a certain budget. The average share of endowment (85.9%) is weakly significantly higher ($p = 0.065$, two-sided Mann-Whitney-*U* test) compared to **Seq_2_C** (71.2%). Comparing specific period intervals reveals some more information about suppliers' behavior. By looking at the first three periods, we observe that the share of endowment, which is provided for the joined R&D project, is always significantly higher ($p \leq 0.037$, two-sided Mann-Whitney-*U* test) in case of **Seq_2_C**. This (weakly) significant ($p \leq 0.088$) effect prevails from period six on (except periods eleven and twelve, $p \geq 0.331$) until the 17th period. In the last three periods, we do not observe any significant dissimilarities with regard to the average share of endowment ($p \geq 0.495$). This indicates that sequential decision-making fosters cooperation.[12] In case of the staged sequence (**Seq_2_C**) more information is available. Hence, the strategic uncertainty gets lowered and suppliers cooperate more.

Figure 6 presents our two sequences, given that all team members receive a random initial endowment in each round (**Seq_1_R** compared to **Seq_2_R**). On the first sight, the staged sequence (**Seq_2_R**) dominates even in case of a random budget. Looking at the average share of contribution we see a significantly higher ($p = 0.038$) average share in case of **Seq_2_R** (76.3%) compared to **Seq_1_R** (64.0%). Comparing specific period intervals reveals some more information about suppliers' behavior: In case of the first five periods, we do not observe a significantly different ($p \geq 0.204$) average share of endowment between the two treatments. From periods eight to 19, **Seq_2_R** (weakly) significantly ($p \leq 0.093$) dominates **Seq_1_R** (with the expectation of periods 14 and 15, $p \geq 0.260$). In the last round, we do not observe a different behavior once more ($p = 0.222$).

Figure 6 Share of endowment, suppliers only, random budget



[12] One could assume that these differences are driven by supplier 1, who might invest much more in **Seq_2** in order to give a signal to his fellow team members. However, we do not observe a significant different share of endowment when comparing suppliers 1, 2 and 3 ($p \geq 0.225$, two-sided Mann-Whitney-*U* test).

We assume that different random budgets lead to different levels of power within the group, which leads to lower contributions. But this setting may also be less vulnerable to free-ride in the last periods. Accordingly, even with random budgeting, sequential decisions foster cooperation. The result observed in our **Seq_1_C** vs. **Seq_2_C** analysis is robust to a variation in the group members' endowments and therefore even holds by different levels of power.

As a further robustness check and to investigate how the invested share by the other group members affects the individual's contribution, we run a Random-Effects[13] General Least Square (GLS) regression with the average share of endowment as dependent variable in periods two[14] to 20. The results are summarized in Table 3.

The dependent variable is a subjects' share of endowment in each period. **Seq_1_R**, **Seq_2_C** and **Seq_2_R** are treatment dummies (with **Seq_1_R** as baseline), indicating an individual's treatment. *Period* is the specific round and *Period 19* plus *Period 20* are dummies, indicating the last two rounds. $AV_{period-1}$ is the lagged average group contribution minus the individual's contribution, *supplier 2* and *supplier 3* are both dummy variables, indicating a subject's role within the group (supplier 1 as baseline). *Age* and *Female* represent the subject's age and gender. The bottom lines of Table 3 contain *p*-values of Wald test for equal treatment dummies.

In specification (1) we use a basic parameterization without controlling for role or demographic effects. We observe a positive and highly significant effect of ***Seq_2_C*** (with **Seq_1_C** as baseline) in line with the results of our non-parametric tests reported above. With certain budgets, the share of invested endowment increases in case of a stepwise decision process. By looking at Wald test *p*-values we see that this assumption significantly holds in case of diverging endowments (**Seq_1_R** = **Seq_2_R**). In addition, we observe a slight increase in the contribution to the joint research project over the time (*Period*) and highly significant negative last round effects (*Period 19* = 1 and *Period 20* =1). Furthermore, we observe a positive and highly significant effect of the lagged share by the other group members to the joint project ($AV_{period-1}$) which is in line with theory. The observed treatment differences are robust when we control for subject's role in parametrization (2) and when we add additional demographics in model (3). Here, we additionally observe that female subjects tend to invest significantly less in the joint R&D project compared to their male counterparts, but the significance and direction of our treatment dummies are not affected even once we run

[13] We choose a random effect approach because our variables of interest are invariant over periods. For a similar approach see e.g. Tan and Bolle (2007).

[14] Period one is missing because of the lagged variable $AV_{period-1}$.

our regression in full parameterization in specification (4). Accordingly, we summarize that our non-parametric tests are robust to different potential influences.

Table 3: Random-effects GLS regression share of endowment, suppliers

	(1)	(2)	(3)	(4)
Seq_1_R	-0.037	-0.037	-0.038	-0.038
	(0.042)	(0.042)	(0.041)	(0.041)
Seq_2_C	0.103^{***}	0.103^{***}	0.101^{***}	0.101^{***}
	(0.034)	(0.034)	(0.032)	(0.032)
Seq_2_R	0.047	0.047	0.037	0.037
	(0.034)	(0.034)	(0.033)	(0.033)
Period	0.002^{*}	0.002^{*}	0.002^{*}	0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
Period 19 = 1	-0.039^{**}	-0.039^{**}	-0.039^{**}	-0.039^{**}
	(0.018)	(0.018)	(0.018)	(0.018)
Period 20 = 1	-0.118^{***}	-0.118^{***}	-0.118^{***}	-0.118^{***}
	(0.029)	(0.029)	(0.029)	(0.029)
$AV_{period-1}$	0.403^{***}	0.403^{***}	0.405^{***}	0.405^{***}
	(0.039)	(0.039)	(0.038)	(0.038)
Supplier 2 = 1		-0.020		-0.020
		(0.031)		(0.030)
Supplier 3 = 1		-0.024		-0.023
		(0.032)		(0.031)
Age			-0.003	-0.003
			(0.004)	(0.004)
Female = 1			-0.053^{**}	-0.052^{**}
			(0.025)	(0.025)
Constant	0.428^{***}	0.443^{***}	0.521^{***}	0.539^{***}
	(0.044)	(0.048)	(0.112)	(0.110)
N	2,736	2,736	2,736	2,736
N in group	144	144	144	144
Wald Tests:				
p-Value: ***Seq_1_R*** = ***Seq_2_R***	0.031	0.030	0.057	0.055
p-Value: ***Seq_2_C*** = ***Seq_2_R***	0.064	0.059	0.030	0.027

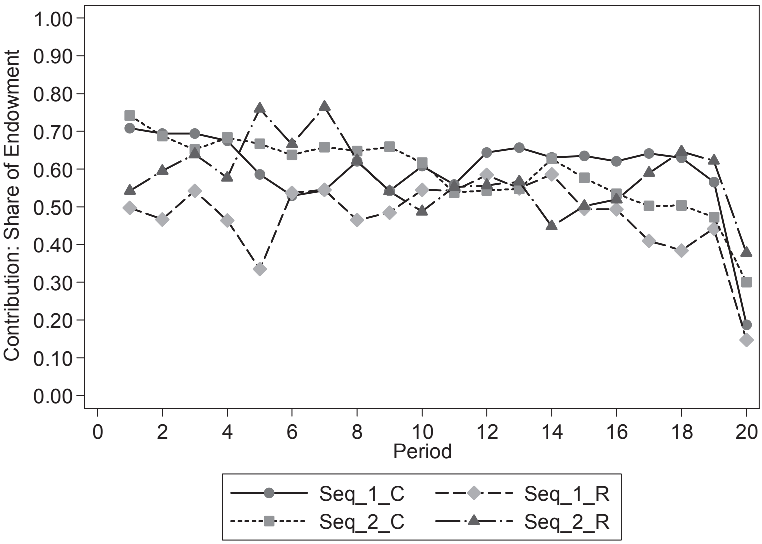
Note: Robust Standard errors in parentheses, * $p < 0.100$, ** $p < 0.050$, *** $p < 0.010$.

Share of endowment and punishment: OEMs only

Next, we analyze the OEMs' behavior regarding their investment in the joint research project (defined as share of endowment) and the punishment they inflict. Figure 7 shows the average share of endowment, which is invested in the joint R&D project by the OEMs, separated by treatment for all 20 periods.

We observe a strong end-game-effect in period 20, leading to average contributions below 40.0%. In addition, we see a higher variation compared to the suppliers' behavior.[15] When focusing on the aggregated behavior over all periods we do not observe significant differences ($p \geq 0.356$, two-sided Mann-Whitney-*U* test) and no treatment seems to dominate. This is also supported by an analysis on period level: We only observe significant differences between **Seq_1_C** and **Seq_1_R** ($p = 0.049$) in period five, weak significant differences in periods five and seven between **Seq_1_R** and **Seq_2_R** ($p \leq 0.058$), and a weak significant difference between **Seq_2_C** and **Seq_2_R** in the first period ($p = 0.092$).

Figure 7: Share of endowment, OEMs only, all treatments



Considering the OEMs' punishment behavior reveals that the level of punishment is not influenced by the treatment in general. By comparing the average punishment (as share of endowment) between our four treatments over all periods we do not observe significant differences ($p \geq 0.126$, with shares of 2.5% in **Seq_1_C**, 3.2% in **Seq_1_R**, 1.8% in **Seq_2_C**, and 2.9% in **Seq_2_R**). But we see some differences in specific rounds: We, like above, focus on the effect of the decision sequence and observe a significant lower ($p = 0.019$) level of punishment in **Seq_1_C** compared to **Seq_2_C** in period two. In periods six, nine, ten and 13, this effect (weakly) significantly ($p \leq 0{,}089$) inverts with a higher level of punishment in **Seq_2_C**

[15] This could also be caused by a lower degree of smoothening compared to the suppliers.

compared to **Seq_1_C**. In case of a random budget, we observe a (weakly) significantly ($p \leq 0.072$) higher level of punishment in **Seq_1_R** compared to **Seq_2_R** in periods three, five and six, and a weak significant effect ($p = 0.071$) in the other direction in the last period.

Equally to our analysis of the suppliers' behavior, we run a Random-Effects GLS regression with the average share of endowment as dependent variable in periods two to 20 to investigate how the invested share by the other group members affects the individual's contribution. The results are shown in Table 4.

Table 4: Random-effects GLS regression share of endowment, OEMs

	(1)	(2)
Seq_1_R	-0.092	-0.060
	(0.088)	(0.090)
Seq_2_C	-0.066	-0.056
	(0.118)	(0.116)
Seq_2_R	-0.029	-0.048
	(0.101)	(0.099)
Period	-0.007^{**}	-0.007^{**}
	(0.003)	(0.003)
Period 19 = 1	0.021	0.021
	(0.036)	(0.036)
Period 20 = 1	-0.243^{***}	-0.244^{***}
	(0.057)	(0.057)
$AV_{period\text{-}1}$	0.359^{***}	0.354^{***}
	(0.083)	(0.083)
Age		0.013
		(0.010)
Female = 1		0.084
		(0.078)
Constant	0.425^{***}	0.063
	(0.079)	(0.242)
N	912	912
N in group	48	48
Wald Tests:		
p-Value: ***Seq_1_R*** = ***Seq_2_R***	0.534	0.907
p-Value: ***Seq_2_C*** = ***Seq_2_R***	0.777	0.947

Note: Robust Standard errors in parentheses, * $p < 0.100$, ** $p < 0.050$, *** $p < 0.010$.

Treatment dummies **Seq_1_R**, **Seq_2_C** and **Seq_2_R** (with **Seq_1_R** as baseline) indicate an individual's treatment. *Period* represents the specific round and *Period 19* and *Period 20* are dummies, indicating the last two rounds of our experiment. *Age* and *Female* are variables capturing potential effects of the individuals' age and gender. We observe a positive and highly significant effect of the lagged share by the other group members to the joint project ($AV_{period\text{-}1}$) and a significant, but small, negative period effect

(*Period*). With regards to the treatment dummies and in line with our non-parametric analysis, we do not observe any significant differences between our four treatments.

In summary, the OEMs' aggregated behavior is not influenced by the treatment. Neither the share of endowment contributed to the joint research project nor the level of punishment significantly differs between our four treatments. However, that should come as no surprise: The OEMs can always observe all suppliers, punish them and decide about his contribution last on the decision sequence regardless of treatment. Therefore, the situation within a decision sequence is not associated with additional information for the OEM.

Welfare: suppliers and OEMs

In a final step, we analyze the (net-) welfare in our four treatments. The calculation of the group welfare in ECU per period were carried out by the following equation:

$$Welfare_g = \sum_{i=1}^{4} ShareProject_i + \sum_{i=1}^{4} Budget_{rem_i} - \sum_{i=1}^{3} Punish_{ef_i} - Punish_{cost_{i=4}} \quad (1)$$

$$with\ g: group\ and\ i: individual\ 1,2,3 = suppliers\ 1,2,3;\ 4 = OEM$$

In equation (1) the welfare for group g ($Welfare_g$) in any period is equal to the sum of the shares received from the joint R&D project ($ShareProject_i$) plus the sum of the remaining budget ($Budget_{rem_i}$) minus the effect of punishment ($Punish_{ef_i}$) minus the costs of punishment ($Punish_{cost_{i=4}}$). In other words, the welfare is the projects surplus and the remaining budgets of all team members less the effect and costs of punishment.

Figure 8 shows the average welfare in ECU in case of a certain budget separated by sequence variations for all 20 periods. At a first glance, **Seq_2_C** dominates in case of certain budget. Aggregating over all rounds yields a weakly significantly ($p = 0.094$, two-sided Mann-Whitney-*U* test) higher welfare in case of **Seq_2_C** (ECU 6,944.2 on average) compared to **Seq_1_C** (ECU 6,432.5). This result seems to be driven by (weak) significant differences in rounds one, two, six, nine and ten only ($p \leq 0.057$). In round 18 and 19, **Seq_1_C** dominates **Seq_2_C**, but this effect remains insignificant.

Figure 9 compares both sequences with random endowments (Treatment **Seq_1_R** vs **Seq_2_R**). At first view **Seq_2_R** dominates **Seq_1_R** even in case of random budgets. By comparing the average over all rounds, we observe a significant ($p = 0.024$) lower welfare in **Seq_1_R** (ECU 5,954.3) compared to **Seq_2_R** (ECU 6,586.3). By looking at each period, we observe (weak) significant ($p \leq 0.099$) differences in rounds five, six, eight, nine, 13, 17 and 19.

Hence, we can conclude that sequence 2 (**Seq_2**) increases the welfare (weakly) significantly in both cases, certain and random endowment.

Figure 8: Welfare in ECU, certain budget

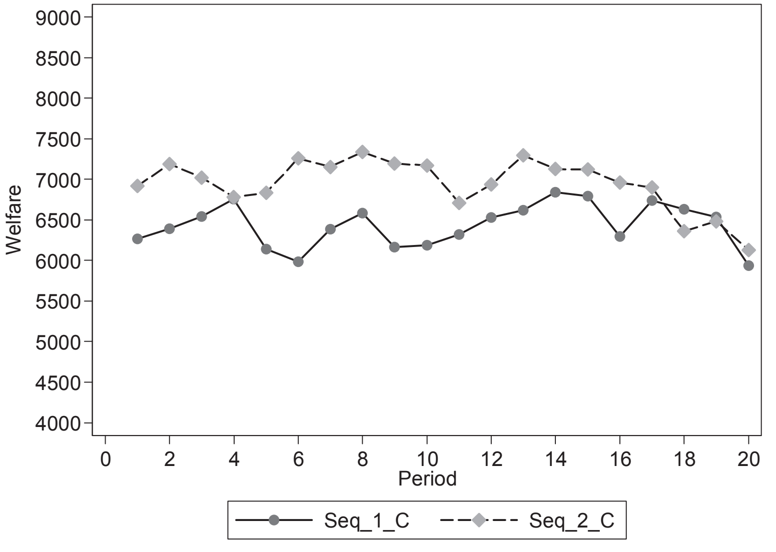
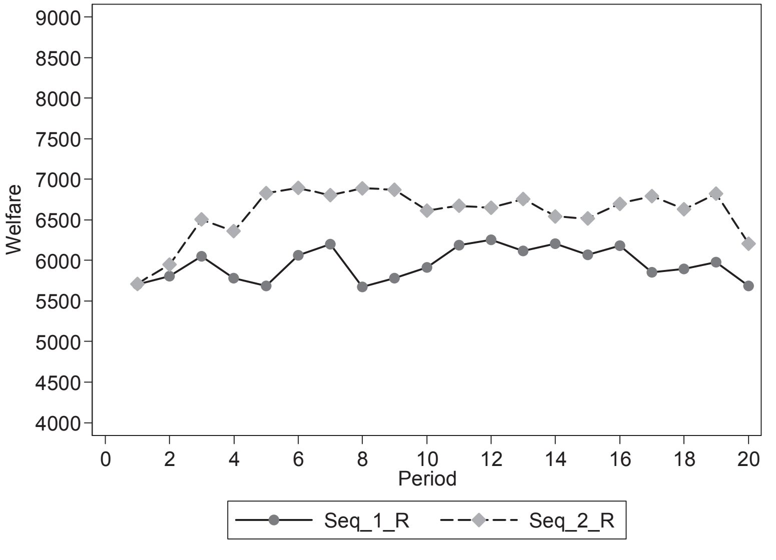


Figure 9: Welfare in ECU, random budget



5 Summary and conclusions

Our study contributes to an in-depth understanding of collective investments in joint R&D projects of firms (i.e. suppliers and OEMs) located at different stages along the automotive value chain. We focus on the effect of decision sequences in our experimental design, which – as we assume - affects the willingness to contribute to a public good by increasing the research and innovation effort. As a robustness check and because of the practical importance of substantially diverging R&D budgets, we include treatments with different endowment distributions (in one case equal endowments, in the other differences between the actors involved). Accordingly, we analyze subjects' behavior (differentiated by suppliers and OEMs) in our four treatments. We account for the average punishment between the treatments and investigate welfare consequences.

The experiment reveals some novel and insightful results. Most notably, by taking sequential decisions, the suppliers significantly increase their share of endowment invested in a joined R&D project from 71.2% to 85.9% on average in case of equal budgets. We observed qualitatively the same results given diverging budgets. Here, the average share increases from 64.0% to 76.3%. The positive effects of sequential decisions are underlined by our welfare analysis. Furthermore, we observe a positive and highly significant effect of the lagged share by the other group members to the joint project in case of suppliers and OEMs.

Hence, the possibility of a supplier to take the lead in the investment process has a significant positive influence on the overall investments in the collaborative R&D project. This holds not only for the case of equal budgets but also in case of varying endowments. The OEMs show a similar behavior in all scenarios, that is, they are not influenced by varying sequences of decision-making or by budget variations. Similarly, with regards to punishments the OEMs do not vary significantly and are overall rather moderate. The existence of the punishment option seems to be sufficient for influencing suppliers' behavior. Table 5 summarizes our main findings and compares our observations with the hypothesis derived in Section 2.

Table 5: Summary of observations

	Hypothesis	Observation
H1	The successive experiment leads to an increase in the average contribution	Accepted: suppliers significantly increase their share of endowment in case of sequential decisions
H2	Higher contributions of one or more actors lead to a higher contribution by the other actors	Accepted: we observe a positive and significant effect of the lagged share by the other group members
H3	Sequential decisions lead to a higher level of economic welfare	Accepted: sequential decisions significantly increase the overall welfare

In summary, collaborative R&D projects are a particularly challenging form of organization due to the public good characteristics of technological knowledge. The involved firms need to be incentivized in order to take collectively optimal R&D investment decisions. The sequential nature of observed cooperation patterns provides a promising way to overcome the low contribution problem related to the public good aspect of R&D cooperation and increases the welfare from innovation cooperation. Our results imply that research cooperation can be initiated and intensified by the actor who takes a leading role. This, in turn, encourages others to follow and contribute. The necessary precondition for mitigating the free-rider problem described above is transparency. Sequential decision-making leads to higher average and individual contributions to the public good and increased economic welfare.

The findings of our experimental study are in line with the results from Steiger and Zultan (2014). Their analysis focuses on the effect of transparency of decisions in teams under increasing returns to scale of cooperation. They show that transparency is important for decision making, such that in general (though not in all cases) increased transparency leads to an increase in cooperation. Our results show that the successive decision mechanism, as it has been observed in research cooperation by Rothgang et al. (2017), works in a similar fashion and shares features with the leader effect that has been scrutinized by other studies (e.g. Chan et al. 1999).

Regarding our treatments with an unequal distribution of the R&D budgets, the results are consistent with findings from Levati et al. (2007). Their analysis looks at the effect of leadership (similar to successive decision-making in our case) on contributions to public goods with an unequal endowment distribution. While other studies show that leadership increases contributions in an environment with equal endowments, an unequal distribution only leads to increased contributions in situations with perfect information of the individuals about the distribution of the initial endowment. As our actors have available information about the endowment structure, our results do not contradict their analysis.

Our results show the effect of decision sequences on the contributions to a public good in an experiment that features a practical decision situation. In addition, we address the influence of cooperation on social welfare. The analysis helps to understand the patterns of cooperation formation that have been observed in the MLF-project that built the starting point for our analysis. In this case study, the initiative to cooperate had originated by few larger steel producing and metal forming firms at the far end of the value chain. It became obvious that the initial investment from these firms lead to an ever-increasing number of participants and – in a second step – also to increased contributions.[16] These contributions were also obviously not

[16] With respect to financial contributions, new ideas and time invested in the project.

impeded by rather different research budgets.[17] Information deficits regarding the potential benefits of cooperation were largest in system suppliers and OEMs who increased their contribution when the information stock was increased during the cooperation. Obviously that kind of development pattern is consistent with the results from our analysis which implies that the initial initiative of some actors leads to higher investments.

It is important to note that our results were obtained by framing our experiment towards a situation that arises within the value chain of the automobile industry which is characterized by close cooperation in the production of a complex good. Similar situations are probable to arise in industries such as aviation or mechanical engineering. In other industries, different patterns of cooperation dynamics might arise which still could be addressed with laboratory experiments.

Yet much remains to be done, particularly when it comes to aspects of R&D cooperation, which go beyond the scope of our study. The study shows that experiments can be a rather useful tool to increase our understanding in practical decision situations. However, our experimental setup is limited to one simple monetary sanctioning mechanism. Our results imply that punishment could be rather a convincing threat which is sufficient to prevent opportunistic behavior and keep actors on track. However, there are many different ways how incentives can be implemented (whether it is in a positive or negative way), which influence the results of experiments such as the number of rounds played. In a one round experiment, Walker and Halloran (2004) find no significant effect neither of punishment nor of rewards. By comparing experiments with ten and fifty periods, Gächter et al. (2008) find that the average contribution increases with the number of periods. A further factor is cost-effectiveness of punishment. Nikiforakis and Norman (2008) show that the effect of punishing on the outcome depends on the effectiveness of the punishing mechanism. The larger the effectivity of punishing, the more substantial is the effect on the overall outcome. Finally, as Egas and Riedl (2008) show, environments with low cost and a high impact of punishment succeed in increasing the contribution to the public good. An in-depth investigation of sanctioning mechanisms in sequential public good experiments – among many other, still widely unexplored issues – provides a highly promising field for future research.

[17] There are rather large differences, ranging from metal forming firms with no fixed research budgets at all to system suppliers and OEMs with research budgets of some billion Euro per year.

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