Endogenous role assignment and team performance*

David J. Cooper#

Florida State University

Matthias Sutter†

University of Innsbruck and University of Gothenburg

Abstract: Team success relies on assigning team members to the right tasks. We use controlled experiments to study how the mechanism used for assigning roles within teams affects team performance. Subjects play the takeover game in teams consisting of a buyer and a seller. Understanding optimal play is very demanding for buyers and trivial for sellers, so teams should perform better if the more able teammate takes the buyer role. When teammates are allowed to jointly choose their roles, the more able teammate tends to become the buyer, but this is more than offset by disruptions to the learning process. Our results indicate that a top-down management approach with exogenous role assignment may be surprisingly good for team performance.

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# Department of Economics, Florida State University, Tallahassee, FL 32306-2180, USA. e-mail: djcooper@fsu.edu

† Department of Public Finance, University of Innsbruck, Universitätsstrasse 15, A-6020 Innsbruck, Austria, and Department of Economics, University of Gothenburg, Vasagatan 1, SE-40530 Göteborg, Sweden. e-mail: matthias.sutter@uibk.ac.at
1) Introduction

Motivated by the observation that many important economic decisions are made by teams rather than individuals, economics has recently witnessed a surge of interest in team decision making. Extending the existing psychology literature to domains of specific interest to economists, experimenters have established that team choices are generally more rational than individuals (e.g., Cooper and Kagel, 2005; Blinder and Morgan, 2005; Kocher and Sutter, 2005; Charness and Jackson, 2007; Luhan, Kocher, and Sutter, 2009; Casari, Zhang, and Jackson, 2012; Charness and Sutter, 2012; Kugler, Kausel, and Kocher, 2012) and more self-interested than individuals (e.g. Bornstein and Yaniv, 1998; Luhan, Kocher, and Sutter, 2009).

These studies have generally not emphasized the internal organization of teams. A universal feature of existing studies is that team members are all engaged in the same task. While appropriate for establishing basic observations about how teams perform relative to individuals, use of homogenous tasks departs significantly from the reality of many team environments. Team members in most environments are filling different roles and completing different tasks with different levels of difficulty. Not all team members are equally well suited for all tasks, so getting the right person assigned to the right task can be an important determinant of team success. It seems natural to give team members input on the assignment of tasks, since they are likely to be better informed about their abilities than any outside observer. It also seems natural that helping individuals assigned to more difficult tasks via communication with their teammates should improve team performance.

In this paper we use controlled experiments to examine role assignment in a task where one role is more cognitively demanding than the other, making proper role assignment crucial for the success of a team. We find that teams perform better when teammates are allowed to chat about their decisions, but, unexpectedly, endogenous role assignment does not improve team performance. This reflects two countervailing forces: endogenous role assignment yields selection in favor of the more able individual being assigned to the more difficult role, but also damages the performance of individuals assigned to the more demanding role controlling for their ability.

Software development provides a good example of an industry where both approaches to role assignment, through an external authority or letting team members decide among themselves about the assignment, are used. Large software projects usually require a development team. The traditional way of running a software development team is to have an externally assigned project manager. Team members do not choose their tasks, but are instead assigned tasks by the project manager. However, over the past decade, software development has moved towards “agile software development”, a broad category that encompasses a number of specific software design approaches such as Scrum, Extreme Programming,
and Crystal Clear. The shift toward agile software development included a move toward teams that are self-managed (Anderson, 2004). Teams using Scrum, for instance, meet on a regular basis to set short-term goals. No specific team member is designated as the team leader. Tasks are assigned via discussion among the team members, with the idea that team members know more about each other and the tasks to be performed than any outside individual.

Because software development offers a broad variety of methods for assigning individuals to tasks, it seems like exactly the right environment for studying the effect of different methods of role assignment. We instead argue that software development illustrates why using field data to study the relative effectiveness of different methods is problematic. Agile software development involves a multitude of changes to traditional methods of software development, and any two implementations differ on multiple dimensions. For example, some implementations of agile software development have team members share a large bullpen office to facilitate communication while others do not. Even if there existed sufficient variation that the effect of different elements of the process could be identified via multivariate regressions, there would remain the problem of endogeneity. It is not random what software development process is adopted by a particular firm and no obvious instrument exists for the process adoption decision. These problems of variation along multiple dimensions and endogeneity are not unique to software development, and are likely to affect any study based on naturally occurring field data.

We therefore turn to laboratory experiments. Using a task where role assignment is critical, we study the relationship between how roles are assigned and team effectiveness. Because the laboratory is a controlled environment, we exogenously determine crucial elements of the environment such as incentives, information available to team members, and (most importantly) the process by which roles are assigned.

In our experiment, subjects play a simplified version of the takeover game (Samuelson and Bazerman, 1985). This game has a Buyer and a Seller. The Seller has a single item to sell. She knows the value of this item while the Buyer only knows the distribution of values and that the value of the item to the Buyer is always 150% of the value to the Seller. The Seller’s payoff maximizing strategy is trivial: she should accept any bid greater than her value. Because of the asymmetric information between Buyers and Sellers concerning the item’s value, the Buyer faces adverse selection. In choosing a bid he needs to understand that the expected value of the item conditional on having his bid accepted is less than the expected value ex ante. The adverse selection is sufficiently severe that submitting a bid equal to the lowest possible value is the Buyer’s expected payoff maximizing strategy.

Previous work on the takeover game has focused on why the winner’s curse (over-bidding) occurs, but our intent is to use the takeover game to understand how task assignment affects team performance. For our purposes, two features of the takeover game are particularly valuable. First, the Buyer and Seller
roles differ greatly in difficulty. The Seller’s optimal strategy is trivial, but previous work (e.g., Grosskopf, Bereby-Meyer and Bazerman, 2007; Bereby-Meyer and Grosskopf, 2008; Charness and Levin, 2009) has established that Buyers have a great deal of difficulty understanding that they need to bid low due to adverse selection. Second, play by freely interacting teams reduces but does not eliminate overbidding in the takeover game (Casari et al., 2012).¹ This allows us to study the relationship between the importance of role assignment and the degree of interaction between teammates.

In the initial phase of the experiment, all subjects play as Buyers facing a series of computerized Sellers. In control sessions the Buyers continue to play against computerized Sellers for the second phase of the experiment. For the other four treatments in our experimental design, subjects are matched into teams of two players each. One teammate plays exclusively as a Buyer and the other plays exclusively as a Seller. Each plays a series of takeover games against Buyers and Sellers from other teams and split their earnings evenly. Teammates never play against each other, so their interests are perfectly aligned. The four treatments with teams systematically vary along two dimensions: (1) the Buyer and Seller roles are either assigned randomly and exogenously or are endogenously agreed upon by the two teammates, and (2) teammates either play independently, only interacting through their shared payoffs, or are given periodic opportunities to chat about how to play the game. Ex ante, we expect either endogenous role assignment or chat between teammates to improve the Buyers’ performance by lowering bids.²

We find that chat leads to significantly lower bids as expected. Endogenous role assignment has little effect, raising (rather than lowering) bids by a small amount that is far from statistical significance. This is surprising since our data has all the necessary conditions for endogenous role selections to lower bids. Bids from the initial phase should provide a clear measure of ability, and the data confirms that bids are significantly lower in the second phase when the more able teammate (i.e., the low bidder in the first phase) is assigned to the Buyer role. Endogenous role selection generates selection in favor of the more able Buyer, with Buyers in the endogenous role selection treatments bidding significantly lower than Sellers. The problem is that Buyers who are endogenously assigned their role bid significantly higher, controlling for ability, than Buyers who are randomly assigned this role. This unexpected effect more than reverses the positive effects of selection in favor of more able subjects. The dialogues between teammates provide direct evidence that endogenous role selection negatively affects the quality of the discussion between teammates on how to play the game.

¹ In Casari et al. (2012) groups consist of three members who are all in the role of buyers (while sellers were computerized). Unlike the work we present below, their paper does not focus on role assignment and how it affects team performance.
² The Seller’s role is sufficiently trivial that we expected subjects to get it right regardless of treatment. The data supports this expectation.
The negative effect of endogenous role selection on Buyers’ performance, controlling for ability, is the primary result of our paper. Given the unexpected nature of this result, any explanation is necessarily \textit{ex post}. The design and data allow us to dismiss some possibilities. For example, subjects are given a large amount of time to discuss their decisions and there are no obvious differences between teams who discuss up until the time limit and those who end early. We therefore can dismiss time constraints as a cause of the negative effect. We instead speculate that we are observing an effect of cognitive load. The intuition is straight forward. Individuals only have a limited budget of cognitive resources available. Adding a task that requires use of these resources necessarily leaves less for other tasks, leading to less rational behavior.\textsuperscript{3} Even though subjects don’t spend a huge amount of time discussing role selection, it presumably requires some thought. This presumably leads to less thought being devoted to bidding, consistent with the reduced time spent discussing how to bid as well as the reduced quality of decisions about bidding.

2) The Takeover Game

Subjects in our experiment played a simplified version of the takeover game. This game involves two individuals, a Buyer and a Seller. The game begins with the Seller drawing a value, \( V \), for an indivisible item. This is the amount the item is worth to her. The possible values are 90, 600, and 1200 experimental points, with each value equally likely to be drawn. The Seller knows the value of the item while the Buyer only knows the distribution of values. The Buyer submits a bid, \( B \), to purchase the item, where bids are restricted to the set of integers between 0 and 2000 (inclusive). The Seller observes the bid and chooses to either accept or reject it. If the bid is accepted, the Buyer’s profit is \( 1.5*V - B \) and the Seller’s profit is \( B - V \). If the bid is rejected, both players’ profits are zero.

The Seller’s optimal strategy is simple – she should accept a bid if it is (weakly) greater than the value and reject otherwise. The Buyer’s optimal bid is less obvious. If the Seller is behaving optimally, the Buyer’s expected payoff maximizing bid is 90. This is also the optimal bid for a risk averse buyer. In evaluating the profitability of a bid, the Buyer has to consider the expected value of the item \textit{subject to the bid being accepted}. In other words, the Buyer must account for adverse selection. Table 1 illustrates the

\textsuperscript{3} Psychology offers many examples where increased cognitive load reduces the ability of individuals to reason and/or learn. For example, Johnson-Laird and Wason (1970) find that increasing the cognitive load of subjects reduces their ability to correctly solve logic problems. In experimental economics the issue of cognitive load has come up in studies of spillover for subjects playing multiple games. For instance, Bednar, Chen, Liu, and Page (2012) compare subjects playing games in isolation with subjects playing paired games. They find efficiency reducing spillovers between games and report evidence that cognitive load is at least partially responsible for the effect. See also Savikhin and Sheremeta (2012) and Falk, Fischbacher and Gaechter (2010) for related work on cognitive spillovers and cognitive load. Increasing cognitive load is also known to have other economically relevant effects, such as changing individuals’ risk and time preferences – see Benjamin, Brown, and Shapiro (2012) for a summary of this literature.
basic features of the Buyer’s problem. A bid of 1200 induces all Sellers to accept the bid, including those with low \((V = 90)\) and medium \((V = 600)\) values. Because the expected value of an item is only 630 points, even after a 50% mark-up it isn’t worth enough to make the bid profitable. The expected loss is large, 255 points, and Buyers lose money for two thirds of their bids. Similar reasoning for a medium bid of 600 yields an expected loss of 82.5 points. Unlike a high bid, however, feedback isn’t going to make it obvious that a bid of 600 is a bad idea, because bids make money as often as they lose money and the expected loss isn’t enormous. Learning to bid 90 is going to be difficult unless the Buyer recognizes the adverse selection problem and realizes that the only way to avoid losing money is to bid at the lowest possible value.

Table 1 about here

Our version of the takeover game borrows important features from Charness and Levin’s (2009) “shifted” versions of the takeover game. The optimal bid of \(B = 90\) earns the Buyer a small but steady profit. This avoids a problem with many versions of the takeover game where optimal play calls for earning no money and essentially taking no actions by never buying the item. Under these circumstances, action bias (Patt and Zeckhauser, 2000) becomes a plausible cause of overbidding that cannot be attributed to a failure to understand the expected payoffs of various bids. Setting a positive minimum value also means that the optimal bid isn’t at the edge of the set of available bids. If pure errors play a role, it is possible to make an error that leads to underbidding as well as errors that lead to overbidding.

3) Experimental Design

Our experiment consisted of two parts. The first part, covering Rounds 1 – 10, was identical in all treatments. The second part (Rounds 11 – 40) differed across treatments. The initial instructions explained only Part 1, including three questions to check for understanding (see the appendix for the instructions). Instructions for Part 2 were distributed after the conclusion of Part 1.

In Part 1, all subjects were in the role of Buyers. Sellers were computerized and always sold the indivisible item if the Buyer’s bid was equal to or larger than the item’s value in a given period. Buyers knew about this rule. Each subject received starting capital of 12 Euros (3000 experimental points) for Part 1 from which possible losses could be covered.\(^4\) After each round, subjects got feedback about the item’s value, whether they had bought the item or not, and how large their profit was.

\(^4\) The 21 subjects who finished Part 1 with a negative balance, in spite of the starting capital, were allowed to continue to Part 2. These subjects were told that their Part 1 losses could be recouped in Part 2. Since all subjects received additional starting capital at the beginning of Part 2, only four Buyers started Part 2 with a net negative balance. If someone still had a loss after Part 2, it was not enforced. This was never mentioned in advance. There were 34 subjects (5.7%) who ended the experiment in the red. The majority of these subjects (21 of 33) come from the Control treatment.
In Part 2 we introduced five different treatments which are explained in the following.

1) **Control.** In this treatment, Rounds 11 – 40 were identical in structure to Rounds 1 – 10. Hence, all subjects remained in the role of Buyers, and Sellers were again computerized. This treatment serves as a benchmark for the possible effects of forming pairs of Buyers and Sellers in the following treatments. Buyers received an additional 10 Euros (2500 experimental points) of capital at the start of Part 2.

2) **No Chat - Random.** Here – and in the other treatments remaining to be introduced – we randomly assigned pairs of subjects to be teammates at the beginning of Part 2. In the **No Chat - Random** treatment, one teammate was randomly assigned to the role of Buyer in Rounds 11 – 40, and the other was assigned to the role of Seller. Subjects were informed about their roles before Round 11, and roles were fixed throughout Part 2. In this treatment and in the others to follow, a Buyer never played the takeover game against the Seller who was his teammate. This was common knowledge. Before Round 11 started, subjects in both roles were asked to enter some information about them that was then shown to their teammate. This information included age, gender, field of study, population of the hometown, working status, experience in experiments, grades in math and German from high school exit exams (“Maturanoten”). For a more detailed description of what data was gathered, see Table A.1 in the Appendix. In addition to this information, each member in the pair was informed about their teammate’s total profit in Part 1. They were not shown the specific bids and values that led to the Part 1 profits. Other than this exchange of information, there was no opportunity for communication between the Buyer and the Seller in a team.

For Part 2, Buyers received 10 Euros (2500 experimental points) as additional starting capital, and Sellers received 2 Euros (500 experimental points). The total profits of a team’s Buyer and Seller in Part 2, including the starting capital, were divided equally between the teammates at the end of Part 2. This feature was stressed in the instructions for Part 2. The feedback after each period in Part 2 was the same as in Part 1 for subjects in the role of Buyer. Sellers got as feedback the bid of the Buyer with whom they were paired in a given period (recall, this was never the Buyer from the Seller’s team), the item’s value, whether the Seller had sold the item, and the resulting profit. Subjects did not receive feedback about their teammate’s outcome.

3) **Chat - Random.** This treatment is identical to **No Chat - Random**, except that before Rounds 11, 21, and 31 the Buyer and the Seller in a team were allowed to chat with each other through an

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5 We, nevertheless, used the 10 Euros starting capital for Buyers (and 2 Euros for Sellers) in order to keep the conditions for Buyers identical across treatments, because in the **Control** treatment they also received 10 Euros for Part 2.
instant messaging program. Hence, although the roles within a team were again assigned randomly, Buyers and Sellers could exchange information and talk about the strategy they wanted to play. The chat was restricted to five minutes, which pilot sessions indicated was more than adequate time for a full discussion of the relevant issues. Subjects were free to say what they wanted in their communication, except for revealing their identity or using abusive language.

4) **No Chat – Endogenous.** This treatment differs from **No Chat - Random** only in the way the roles within each team were determined, but is identical in every other respect. After seeing the information (age, gender, etc.) about the other member of the team, each member could make proposals about how to assign roles by clicking on a specific assignment on the computer screen and sending the proposal to the other member. Proposals for role assignment could be accompanied by selecting from a pre-arranged list of reasons. Possible reasons were (i) because one member did better in Part 1, (ii) because a particular role was easier to play, (iii), because a particular role was more fun, and (iv) because a subject did not like to take risks. These four reasons were the most common justifications for wanting a particular role in the Chat-Endogenous treatment (see below). Subjects were free to send as many messages back and forth as they wanted within a two minute window. Pretesting indicated that this was more than sufficient time for teams to exchange messages. The idea was to let subjects communicate about role assignment, as in the Chat-Endogenous treatment, but to eliminate any possibility of discussing how to bid.

After the two minutes for communication were over, subjects had to enter which role they wanted. If both teammates entered the same role, implying a conflict of interest, the role assignment was randomly determined. Otherwise, roles were assigned as requested by the teammates.

5) **Chat – Endogenous.** This treatment is identical to **Chat - Random**, except that roles were determined endogenously within each team. After the five minutes of chat before Round 11, the teammates were assigned roles using the same mechanism as in **No Chat – Endogenous** (teammates simultaneously enter which role they want, and conflicts are resolved randomly). The instructions for the chat gave subjects no guidance on the content of their discussions, but they did know how roles would be assigned prior to beginning the chat and most teams discussed role assignment. Note that the assignment of roles could not be changed during the chats before Rounds 21 and 31.

The experiment was run with a total of 592 participants, all of them students at the University of Innsbruck (which has a total of about 28,000 students). Recruitment was done using ORSEE (Greiner, 2004), and the sessions were computerized with zTree (Fischbacher, 2007). We had 112 participants in
treatment Control, and 120 in each of the other four treatments. No subject participated in more than one session. On average, an experimental session lasted about 90 minutes. The average earnings per subject were 17 Euros.

4) Hypotheses

A bid of 90 maximizes expected value assuming no errors on the part of Sellers. If we make the more realistic assumption that some sellers will reject bids that yield them very small profits, a rational but risk averse individual would choose a slightly higher bid than 90. We therefore define a Buyer as submitting an “optimal bid” if he bids in the range $90 \leq B < 135$. Only bids in this range have positive expected value in theory, and in practice bids in this range are clearly payoff maximizing (as will be shown in Section 5). Given the results of previous studies on the winner’s curse and the takeover game, we anticipate subjects will have difficulty learning to bid optimally. While some Buyers no doubt stumble on optimal bidding by chance, having the basic insight of adverse selection should lead directly to bidding optimally. Moreover, once gained this insight is easily transmitted to a teammate. Optimal bidding therefore falls roughly into the class of “eureka” problems – difficult problems whose solution can be easily explained to another individual once the underlying logic is understood.

Comparing the Control and No Chat – Random treatments, differences in bidding can occur because Buyers in the No Chat – Random treatment share their payoffs with a teammate or because computerized Sellers do not make errors while humans potentially do. The latter possibility can largely be dismissed, as documented in Section 5. Sharing payoffs could lead to more substantial differences in bidding. Suppose that the effort spent on figuring out how to bid optimally is costly. If we assume that our subjects are largely self-regarding (i.e. put little weight on the payoffs of others), the rewards from learning to bid optimally are larger when Buyers keep their entire payoff rather than sharing it with a teammate. Combined with effort costs, this implies that bids will be lower in the Control treatment than in the No Chat – Random treatment.

Hypothesis 1: Bids will be lower in Rounds 11 – 40 of the Control treatment than in the No Chat – Random treatment.

In treatments with chat, the Buyer and Seller in a team get multiple possibilities to discuss bidding. If the Seller has learned to bid optimally and understands why this is a good strategy (i.e. understands the adverse selection), she should communicate her insights to the Buyer since profits are shared. Even if the Buyer has not previously learned to bid optimally, he should recognize the optimal strategy when it is

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6 Most optimal bids are in the lower part of this range; 93% of optimal bids are in the range 90 – 100.
7 The Wason selection task (Wason, 1966) is an archetypical example of a eureka problems. See Maciejovsky and Budescu (2007) for a discussion of teams solving the Wason selection task.
explained to him and bid optimally in the future. This is the essence of the “truth-wins” model of team decision making pioneered by Lorge and Solomon (1955). A freely communicating team should perform no worse at solving eureka problems than the most able member of the team would perform. Although the truth-wins model is often too optimistic about the performance of teams, experimental studies by economists and psychologists universally find that teams outperform individuals at solving eureka problems since at least some useful sharing of insights takes place between teammates.\(^8\) This implies that bids will be lower in treatments with chat than the corresponding treatments without chat.

**Hypothesis 2:** Bids will be lower in Rounds 11 – 40 in treatments with chat than in treatments without chat.

In the treatments with endogenous role assignment it is no longer random who receives the role of Buyer. If the goal is to make as much money as possible, the teammates should attempt to get the most able individual in the role of Buyer since the role of Seller is trivial and, as shall be seen, it matters little who fills this role. The teammates have access to an excellent indicator for who will do a better job as the Buyer – their earnings from the first ten rounds. There is high correlation between earnings in the first ten rounds and bidding low in the first ten rounds, and individuals who bid low in Rounds 1 – 10 also tend to bid low in Rounds 11 – 40.\(^9\) If teams systematically pick the individual who earned more in Rounds 1 – 10 to be the Buyer for Rounds 11 – 40, we expect that they will on average bid lower and earn more in Rounds 11 – 40 than teams with randomly selected roles.

**Hypothesis 3:** Bids will be lower in Rounds 11 – 40 in treatments with endogenous role assignment than in treatments with randomly assigned roles.

We have no clear prediction about how the effect of role assignment should vary when chat is or is not available. On the one hand, having chat may strengthen the selection effect. We have given subjects in **No Chat – Endogenous** a selection of messages that includes the most commonly used justifications for wanting a particular role in **Chat – Endogenous**, but their ability to communicate is still necessarily limited. This limitation could plausibly affect their ability to assign the more able teammate to the Buyer role. On the flip side, role assignment should be less important in **Chat – Endogenous**. Teammates in this treatment have multiple opportunities to communicate. If the Seller is more insightful than the Buyer, she can pass her insights along to the Buyer. It therefore ought to matter less whether the more able individual becomes the Buyer. These two effects, better selection and less importance for

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\(^9\) The correlation between an individual’s average bid and average points earned in Rounds 1 – 10 is -.599. This is statistically significant at the 1% level (t = 17.54). Looking at the **Control** treatment, where nothing changes between Rounds 1 – 10 and Rounds 11 – 40, the correlation between an individual’s average bids in Rounds 1 – 10 and Rounds 11 – 40 is .613 (p < .01).
selection, have opposite signs. Whether endogenous role assignment matters more with or without chat is an empirical question.

5) Results

5.1 Rounds 1 – 10: In all treatments, subjects begin the experiment by playing ten rounds as a Buyer facing the computer in the role of Seller. The cluster of bars on the left side of Figure 1 shows the distribution of bids for Rounds 1 – 10. Bids have been broken into the same seven categories used in Table 1 to show the logic of bidding a low amount. There are four categories (B < 90, 135 ≤ B < 600, 900 ≤ B < 1200, and B ≥ 1800) where the Buyer never earns money unless the Seller makes an error. Choices in these four categories, which can be regarded as unambiguous errors, are rare. The remaining three categories (90 ≤ B < 135, 600 ≤ B < 900, and 1200 ≤ B ≤ 1800) can make money if the right value is drawn. As explained previously, only the first category (90 ≤ B < 135) has positive expected value.

A little less than half of the bids are optimal (90 ≤ B < 135) in the first ten rounds. Many subjects immediately grasp the need to bid optimally, but many don’t. This is a scenario in which team play with communication should help since there will be many matches between an individual who doesn’t bid optimally with a subject who does. Of course, subjects don’t fall neatly into categories of those who “get it” and those who don’t. Only 10% of the subjects never bid optimally in Rounds 1 – 10 and only 17% always bid optimally. Looking at demographic effects on bidding behavior, we find that men bid significantly lower than women (average bids of 366 vs. 425; p < .05 in a regression not shown here) and that subjects with the best math grade bid lower than the other subjects (average bids of 337 vs. 410; p < .05). There is no significant effect from a subject’s age or German score.

5.2 Sellers in Round 11 – 40: Underlying the hypotheses developed in Section 4 is an assumption that Sellers always behave optimally (in terms of maximizing monetary payoffs), accepting bids that are strictly greater than their value and rejecting bids strictly less than their value. In the Control treatment this happens by design, and suboptimal decisions by Sellers in the other four treatments are relatively rare. Define an error as rejecting a bid strictly greater than the item’s value or accepting a bid strictly less than the item’s value. Errors are observed for only 4% of observations in Rounds 11 – 40. It was inevitable that human Sellers would make at least some errors. The critical issues are whether the error rate varies across the four treatments with human Sellers and whether errors change the logic in favor of submitting an optimal bid (90 ≤ B < 135). Answering the first question, error rates vary little across
treatments: 4.1% for \textbf{No Chat – Random}, 4.4% in \textbf{Chat – Random}, 2.6% in \textbf{No Chat – Endogenous}, and 3.8% in \textbf{Chat – Endogenous}. The differences between treatments are not significant.\footnote{To test the statistical significance of differences between treatments, we ran a probit regression using all observations with human Sellers where an error was possible (i.e. bid \neq value). The independent variables were treatment dummies (\textbf{Chat – Random}, \textbf{No Chat – Endogenous}, and \textbf{Chat – Endogenous}) and controls for the value, bid, and time period. Using the \textbf{No Chat – Random} treatment as the base, the parameter estimates for the three treatment dummies were .023, -.205, and -.027 with standard errors (corrected for clustering) of .166, .163, and .185. None of the differences between treatments are statistically significant and the three treatment dummies are not jointly significant ($\chi^2 = 2.85; 2$ d.f.; $p > .10$).}

Turning to the second issue, even with Sellers’ errors it remains optimal to submit a bid in the range $90 \leq B < 135$. Across the four treatments with human Sellers, the average payoff in Rounds 11 – 40 from submitting a bid in this range was 21 points which is unambiguously higher than the average payoff from submitting a bid in the range $600 \leq B < 900$ (-89 points) or the range $1200 \leq B < 1800$ (-299 points). For all four treatments with human Sellers the average payoff from submitting a bid in the range $90 \leq B < 135$ is at least 100 points higher than the average payoff from submitting a bid in the range $600 \leq B < 900$. As expected, these differences in payoffs are driven by adverse selection. Subjects who submit bids in the range $600 < B < 900$ almost always get their bid accepted for middle value items (93%). The problem is that these bids are also almost always accepted for low value items (94%) and almost never accepted for high value items (2%).

5.3 Treatment Effects for Buyers: Figure 2 shows average bids by Buyers in all five treatments. The data is broken down into ten round blocks and data is included from Rounds 1 – 10, the rounds before the treatments are in effect, to show the differing starting points for the treatments. The data for Rounds 1 – 10 is taken from all subjects, including those who became Sellers in Rounds 11 – 40.

\begin{figure}[h]
\centering
\caption{Average bids by Buyers in all five treatments.}
\end{figure}


Figures 3 and 4 illustrate two different ways that endogenous role selection could affect bids. First, endogenous role assignment is predicted to reduce bids relative to random role assignment because of selection. Teammates who are better at the difficult problem of bidding should get the more challenging role of Buyer. The best-case scenario is “perfect role assignment,” where the most able individual is \textit{always} assigned the more critical role of Buyer. We did not run a treatment with exogenously imposed
perfect role assignment, but our design makes it possible to replicate what data from such a treatment would have looked like. Using bids in Rounds 1 – 10 as a proxy for ability as a Buyer, we can replicate a treatment with exogenous perfect role assignment by using data from the treatments with random role assignment and selecting only those teams where the low bidder in Rounds 1 – 10 is randomly assigned the Buyer role.\footnote{This subsample replicates exogenous perfect role assignment because there is no selection affecting whether the low bidder becomes the Buyer or the Seller.} Data from this subsample provides a baseline for how well endogenous role selection would have performed if it had no effect on learning and yielded perfect role selection.

Figure 3 displays average bids from the two treatments with random role assignment (solid lines) along with average bids from the subset of teams in these treatments where the low bidder in Rounds 1 – 10 became the Buyer (dashed lines). Arrows have been added to make it easier to see the effects of endogenous role assignment. In both cases, perfect role assignment leads to far lower bids in Rounds 11 – 40 than random role assignment. If the only effect of endogenous role assignment was to always get the right teammate into the Buyer role, we should have seen a clear reduction in bids consistent with Hypothesis 3.

Figure 3 about here

Perfect role assignment is probably too much to hope for, but, as is shown in Section 5.4, the endogenous role assignment treatments did lead to significant selection in favor of the teammate who bid less in Rounds 1 – 10. The reason that the endogenous role assignment treatments do not reduce bids is because they also affect learning.

Figure 4 about here

The effect of endogenous role assignment on learning is illustrated by Figure 4. This figure is based on bids from all treatments except the control treatment. Treatments are paired by whether or not chat is available (No Chat – Random vs No Chat – Endogenous and Chat – Random vs. Chat – Endogenous) to isolate effects due to endogenous role assignment. For the treatments with random role assignment the graph shows the average bids of subjects who were assigned the roles of Buyers in Rounds 11 – 40 broken down by ten round blocks. Note that this differs from Figure 2, which displays the average bids of all subjects in Rounds 1 – 10. For the treatments with endogenous role assignment, the average bids in Rounds 1 – 10 are adjusted to equal those in the paired treatment with random role assignment. (The starting points for the two treatments with random role assignment were very similar, so it appears that the four treatments are starting at the same point.) In subsequent ten round blocks the average bids are changed as they did in the real data from the endogenous role assignment treatments. Figure 4 therefore shows how the data would evolve if endogenous role assignment had no effect on role
selection (yielding equal starting positions), leaving only the effect on learning. Arrows have again been added to make it easier to see the effects of endogenous role assignment. Endogenous role assignment slows the learning process both with and without chat, with the effect being somewhat larger with chat. This unexpected harmful effect of endogenous role assignment on learning counteracts the positive effect of better role assignment and drives the most surprising result of our paper, the failure of Hypothesis 3.

As a secondary point, Figure 4 shows that the effect of endogenous role assignment, after eliminating effects due to selection, is not vanishing with experience. It narrows slightly with chat and grows somewhat without chat, but both changes are small. Even though endogenous role selection only comes into play at one point in time relatively early in the experiment, Buyers never seem to catch up from the disruption that it causes.

Table 2 about here

The regressions reported in Table 2 are designed to analyze the data in more detail. The dataset for these regressions includes all observations from our data. The dependent variable is the amount bid by the Buyer. Robust standard errors are reported in parentheses.

An obvious feature of the data is strong individual effects. To correct for these, all of the models use a linear specification with fixed effects. The fixed effects are identified from choices in Rounds 1 – 10, before any of the treatments take effect. The first row of Table 2 identifies the unit being used for the fixed effects: Models 1 and 3 use fixed effects identified from early choices (Rounds 1 – 10) by both members of a team while Models 2 and 4 use fixed effects based only on early choices by the teammate who ended up in the Buyer role for Rounds 11 – 40. The different methods allow us to isolate how much of the observed treatment effects are due to changes in the learning process. If the fixed effects are at the team level (Models 1 and 3), the estimated effects of endogenous role assignment include the impact through selection and the impact through changes in the learning process because the fixed effects correction does not account for the possibility that Buyers in the No Chat – Endogenous and Chat – Endogenous treatments bid systematically lower than their teammates in Rounds 1 – 10. The estimated differences in Models 1 and 3 parallel those observed in Figure 2. The estimated treatment effects only reflect effects due to changes in the learning process when the fixed effect is at the Buyer level (Models 2 and 4) since the regression now accounts for the differing behavior of Buyers and Sellers in Rounds 1 – 10 with endogenous role assignment. The estimated treatment effects in Models 2 and 4 are analogous to those shown in Figure 4.

Models 1 and 2 are basic regressions checking whether the effects of chat and endogenous role assignment are significant. A dummy is included for Rounds 11 – 40 as well as interactions between the dummy for Rounds 11 – 40 and dummies for the Control treatment, the treatments with chat (Chat –
Random and Chat – Endogenous), and the treatments with endogenous role assignment (No Chat – Endogenous and Chat – Endogenous). These interaction terms are the critical variables that allow us to test Hypotheses 1 – 3.¹²

The results of Models 1 and 2 provide little support for Hypothesis 1. Bids in Rounds 11 – 40 are lower in the Control treatment than in the No Chat – Random treatment, but the effect is weak and not statistically significant. Hypothesis 2 receives strong support from the data, as bids in Rounds 11 – 40 are significantly lower in the treatments with chat for both Models 1 and 2. The big surprise is how badly Hypothesis 3 does. If this hypothesis is correct, the estimate for “Rounds 11 – 40 * Endogenous Roles” should be negative and significant in Model 1 where the effects of selection work in favor of finding a reduction in bids due to endogenous role assignment. Instead, the estimated effect in Model 1 is small and positive. When effects due to selection are eliminated by having fixed effects at the Buyer level (Model 2), the effect of endogenous role assignment on bids for Rounds 11 – 40 becomes significant and positive. Combining the results from Models 1 and 2, the benefits of selection with endogenous role assignment are more than counter-balanced by the unexpected harmful effects on learning.

Models 3 and 4 modify Models 1 and 2, respectively, by adding controls for the Buyers’ demographic characteristics: gender (0 = male, 1 = female), age, math score, and German score. For the math and German scores, lower numbers indicate better grades. All of these variables are interacted with the dummy for Part 2 (Rounds 11 – 40) to avoid collinearity with the fixed effects. The results of Models 3 and 4 parallel those of Models 1 and 2 as far as Hypotheses 1 – 3 are concerned. Looking at the estimates for the demographic variables, gender is negative and significant. This doesn’t mean that women bid lower than men in Rounds 11 – 40, but rather that women are catching up over time. Recall that women bid significantly higher than men in Rounds 1 – 10, a difference which is soaked up by the fixed effects in the regressions. In Rounds 11 – 40, average bids are essentially identical for men and women (296 for men vs. 299 for women). None of the other demographic variables are statistically significant in either Model 3 or Model 4.¹³

In developing hypotheses about the treatment effects, we noted the lack of a clear prediction about how the effect of endogenous role assignment would vary depending on whether or not chat was available. To check whether or not the effect varies in practice, we’ve modified Models 3 and 4 to separately estimate the effect of endogenous role assignment with and without chat (see Table A.2 in the appendix for these regressions). The effect of endogenous role assignment is larger with chat regardless

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¹² The interaction with the dummy for Rounds 11 - 40 is necessary to avoid collinearity with the fixed effects.
¹³ These results are robust to restricting the sample to the three treatments without chat (i.e. the cases where the effects of a Buyers’ characteristics cannot be affected by interaction with the Seller).
of whether the fixed effects are at the team or Buyer level, but in neither model is the difference between the effects with and without chat statistically significant.\textsuperscript{14}

We’ve also modified Models 3 and 4 by interacting the dummies for Control, chat, and endogenous role selection with dummies for each ten round block. This lets us see whether the treatment effects fade with experience. The results of these modified regressions are consistent with the results of Models 3 and 4. Specifically, consistent with our discussion of Figure 4, the effect of endogenous role selection, after controlling for any effects due to selection, does not get weaker with experience.

We summarize the results up to this point by revisiting our initial hypotheses. The following conclusions refer to bids in Rounds 11 – 40.

\textit{Conclusion 1:} Bids are lower in the Control treatment than in the No Chat – Random treatment, but the differences are generally small and not statistically significant. We find little support for Hypothesis 1.

\textit{Conclusion 2:} Bids are lower in treatments with chat than in the corresponding treatments without chat. The data supports Hypothesis 2.

\textit{Conclusion 3:} Bids are higher in treatments with endogenous role assignment than in the corresponding treatments with random role assignment. This difference is significant when effects due to changes in the learning process are isolated. The data provides no support for Hypothesis 3, and instead indicates that endogenous role assignment harms the ability of Buyers to learn the optimal bidding strategy.

\textbf{5.4 Comparing Buyers to Sellers in the Endogenous Role Assignment Treatments:} This subsection examines more closely how roles are assigned in the two treatments with endogenous role assignment. Table 3 compares Buyers and Sellers along a number of dimensions. Recall that prior to selecting a Buyer the subjects were given information about their teammate’s age, gender, math score, German score, and earnings in Rounds 1 – 10. Table 3 shows, for each of these characteristics, the median values (except for gender where we report the proportion of women) for subjects who ended up in the roles of Buyer and Seller broken down by treatment. The final row of Table 3 shows the median of an individual’s average bids in Rounds 1 – 10.\textsuperscript{15} Although subjects did not know the average bids of their teammate in Rounds 1 – 10, this is a natural measure of who showed more ability in the early rounds. For each characteristic in each treatment, we ran a Wilcoxon signed rank test of the null hypothesis that the median difference between the Buyer and Seller in a pair equals zero.\textsuperscript{16}

\textit{Table 3 about here}

\textsuperscript{14} The respective differences are 88.22 and 57.74 with standard errors of 52.31 and 57.37.

\textsuperscript{15} For each subject we calculate the average bid in Rounds 1 – 10. For each cell we report the median of these average bids.

\textsuperscript{16} The number of observations for each test is 60, the number of pairs in each treatment. An observation consists of the difference between the Buyer and Seller in a pair for the characteristic in question.
The demographic characteristics do not differ significantly between Buyers and Sellers with one exception: in No Chat – Endogenous women are less likely to become Buyers with the difference being weakly significant. More importantly, endogenous role assignment systematically puts the teammate who did a better job of bidding in Rounds 1 – 10 into the Buyer role. Average bids in Rounds 1 - 10 are a more accurate measure of performance as a Buyer than earnings since the latter are partially a matter of luck. Buyers’ average bids in Rounds 1 – 10 are significantly lower than the Sellers’ average bid in both No Chat – Endogenous and Chat – Endogenous. For 41 of 58 pairs (71%) in No Chat – Endogenous and 39 of 60 pairs (65%) in Chat – Endogenous, the subject who bid less in Rounds 1 – 10 became the Buyer. Hypothesis 3 is based on an assumption that endogenous role assignment leads to more able individuals being selected into the Buyer role. This underlying assumption holds for both treatments with endogenous role assignment. The weak effect of endogenous role assignment on bids in Rounds 11 – 40 can not be attributed to a lack of selection.

Conclusion 4: In both treatments with endogenous role assignment, Buyers bid significantly less in Rounds 1 – 10 than the Sellers they are paired with.

5.5 Does It Matter Who Becomes the Buyer? It would matter little whether Buyers bid less than Sellers for Rounds 1 – 10 if teams performed the same regardless of which teammate took which role. Figure 5 shows otherwise. This figure compares the average bid in Rounds 11 – 40 for teams where the teammate who bid (strictly) lower on average in Rounds 1 – 10 becomes the Buyer with teams where the teammate who bid lower becomes the Seller. The data is subdivided into the two treatments with teams and no chat (No Chat – Random and No Chat – Endogenous) and the two treatments with teams and chat (Chat – Random and Chat – Endogenous).

In both cases the average bid for Rounds 11 – 40 is lower when the teammate who bid lower in Rounds 1 – 10 is given the role of Buyer, but the effect is quite a bit stronger in the treatments without chat than in those with chat. With chat, a Seller who understands the benefits of bidding low can pass this understanding on to the Buyer. This should lead to lower bids and average bids depending less on the identity of the Buyer with chat, exactly the patterns observed in Figure 5. The extreme case of this is the truth wins model, which predicts that the identity of the Buyer is irrelevant in the treatments with chat.
because Buyers and Sellers will perfectly share their insights. The data shown in Figure 5 is not consistent with this prediction.

Table 4 about here

The regressions shown in Table 4 put the preceding observations on a firm statistical footing and further explore the performance of the truth wins model. For both regressions the dependent variable is a team’s average bid for Rounds 11 – 40, yielding a single observation per team. Model 1 includes data from all four treatments with teams. The independent variables are a dummy for the two treatments with chat, an interaction between a dummy for treatments without chat and a dummy for teams where the Buyer is the teammate who bid lower (on average) in Rounds 1 – 10, and an interaction between a dummy for treatments with chat and a dummy for teams where the Buyer is the teammate who bid lower (on average) in Rounds 1 – 10. The parameter estimate for the first of the interaction terms is large and significant at the 1% level. Not surprisingly, bids in Rounds 11 – 40 are very sensitive to the Buyer’s identity when the teammates cannot communicate. The parameter estimate for the second interaction term is smaller, but still significant at the 5% level. Consistent with our impression from Figure 5, who becomes the Buyer is less important when teammates can chat, but still matters.

Model 2 only includes data from the two treatments with chat. The independent variables are the Buyer’s and Seller’s average bids for Rounds 1 – 10 interacted with dummies for the Buyer being the low bidder (on average) in Rounds 1 – 10 and the Seller being the low bidder in Rounds 1 – 10. (Note that we are referring to the Seller who is the Buyer’s teammate, not one of the Sellers he is playing against.) Under the truth wins model, a team’s performance should be equivalent to the performance of its more able member. This implies that bids in Rounds 11 – 40 should depend more strongly on the bids in Rounds 1 – 10 of the teammate who bid lower (and hence is presumably more able). When the Buyer was the low bidder, this prediction is confirmed. The estimate for the Buyer’s average bid in Rounds 1 – 10 is significant at the 5% level while the estimate for the Seller’s average bid is smaller and not significant. The results do not look as good for the truth wins model if the Seller was the low bidder. The estimate for the Buyer’s average bid is now significant at the 1% level. The effect of the Seller’s average bid once again is small and not significant. Even if the Seller was the more able bidder in Rounds 1 – 10 and the Seller can communicate her insights with the Buyer, bids in Rounds 11 – 40 are more strongly influenced by the Buyer’s early behavior than the Seller’s. Moreover, the relationship between bids in Rounds 11 – 40 and bids by the Buyer and Seller in Rounds 1 – 10 does not depend on whether the Buyer or the Seller

19 The fixed effect approach used in Table 2 isn’t feasible here, since the fixed effects would be collinear with the independent variables.
bid lower in Rounds 1 – 10. “Buyer wins” would be a more accurate description of our data than “truth wins”. It follows that even with chat it matters which teammate is chosen as the Buyer.

While the truth wins model performs poorly, the sellers’ advice does have some impact on bidding. If we rerun Model 2 without the interaction terms for which teammate was the low bidder (i.e. the only independent variables are the Buyer’s and Seller’s average bids for Rounds 1 – 10), the estimated effect of the Seller’s average bid in Rounds 1 – 10, while much smaller than the effect of the Buyer’s average bid, is significant at the 10% level.\footnote{The parameter estimates for the Buyer and Seller average bids in Rounds 1 – 10 were .302 and .120 with standard errors of .065 and .066.}

**Conclusion 5:** Both without and with chat, teams where the Buyer bid lower than the Seller in Rounds 1 – 10 have lower bids in Rounds 11 – 40. Even with chat, bids in Rounds 11 – 40 depend more on the Buyer’s behavior in Rounds 1 – 10 than the Seller’s early behavior.

### 5.6 Content of Conversations:

When Buyers are randomly selected, chat improves the quality of bidding, albeit less than the truth wins model would suggest. Given that the more able teammate, as measured by bids in Rounds 1 – 10, generally ends up as the Buyer in the Chat – Endogenous treatment, we would expect that bids would be even lower in this treatment than in the Chat – Random treatment. The fact that bids are *higher* in the Chat – Endogenous treatment, significantly so if we control for selection into the Buyer role, suggests that something must be going wrong in the interaction between teammates. To determine what exactly causes the problem, we turn to the content of the conversation between teammates.

We focus on the conversations that took place between Round 10 and Round 11. As can be seen in Figure 4, this is where the major divergence between the two chat treatments occurs. Recall that subjects were given five minutes to chat and could not move on to the next stage of the experiment until the five minutes had elapsed. The goal was to give subjects adequate time to discuss how to bid and (when relevant) role assignment without any incentive to rush through the conversation to make the experiment shorter. Subjects indeed chatted extensively, with the average team sending 25.0 messages during the five minutes. Teams in the Chat – Random treatment sent slightly more messages on average than teams in the Chat – Endogenous treatment, 26.2 vs. 23.8 ($t = 1.41; p = 0.161$), even though teams in the Chat – Random treatment did not need to discuss who took which role.

Looking at what teams said, we see significant differences between the two chat treatments. We coded every team for whether they discussed how to bid and, as a subcategory of this, if they specifically discussed the benefits of optimal bids. The coding was initially done independently by two research assistants. We then had the two coders discuss all the discrepancies in the coding and agree on a single decision for coding. This final coding was used for the analysis to be reported in the following. We
allowed for the possibility that even after discussion the coders would not agree on a coding. In these rare cases (1 observation) the coding was assigned a value of $\frac{1}{2}$. Using a single coding simplifies our discussion of the chat content but has little effect on our conclusions since there was a high degree of agreement between the two initial codings.\footnote{The cross-coder correlation was 0.55 for the category “discussed how to bid” and 0.49 for “bidding low”, both significant at the 5\% level. An average cross-coder correlation of around 0.5 (as in our case) is well accepted in social psychology (see, e.g., Orbell et al., 1988).}

In the **Chat – Random** treatment, 78\% of the teams discussed how to bid, but in the **Chat – Endogenous** treatment only 61\% of the teams did so. This difference is significant at the 5\% level ($t = 2.12; p = .036$). Even stronger, more teams specifically discussed optimal bidding in the **Chat – Random** treatment (63\%) than in the **Chat – Endogenous** treatment (35\%) with the difference significant at the 1\% level ($t = 3.12; p = .002$). Teams in **Chat – Endogenous** do a poor job of discussing how to play the takeover game, helping to explain why endogenous role selection harms Buyers’ ability to learn to bid optimally.

One possible explanation for the relative lack of substantive conversations in the **Chat – Endogenous** treatment is the time constraint. Even with the generous time provided for chat, if teams spend most of this time discussing who should take which role it may leave insufficient time to discuss how to bid. Two features of the data argue that the time constraint does not play an important role in reducing discussions of bidding. First, the chat content for teams that talk up to the time constraint isn’t much different from those who do not. The 41 teams in the **Chat – Endogenous** treatment that sent a message in the last 20 seconds (and hence were possibly time constrained) were slightly, but insignificantly, more likely than average to have discussed how to bid (65\% vs. 61\% for all 60 teams) and to have specifically discussed bidding low (37\% vs. 35\% for all 60 teams). Second, the vast majority of the discussions on role assignment were short. The most common pattern was that one of the teammates proposed a role, the other accepted the proposal, and they moved on to other things.\footnote{The following exchange is typical:}

Subject A: Seller or buyer?
Subject B: buyer
Subject A: ok
Subject B: ok

The relative failure of teams in the **Chat – Endogenous** treatment to discuss bidding in general, especially bidding low, largely explains why bids are significantly higher than in the **Chat – Random** treatment after controlling for selection into the Buyer role. With Buyer fixed effects, the estimated difference between the two chat treatments in Rounds 11 – 40 is 89.22 with a robust standard error of 45.80 (see Table A.2 in the appendix). If this regression is modified to include a control for whether the
team discussed optimal bidding, the estimated difference drops to 46.90 with a robust standard error of 44.76. The difference between the treatments is halved and is no longer statistically significant. Hence, even with a fairly crude control for what is being said between Rounds 10 and 11, a large fraction of the higher bids in Chat – Endogenous relative to Chat – Random can be accounted for.

**Conclusion 6:** Teams in Chat – Endogenous send significantly fewer messages between Rounds 10 and 11, are significantly less likely to discuss bidding, and are significantly less likely to discuss optimal bids than teams in Chat – Random. Controlling for differences in chat content explains a large fraction of why bids are significantly higher in Chat – Endogenous than in Chat – Random after controlling for selection.

Although the teammate who bid lower in Rounds 1 – 10 was significantly more likely to become the Buyer in both treatments with endogenous role assignment, this was far from universal. Pooling across the two treatments, almost a third of the teams (38/118) picked the individual who bid higher in Rounds 1 – 10 as the Buyer. These failures cannot be attributed to small differences in average bidding, as the difference in average bids was greater than 100 for 28 of the 38 teams where the low bidder did not become the Buyer. The message content helps explain why the low bidder did not always become the Buyer.

Almost all of the teams (54/60) in Chat – Endogenous discussed which teammate should be the Buyer, but impasses where teammates failed to implement an agreement on roles are not uncommon (18/54). Even among the 36 teams who successfully implemented an agreement on roles, 11 chose the teammate who bid higher in Rounds 1 – 10 as the Buyer. The discussions of role assignment are typically brief and often miss basic points. For example, only 9 teams discussed performance in Rounds 1 – 10 as a reason for assigning roles. Not only did endogenous role assignment harm teams’ discussion of how to bid, but they also had low quality discussions about who should be the Buyer.

The discussion of role assignment went a little better in No Chat – Endogenous, but not much. Every team sent at least some messages, with an average of 3.7 messages sent between teammates. Most teams reached an agreement (42/60), and most of those agreements were justified on the basis of who had performed better in Rounds 1 – 10 (28/42). This sounds good until you notice that less than half the teams reached an agreement based on performance in the early rounds! In this light, it is surprising that teams did as well as they did at assigning the low bidder to the role of Buyer.

**6) Conclusion**

The primary purpose of our study was to investigate the relationship between how roles are assigned within a work team and team performance when teams consist of pairs where one member has a considerably more difficult task than the other member. We found that teams perform better when team
members can communicate with each other and share information and discuss strategies. When team members are also allowed to assign roles endogenously, this feature has a positive effect on role assignment, leading to assigning the more able persons to the more difficult Buyer role. However, controlling for this selection, we find that endogenous role assignment increases Buyers’ bids, completely counteracting the helpful effects of selection. The latter result is surprising and casts doubt on whether self-management of teams and internal role assignment is good for team performance and thus for companies in general.

Our results suggest some counter-intuitive advice for the assignment of tasks in teams. It is common wisdom that more employee involvement is better and that top-down management is counter-productive. There is certainly some truth to these assertions (see Ichniowski and Shaw, 1999), but traditional top-down management may not be entirely bad. When employees actively participate in choosing their roles, this increases the number of tasks that they need to perform. If there is interference between tasks and managers are reasonably well informed about workers’ abilities, exogenously assigning roles may free up employees’ attention to focus on more critical tasks.

A final question is why endogenous role assignment has a negative effect on Buyers’ performance. This effect was unexpected, so our experiments aren’t designed to answer this question per se. Nonetheless, the experimental design and data allow us to eliminate some possibilities. Time constraints do not explain the effect, since subjects are given more than adequate time for discussion, only hold brief discussions about role assignment, and do not appear to behave any differently in teams where the time constraint binds. The fact that the effect isn’t dying out also suggests that the issue is not time constraints. Monetary incentives are held constant between sessions with random and endogenous role assignment, and therefore cannot explain the effect. Another possibility is that Buyers didn’t want the role, and are bidding higher to intentionally harm their teammate. Given that we don’t observe dialogues where teammates fight over who should get the Seller role, this seems unlikely. This leaves us with the possibility raised in the introduction. Having subjects responsible for assigning roles increases their cognitive load. With less cognitive resources available to think about bidding, we see less rational behavior both in terms of the discussions and actual bids. Subject to confirmation in future sessions, we observe a well-known psychological factor having a major economic impact in an experiment that was not designed to generate an effect due to cognitive load. This suggests the need for further study of how loading employees with extra tasks, even ones that they might view as desirable, can harm their performance.
References


### Tables and Figures

#### Table 1: Bidding strategies

<table>
<thead>
<tr>
<th>Bid</th>
<th>Value 90</th>
<th>Value 600</th>
<th>Value 1200</th>
<th>1.5 * Expected Value if Accepted</th>
<th>Ever Profitable?</th>
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<td>Reject</td>
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<td>Accept</td>
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#### Table 2: Regressions for Treatment Effects

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1 Team</th>
<th>Model 2 Buyer</th>
<th>Model 3 Team</th>
<th>Model 4 Buyer</th>
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<td>Rounds 11 - 40</td>
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<td>-95.30***</td>
<td>-24.07</td>
<td>-41.67</td>
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<td>(24.07)</td>
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<td>Rounds 11 – 40 * Gender</td>
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<td>72.91***</td>
<td>2.48</td>
<td>60.74**</td>
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<td>(29.18)</td>
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<td>Endogenous Roles</td>
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<td>(22.92)</td>
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<td></td>
<td>(5.29)</td>
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<td>Rounds 11 – 40 * Math Score</td>
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<td></td>
<td>(13.25)</td>
<td>(13.04)</td>
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</table>

Notes: All regressions include 16,480 observations from 592 individuals (352 teams). Robust standard errors are reported in parentheses. Three (***) , two (**) , and one (*) stars indicate statistical significance at the 1%, 5%, and 10% levels respectively.
Table 3: Median Characteristics of Buyers and Sellers

<table>
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<tr>
<th></th>
<th>No Chat – Endogenous</th>
<th>Chat – Endogenous</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Buyer</td>
<td>Seller</td>
</tr>
<tr>
<td>Age (in categories)(^a)</td>
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</tr>
<tr>
<td>Gender(^b)</td>
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<td>.483</td>
</tr>
<tr>
<td>Math Score(^c)</td>
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</tr>
<tr>
<td>German Score(^c)</td>
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<td>2.0</td>
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<td>Earnings Rounds 1 – 10(^d)</td>
<td>67.0</td>
<td>-642.5</td>
</tr>
<tr>
<td>Bid, Rounds. 1 - 10</td>
<td>318.5</td>
<td>447.2</td>
</tr>
</tbody>
</table>

Notes: Three (***) and two (**) stars indicate statistical significance at the 1%, 5%, and 10% levels respectively.

\(^a\) Age was coded as follows: 0=18 years or younger; 1=19 years; 2=20 years; 3=21 years; 4=22 years; 5=23 years; 6=24 years; 7=25 years; 8=26 years or older.

\(^b\) Gender was coded as follows: 0 = Male; 1 = Female.

\(^c\) Lower grades are better in the Austrian school system. Grades were coded from 1 to 5.

\(^d\) Earnings do not include the starting capital of 3000 experimental points.
<table>
<thead>
<tr>
<th>Dataset</th>
<th>Model 1</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Team Sessions</td>
<td>Chat Sessions</td>
</tr>
<tr>
<td># Subjects</td>
<td>240</td>
<td>120</td>
</tr>
<tr>
<td>Chat</td>
<td>-83.71*** (26.63)</td>
<td>\n</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors are reported in parentheses. Three (***), two (**), and one (*) stars indicate statistical significance at the 1%, 5%, and 10% levels respectively.
Figure 5: The Effect of Buyer Selection

[Bar chart showing the average bid for periods 11-40 for 'No Chat' and 'Chat' conditions. The chart compares buyer bids that are lower in rounds 1-10 and seller bids that are lower in rounds 1-10.]
Appendix – Experimental instructions

Instructions for the experiment

Welcome to this experiment! Thank you for taking your time to participate. Please refrain from talking to other participants until the experiment is finished. In case you have any questions after we have read through the instructions, please raise your hand and an experimenter will come to your seat and will answer it.

Two parts of the experiment
This experiment has two parts. In the following, you’ll get the instructions for part 1. The instructions for part 2 will be distributed at the end of part 1.

Instructions for part 1

Initial endowment
For part 1 you get an initial endowment of 12 €. This endowment will be included in the profit for the first period.

Number of periods
Part 1 has 10 periods. In each single period, you can buy cards, the value of which will be determined randomly. We will now explain the exact procedure within each period.

Submitting bids for a card in each period
In each period, you can submit a bid for a card that has a certain nominal value. This nominal value will be determined randomly in each period. A card can have three possible nominal values (in points):

- 90
- 600
- 1,200

Each of these three values is equally likely to be drawn. In other words, this means that each nominal value will be realized with a probability of 1/3. The realization of nominal values is independent across periods. This means that the realization in the preceding period has no influence whatsoever on the realization in the current period.

You will submit a bid for a card before you learn about the realized nominal value. The bid must be an integer number in the interval from 0 (zero) to 2,000 (with 0 and 2,000 included in the interval). The actual nominal value will be determined after you have submitted your bid.

Profits from bids
If your bid is larger or equal to the nominal value of the card, then you buy the card. In this case you get 150% of the card’s nominal value. However, you also have to buy the card in this case.

If your bid is smaller than the nominal value, then you don’t buy the card. This means that no transaction takes place, and you don’t earn anything in this case.
An example:
Consider the case in which you bid 712 for the card:
1. Assume that the card’s nominal value is 600. In this case, you buy the card. This means that you receive $600 \times 1.5 = 900$ points. You have to pay 712 according to your bid. This yields a profit of 188 (= value of 900 to you as the buyer – bid of 712).
2. Assume that the card’s nominal value is 90. Then you buy the card and it is worth 135 for you (= 90 \times 1.5). In this case your profit is negative: -577 (= 135 – 712).
3. Assume that the card’s nominal value is 1,200. Then you don’t buy the card and this period’s profit is 0 for you.

At the end of each period you will see an "outcome screen", on which there is a list that contains for all previous periods the following information: your bid, the nominal value of the card, whether you have bought the card or not, and the profit.

At the end the experiment all profits of each period will be added up and paid to you. The exchange rate of points earned in the experiment into Euros is the following:

\[
2.5 \text{ Points} = 0.01 \text{ €}.
\]

Some examples to be worked on before the start of part 1

Assume you bid 128 and the card’s nominal value is 90. How much do you earn?

Assume you bid 767 and the card’s nominal value is 1,200. How much do you earn?

Assume you bid 791 and the card’s nominal value is 90. How much do you earn?
Instructions for part 2 (these are for the Chat – Endogenous treatment; instructions for the other treatments are analogous and available upon request)

Roles of buyers and sellers
Part 2 is similar to part 1. However, in this part there will be buyers and sellers of cards. The task that each role has to perform is explained below.

Number of periods
Part 2 has 30 periods.

Fixed pairs and how to assign roles
It is important in this part that at the beginning of it, fixed pairs of buyers and sellers will be formed. These pairs will remain fixed throughout the whole part 2. The fixed pairs have a strong influence on the profits from this part (see more on this at the end of the instructions for part 2!).

At the beginning of part 2 you will have an option to exchange messages with the partner in your pair. For this purpose, we have installed an instant-messaging-program in the software. In order to use it, you have to write your message into the empty row at the bottom of your screen, and then you have to push “Enter” to send your message to your partner. Once you send you send a message, it is shown on your partner’s screen and on your screen (above the empty row). Note that no other participant in the room can see your message.

You can send any message you like, expect for the following limitations:
- Please do not reveal your identity. This also includes information that allows your personal identification.
- Please do not use any abusive language.

Before you can start using the instant-messaging-program, you’ll receive some information about the partner in your pair. More precisely, you’ll be informed about his or her age, gender, field of study, population of hometown, working status, experience with economic experiments and the profit in part 1.

At the end of the 5 minutes of chatting in the instant-messaging-program, you need to indicate whether you would prefer to be buyer or seller. If one person in a pair indicates a preference for being in the role of buyer, and the other person indicates a preference for the role of seller, then the roles will be assigned exactly as preferred by both members of the pair. If this is not the case, then roles will be assigned randomly.

Before period 21 and 31 you will again have 5 minutes time to exchange messages with your partner. Roles may not be changed in the course of communication before these periods, however. As soon as the periods start, no further communication is possible.

Interaction of buyers and sellers
In each period there will be an interaction between a buyer and a seller, in which they decide about buying, or respectively selling, a card. It is very important to note that you will never
interact with the partner in your team! This means that if you are a buyer, for example, you will never trade with the seller in your pair, and vice versa. In each period, it will be randomly determined which buyer will interact with which seller (taking care of the limitation that interaction within pairs is impossible). In each period it is equally likely to interact with any of the participants in the opposite role of yours. Recall that the interaction always takes place with someone from a different pair.

**How to buy a card in each period**

Buyers are in the same situation as all participants were in part 1 of the experiment. In each period you can bid in the role of buyer for a card. The card’s nominal value will be determined randomly as in part 1. To remember: the nominal value may be 90, 600, or 1,200, with equal probability.

In each period, you have to submit a bid as an integer number from 0 to 2,000, including both 0 and 2,000. The card’s nominal value will be determined and revealed after you have placed your bid.

As the **buyer**, you get an initial endowment of **10 €** for part 2, and as **seller** you get **2 €**. This endowment will be added to the profit in the first period of part 2. However, please note the rules for determining payoffs within pairs at the end of this set of instructions!

**Selling a card in each period and profits of the seller**

In the role of seller you are the owner of the card that can be sold in each period and for which the buyer places a bid. You can earn money in the role of seller if you sell the card to the buyer. You will be informed about the card’s nominal value (either 90, 600, or 1,200) and the buyer’s bid before you decide whether or not to sell your card. If you sell the card, then you earn the **buyer’s bid minus the card’s nominal value**. For example, if the card has a nominal value of 600 and the buyer has bid 712, then you earn 112 points if you sell the card. Assume that the card had a nominal value of 600, the buyer bid 457 and you sold it, then you lose 143 points. Whenever you don’t sell the card, then you don’t earn anything in this period, but you also don’t lose anything.

**Profits from buying a card**

As in part 1, a buyer gets 150% of the card’s nominal value if the seller sold it to him or her. Once the seller has sold the card, the buyer has to buy it.

An example:
Assume that in the role of buyer you have bid 712 points and that the realized nominal value is 600:

1. If the seller sells the card, then the buyer earns 188 points ( = 600 * 1,5 – 712)
2. If the seller does not sell the card, then the buyer earns zero.

**Feedback**
At the end of each period you will see an “outcome screen“ on which you’ll see for all previous periods of part 2 the following information: the card’s nominal value, the buyer’s bid, whether the seller has sold the card, and your profit.

**Rules for profits within pairs**
At the end of the experiment, all profits from each period of part 2 will be added up. Then the profits of the buyer and the seller within a pair will be summed and both members of the pair will receive exactly one half of the joint profits from part 2. This includes also sharing the initial endowments from the beginning of part 2. The exchange rate is again:

$$2.5\text{points} = 0.01 \text{€}.$$
Table A.1. Demographic data collected at the end of part 1 of the experiment.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0=18 years or younger; 1=19 years; 2=20 years; 3=21 years; 4=22 years; 5=23 years; 6=24 years; 7=25 years; 8=26 years or older.</td>
</tr>
<tr>
<td>Gender</td>
<td>1=female; 0=male.</td>
</tr>
<tr>
<td>Field of study</td>
<td>0=economics and business; 1=medicine; 2=political science; 3=psychology; 4=sociology; 5=other.</td>
</tr>
<tr>
<td>Population of hometown</td>
<td>0=under 5.000; 1=5.000 to 10.000; 2=10.000 to 25.000; 3=25.000 to 50.000; 4=50.000 to 100.000; 5=100.000 to 500.000; 6=more than 500.000.</td>
</tr>
<tr>
<td>Working status</td>
<td>0=Full time student; 1=Full time student plus part time worker; 2=Full time student and full time worker; 3=Part time student; 4=Part time student and part time worker; 5=Part time student and full time worker; 6=neither student nor worker; 7=No student, but part time worker; 8=No student, but full time worker.</td>
</tr>
<tr>
<td>Experience with experiments</td>
<td>0=never participated before; 1=1 to 3 times participated; 2=4 to 10 times participated; 3=11 to 20 times participated; 4=more than 20 times participated.</td>
</tr>
<tr>
<td>Math grade in high-school leaving exam (&quot;Matura&quot;)</td>
<td>Grades range from 1 to 5 (in integers). “1” is the best grade, “5” the worst.</td>
</tr>
<tr>
<td>German grade in high-school leaving exam (&quot;Matura&quot;)</td>
<td>Grades range from 1 to 5 (in integers). “1” is the best grade, “5” the worst.</td>
</tr>
</tbody>
</table>
Table A.2: Regressions for Treatment Effects

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 5 Team</th>
<th>Model 6 Buyer</th>
<th>Model 7 Buyer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rounds 11 - 40</td>
<td>-2.41</td>
<td>-26.25</td>
<td>-20.23</td>
</tr>
<tr>
<td></td>
<td>(49.00)</td>
<td>(49.20)</td>
<td>(48.39)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>-54.77*</td>
<td>-23.41</td>
<td>-22.80</td>
</tr>
<tr>
<td>* Control</td>
<td>(32.33)</td>
<td>(32.69)</td>
<td>(32.70)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>-105.69***</td>
<td>-92.89**</td>
<td>2.83</td>
</tr>
<tr>
<td>* Chat</td>
<td>(37.11)</td>
<td>(42.93)</td>
<td>(49.88)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>-68.80***</td>
<td>-79.49***</td>
<td>-71.48***</td>
</tr>
<tr>
<td>* Gender</td>
<td>(22.98)</td>
<td>(24.29)</td>
<td>(23.70)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>1.12</td>
<td>-0.19</td>
<td>-0.31</td>
</tr>
<tr>
<td>* Age</td>
<td>(5.33)</td>
<td>(5.49)</td>
<td>(5.36)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>-0.40</td>
<td>-7.73</td>
<td>-12.73</td>
</tr>
<tr>
<td>* Math Score</td>
<td>(10.78)</td>
<td>(11.48)</td>
<td>(11.12)</td>
</tr>
<tr>
<td>Rounds 11 – 40</td>
<td>-10.04</td>
<td>1.11</td>
<td>-1.18</td>
</tr>
<tr>
<td>* German Score</td>
<td>(13.23)</td>
<td>(12.94)</td>
<td>(12.69)</td>
</tr>
<tr>
<td>Rounds 11 – 40 *</td>
<td>-38.99</td>
<td>31.10</td>
<td>34.29</td>
</tr>
<tr>
<td>No chat &amp; Endogenous</td>
<td>(36.97)</td>
<td>(34.07)</td>
<td>(34.09)</td>
</tr>
<tr>
<td>Rounds 11 – 40 *</td>
<td>42.27</td>
<td>89.22*</td>
<td>46.90</td>
</tr>
<tr>
<td>Chat &amp; Endogenous</td>
<td>(36.54)</td>
<td>(45.80)</td>
<td>(44.76)</td>
</tr>
<tr>
<td>Rounds 11 – 40 *</td>
<td>-152.50***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discussed Optimal Bidding</td>
<td></td>
<td></td>
<td>(44.84)</td>
</tr>
</tbody>
</table>

Notes: All regressions include 16,480 observations from 592 individuals (352 teams). Robust standard errors are reported in parentheses. Three (***)**, two (**), and one (*) stars indicate statistical significance at the 1%, 5%, and 10% levels respectively.