The Emergence of Language Differences in Artificial Codes*

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Abstract

The paper studies how common codes of artificial language in communication are developed in the laboratory. We find that codes emerging from an environment with more variable spatial positions tend to use a limited set of symbols to represent positions, whereas codes emerging from an environment with more variable geometric shapes tend to discriminate among shapes. The paper also experimentally shows that "language" affects the way its "speakers" share the view about a novel figure.

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JEL classification: C72, C92, Z1

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1 Introduction

In a neat book, Rubinstein (2000) proposes an agenda of the "economic-like" analysis to the issues in linguistics and reviews the investigation of some common properties of languages.[1] In the subsequently emerging field of economics of language, while the methodology is suggested to be taken from economics, the problem sets are not restricted to linguistics but also pertain to organizational studies (e.g., the investigations of organizational codes and organizational cultures as done in Cremer, Garicano and Prat (2007) and Weber and Camerer (2003)). In this paper, we study how symbolic resources are allocated under different communication environments, from the perspective of economics. In our laboratory experiments, we show the emergence of language differences in artificial codes in simple communication games, and illustrate the potential impact of these differences on coordination in the presence of a novel state.

If certain linguistic properties are shared by all languages as argued by Rubinstein (1996, 2000), why do we observe dramatic language differences across organizations or societies?[2] We propose a simple model of communication game that allows environmental parameters to differ with respect to the variability of certain dimensions in the state space. Two players, a sender and a receiver, play a simple communication game in the absence of conflicting interests.[3] The sender sends a message without any pre-determined meaning to communicate a state of nature to the receiver. The state space involves finite sets of different attributes. We consider different scenarios in which variability differs in the attributes. We assume that there are three states and two messages. The sender is thus not able to fully articulate all the states. This assumption captures the limited expressive power of individuals and reflects the scarcity of symbolic resource in our natural language.[4]

[1]In the economics literature, it is Marschak (1965) who first promoted the "linguistic turn" in economics. Along this line, Lipman (2003) also provides an excellent survey on economics and language.

[2]See Section 5 for a review of the literature on some language differences relevant for this paper.

[3]Blume (2000, 2005) is the first to theoretically study optimal languages in sender-receiver games and coin the notions of learning and learning efficiency in such games. He shows that the structure of language facilitates learning and that the learning-efficient language may use the structure of the state space.

[4]Rubinstein (1996) characterizes informative languages that minimize the expected imprecise descriptions. The vocabulary generated from a binary term in his model inevitably causes com-

We show that a combination of universal optimization rules and idiosyncratic environmental parameters gives rise to some language differences. We rely on two universal optimization rules to guide the development of common codes or artificial languages: optimality and attribute-based categorization. For communication efficiency, optimality suggests that a common code should minimize expected communication errors by using the limited symbolic resources to represent the most likely states. On top of this, attribute-based categorization suggests that states should be grouped based on their similar properties/attributes (e.g., Cohen and Lefebvre, 2005). A language with attribute-based categorization distinguishing the attribute with higher variability enables the shared language to be learned from the minimal number of observations and thus satisfies learning efficiency.

Following our preliminaries, we conduct an incentivized laboratory experiment involving 102 participants from the student pool of Wuhan University (WHU) in China.[5] The participants were asked to play the communication game in two different treatments. To decontextualize any existing communication convention among the participants, we used abstract geometrical figures to represent the states of nature, and let participants communicate using abstract symbols without any prior meaning. The states of nature involve various geometric shapes, $\bullet$, $\bigcirc$ and $\triangle$ and their (horizontal or vertical) spatial positions (relations). The two treatments differ in the relative variability of the two attributes: geometric shapes and spatial positions. Participants were asked to use only one symbol $+$ or $\times$ in their communication. According to our model, when the state space has higher variability in spatial positions than that of geometric shapes, the rules of optimality and attribute-based categorization will guide players to use limited symbols to represent spatial positions, leading to a position-prominent language; otherwise, a shape-prominent language will emerge.

After 30 rounds of communication, languages in artificial codes turn to be optimal and satisfy attribute-based categorization in most cases of both treatments. We

munication errors. Relatedly, Cremer, Garicano and Prat (2007) assume the scarcity of codes in technical languages for firms.

[5] We also conducted several experimental sessions in the Hong Kong University of Science and Technology (HKUST) and the Shanghai University of Finance and Economics (SHUFE), involving 46 subjects. The results from these sessions are qualitatively the same as those reported in the current paper.

observe position-prominent (shape-prominent) languages from the treatment when the position (shape) attribute entails a higher variability. Our results thus highlight the importance of environmental parameters in determining the emergence and evolution of common codes. That is, with players adapting to different environments in optimizing communication and learning efficiency, different languages we observe in the laboratory are largely driven by the variability of different attributes in different environments where participants interact. This is in line with Arrow's (1974) argument that specialized "codes" in organizations emerge to economize in communication costs. The endogenous emergence of position-shape differentiation of the artificial languages from our experiment can also be related to certain different characteristics of natural languages in different social organizations as discussed in Section 5 of this paper.

In line with Rubinstein's (2000) theoretical approach to optimal languages, Cremer et al (2007) investigate efficient organizational codes and relate it to the boundary of the firm. Weber and Camerer (2003) study the emergence of shared meanings in language, which they call organizational cultures, and their consequences when the boundary of the organization is extended. Different from Weber and Camerer's (2003) experiment that allows the use of natural languages, we investigate artificial languages endogenously emerged in the laboratory as in Blume, DeJong, Kim and Sprinkle (1998) and Selten and Warglien (2007). Blume et al. (1998) is the first to experimentally study the emergence of common codes from initially meaningless messages. While Selten and Warglien (2007) examine the grammar-like structures of languages (compositionality in particular), we focus on how common optimization rules together with idiosyncratic environmental parameters lead to the emergence of language differences.

Our experiment also investigates how the subjects with language differences describe a novel state. At the end of our treatments, participants were unexpectedly asked to play in a bonus round in which they had to coordinate with each other in describing a novel figure that had never appeared before. Two familiar figures were presented to participants. One shared the same spatial position with the novel figure but differing in the geometric shape, while the other sharing the same shape with the novel figure but differing in the position. Then the participants were asked to choose the one that describes the novel figure better in their views.[6] This design is inspired by Chiu (1972) and Ji, Zhang and Nisbett (2004) who show that American children have a preference for grouping objects on the basis of "taxonomic" category, e.g. pandas and monkeys, whereas Chinese children show a preference for grouping on the basis of relationships, e.g. monkeys and bananas (as monkeys eat bananas).

We find that participants "speaking" different artificial languages tend to choose different figures to describe the novel figure. Participants with shape-prominent (position-prominent) languages were more likely to choose the figure sharing the same shape (position) to represent the novel figure. This effect persists even after we control for the environment in which they interact. This finding suggests that common codes that people use to communicate in an abstract setting appear to influence the way people share the view about the novel figure. Our explanation is that the language that players "speak" facilitate them to identify a focal point for the coordination in the bonus stage.

The paper proceeds as follows. Section 2 introduces a simple model of communication games as our preliminaries. Section 3 presents the experimental design and procedures. Section 4 reports the experimental results. Section 5 discusses some topics in the related literature of psychology, linguistics and economic history, and explores possible interpretations of our experiment. The last section concludes.

2 Preliminaries

In this section, we introduce the simplest possible model that captures environments differing with respect to the variability of certain attributes and investigate how different languages in artificial codes emerge and how these endogenously emerged languages may interact with the players' subsequent coordination behaviors.

Two players, a sender and a receiver, play a pure-coordination game. While the receiver does not know the state of nature $\omega \in \Omega$, the sender knows it, and sends a message $m \in M$ to the receiver. If the receiver indicates the state correctly, the

[6] The exact question we used in the bonus round was "Here is a new figure that has never appeared in the previous rounds. Which of the following figures below describes this new figure better?"

communication is successful, and both players receive a positive payoff normalized to one; both obtain zero, otherwise. Following Blume (2005), we define a *language* as a strategy of the sender, i.e. a mapping from the state space to the message space.

We let the state space be multidimensional, $\Omega = S \times R \times O$, where $S = \{s\}$, a singleton, $O = \{a, b\}$, and $R = \{\alpha, \beta\}$. Suppose that the probabilities of states $p_{\alpha o} > p_{\beta a} > p_{\beta b} = 0$ for any $o \in O$ where $\sum_{\omega \in \Omega} p_\omega = 1$.[7] Here, the sender and the receiver interact in an environment in which the attribute O is more variable relative to the attribute R. The message space is $M = \{+, \times\}$. Thus, the sender and the receiver cannot form a perfect language that could describe all states of nature, as there are three states and two messages.[8]

We focus on the perfect Bayesian equilibrium in pure strategies. It turns out that every pure strategy of the sender is an equilibrium language.[9] In the absence of conflicting interests between the sender and receiver, we are interested in the equilibrium language that maximizes the likelihood of successful communication, which we call an optimal language. In the optimal language, it is straightforward that the sender will assign the two distinct messages to the two most likely states αa and αb respectively, and knowing this, the receiver will always indicate one of the two most likely states depending on the message received.[10] Table 1 presents two examples of optimal languages. If the players "speak" any of the languages in Table 1, the most likely states, αa and αb, will be communicated, while the less likely state, βa,

[7] We assume $p_{\beta b} = 0$ in order to investigate how players describe a novel state βb in our experimental study in the simplest way.

[8] As discussed in the introduction, this assumption captures the limitation of human expressive power. Alternatively, Selten and Warglien (2007) and Hong, Lim and Zhao (2017) design laboratory experiments of communication games with unlimited messages, attempting to explore grammatical structures of artificial codes.

[9] To see it, let $q(\omega) \in M$ for all $\omega \in \Omega$ denote the sender's strategy, and $y(m) \in \Omega$ for all $m \in M$ denote the receiver's strategy. Given any q, the receiver's posterior belief becomes

$$\mu(\omega|m) = \frac{p_\omega 1_{\{m\}}(q(\omega))}{\sum_{\omega' \in \Omega} p_{\omega'} 1_{\{m\}}(q(\omega'))}$$

where $1_{\{m\}}$ is an indicator function. Let $\overline{\Omega}_m \equiv \{\omega : \forall \omega' \in \Omega, \mu(\omega|m) \geq \mu(\omega'|m)\}$. The receiver's best response is $y(m) \in \overline{\Omega}_m$. The receiver indicates the state (or, one of the states) that maximize(s) the likelihood of successful communication. With appropriately chosen out-of-equilibrium beliefs (whenever they matter), for any ω, there can be no message $m' \neq m$ such that $y(m') = \omega \neq y(m)$, so that the sender has no incentive to deviate from this q.

[10] Relatedly, in a Sender-Receiver coordination game, Cremer et al (2007) derive efficient organizational codes that use precise words for frequent events and vague words for unusual ones.

will not. In Table 1(a), the sender in states $\{\alpha a, \beta a\}$ sends a common message and the sender in αb sends the other message. This implies that the players will use the binary messages to represent the attribute O, distinguishing between a and b. Table 1(b) shows another optimal language in which the sender in states $\{\alpha b, \beta a\}$ sends a common message and the sender in αa sends the other message. This language does not exhibit attribute-based categorization as that in Table 1(a).[11]

Although the two languages in Table 1 are both optimal in terms of (static) communication efficiency, the former language has an advantage over the latter one in terms of the notion of learning efficiency (Blume, 2005), which is also closely related to describability as discussed in Rubinstein (2000). Imagine that the receiver learns the sender's language from observations that consist of pairs of states and the corresponding messages. We say that an optimal language is *learning efficient* if it minimizes the number of observations that are needed for the receiver to learn the mapping between the most likely states to be communicated ($\alpha a, \alpha b$ in this case) and the messages. The language in Table 1(a) represents the dimension O of the state space distinguishing a and b. This facilitates learning of the language as the players only need any single observation (including an observation involving the least likely state) to learn the mapping between the set of most likely states and the message space.

R, O	a	b
α	$+$	$\times$
β	$+$	N/A

(a) A language with attribute-based categorization

R, O	a	b
α	$+$	$\times$
β	$\times$	N/A

(b) A language without attribute-based categorization

Table 1: Optimal languages when $p_{\alpha o} > p_{\beta a} > p_{\beta b} = 0$

Similarly, when $p_{ra} > p_{\alpha b} > p_{\beta b} = 0$ for any $r \in R$ so that the attribute R is more variable relative to the attribute O, one can show that if one message is assigned to states αa and αb and the other message to state βa, then this language is optimal and learning-efficient. That is, the term in the language distinguishes between α and β in the attribute R. The other optimal language, which uses one message to represent αa

[11]For a review of the topic on categorization in cognitive science, see, e.g. Cohen and Lefebvre (2005). Attribute-based categorization appears to be universal in human cognition. Smith and Kemler (1977) highlight the cognitive development of attribute-based categorization in young children.

and the other to represent αb and βa, does not exhibit attribute-based categorization.

R, O	a	b
α	$+$	$\times$
β	$+$	βa or αb?

(a)

R, O	a	b
α	$+$	$+$
β	$\times$	βa or αb?

(b)

Table 2: Novel state βb in different languages

One may wonder whether languages that players have used affect their subsequent coordination. Suppose that the players, after developing certain languages, are asked to use either state αb or βa to describe a novel state βb. The success of this task depends on whether the players could coordinate by choosing the same state. The languages that players have used in communication may provide the players with a focal point in their coordination: The players sharing a language with attribute-based categorization may use the figure (αb or βa) that is similar to the novel figure in terms of the attribute stressed by the language they "speak". This mechanism is similar to the use of historical precedents in coordination documented in the experimental economics literature (see, e.g. Devetag and Ortmann (2007) for a review).[12]

Table 2 reproduces two languages (with attribute-based categorization) considered in the examples above. On the one hand, if the language separately represents a and b (Table 2(a)), then it is more focal for the players "speaking" this language to use αb rather than with βa to describe βb, the ex-ante novel state, because of the greater emphasis on the attribute O in the language. On the other hand, if the language separately represents α and β (Table 2(b)), then one may expect that players "speaking" this language are more likely to choose βa rather than αb in the coordination because of the greater emphasis on the attribute R in the language. We shall explore this issue further when formulating the experimental design and hypotheses in Section 3.[13]

[12] In discussing our experimental findings on this issue, the last paragraph of Section 4 reviews the relevant literature.

[13] While the problem here is context-free, it is inspired by the design and finding in Chiu (1972) and Ji, Zhang and Nisbett (2004) in which the use of languages affects how children group objects (discussed in the introduction). Section 5 also relates our study to the psychology and linguistics literature.

3 Experimental Design

3.1 Design and Hypotheses

We design two treatments to capture the different scenarios according to the examples of the model in the previous section: treatment O (where the dimension O is more variable) and treatment R (where the dimension R is more variable). The only difference between these two treatments lies in the distribution of the state space. Letting $p_{\beta b} = 0$, in treatment O, we have

$$p_{\alpha a} = p_{\alpha b} = \frac{4}{9} > p_{\beta a} = \frac{1}{9}, \tag{1}$$

while in treatment R,

$$p_{\alpha a} = p_{\beta a} = \frac{4}{9} > p_{\alpha b} = \frac{1}{9}. \tag{2}$$

In order to visualize the states of nature for the subjects, we use abstract geometrical figures to denote the states. In particular, we use geometric shapes $\bullet$, $\triangle$, and $\bigcirc$ to denote s, a, and b respectively, the elements in S and O. We use spatial relations/positions between s and $o \in O$ to denote elements in R: the vertical positioning between the two denotes α, while the horizontal positioning denotes β. With $p_{\beta b} = 0$, the state space is thus $\{\overset{\bullet}{\triangle}, \overset{\bullet}{\bigcirc}, \bullet\,\triangle\}$. To implement the state space and its prior distribution in the simplest possible way, we define the (probability-)adjusted state space as a set of figures in which the number of each figure in the state space is adjusted according to the prior probability. Specifically, the adjusted state space contains 9 figures, each of which has an equal chance of being selected. In the treatment O, implementing the distribution in (1) the adjusted state space contains 9 figures: 4 $\overset{\bullet}{\triangle}$'s, 4 $\overset{\bullet}{\bigcirc}$'s, and 1 $\bullet\,\triangle$, each occurring with equal probability. In the treatment R, implementing the distribution in (2), the adjusted state space contains 9 figures: 4 $\overset{\bullet}{\triangle}$'s, 1 $\overset{\bullet}{\bigcirc}$, and 4 $\bullet\,\triangle$'s, each occurring with equal probability. We call $\bullet\,\triangle$ in the treatment O and $\overset{\bullet}{\bigcirc}$ in the treatment R rare figures given their lower probability of occurrence.

At the beginning of each round, both players in a group observe the set of 9 figures.[14] One figure is randomly chosen and privately revealed to the sender in the group. After observing the chosen figure, the sender is asked to send a message from $\{+, \times\}$. After receiving the message, the receiver is asked to indicate which figure is realized. The communication is said to be successful if the receiver indicates the figure correctly. After the receiver's decision, some feedback on the outcome of the round was provided, such as the chosen figure, the message sent by the sender, the figure indicated by the receiver and whether or not the communication is successful. Each group interacted for 30 rounds. Table 3 summarizes the experimental design. More details can be found in the English translation of the experimental instructions in the Online Appendix A.

Treatment	State Space			Message Space
Treatment O	4 $\overset{\bullet}{\triangle}$	4 $\overset{\bullet}{\bigcirc}$	1 $\bullet\triangle$	$\{+, \times\}$
Treatment R	4 $\overset{\bullet}{\triangle}$	1 $\overset{\bullet}{\bigcirc}$	4 $\bullet\triangle$	$\{+, \times\}$

Table 3: Summary of Experimental Design

The following hypothesis arises from the property of optimality in languages.

Hypothesis 1 (Optimality) *In the treatments O and R, the 2 non-rare figures are more often successfully communicated than the rare figure.*

As discussed in Section 2, with attribute-based categorization, a language distinguishing a ($\triangle$) and b ($\bigcirc$) would emerge in the treatment O whereas a language distinguishing α (vertical positioning) and β (horizontal positioning) would emerge in the treatment R. We will call the former a shape-prominent language and the latter a position-prominent language. Thus, we have the following hypothesis:

[14]For each player and in each round, the positions of these figures are randomly determined.

Hypothesis 2 (Shape/Position Prominence) *Shape-prominent languages emerge more often in the treatment O than in the treatment R whereas position-prominent languages emerge more often in the treatment R than in the treatment O.*

To explore whether language affects participant's subsequent coordination behavior, we add a bonus round at the end of our experiment, which is a surprise to the subjects as it was not told in the experimental instructions. In this bonus round, the sender and the receiver observe a figure $\bullet \bigcirc$ (which does not appear in the state space shown to them), and are asked to choose one of the two figures $\begin{array}{c}\bullet\\ \bigcirc\end{array}$ or $\bullet \triangle$ to describe this novel state. Figure 1 presents the English translation of the z-Tree screen shot for the bonus round.[15] Only if two players in a group choose the same figure is the group coordination deemed successful in this bonus round and a bonus payment awarded to both of them.

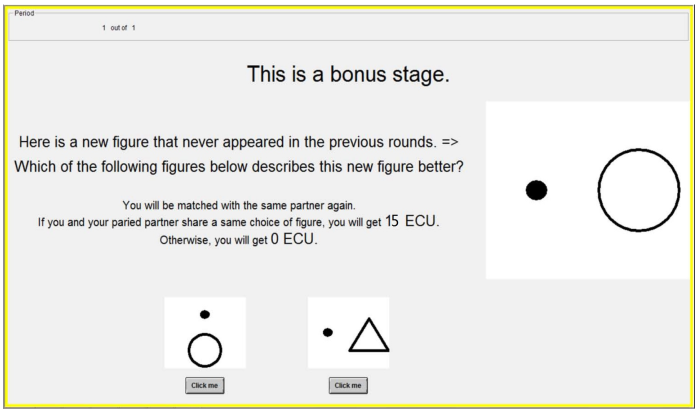


Figure 1: Novel State: z-Tree Screen Shot

The focal point argument in Section 2 suggests that if the language emerging under the treatment O appears to be shape-prominent distinguishing $\triangle$ and $\bigcirc$ and the language emerging from treatment R appears to be position-prominent differentiating vertical and horizontal relations, then participants under the former treatment must be inclined to rely on the shape dimension as their focal point and participants under the latter treatment must be inclined to find the dimension of spatial relations more focal in the bonus round. Thus, we have the following hypothesis.

[15]Participants are told that the order in which the two choices appear at the bottom of their screen is randomly determined.

Hypothesis 3 (Novel State) *Facing the novel figure* $\bullet\bigcirc$, *participants in the treatment O are more likely to choose* $\begin{matrix}\bullet\\ \bigcirc\end{matrix}$ *while participants in the treatment R are more likely to choose* $\bullet\,\triangle$.

3.2 Experimental Procedures

This subsection describes the experimental procedures. We conducted our experiment in the economics laboratory at Wuhan University, China in November 2015 and September 2016, using z-Tree program (Fischbacher, 2007). We used a between-subject design. 4 experimental sessions were conducted for treatment O, while 5 sessions were conducted for treatment R. Each session involved 6-16 student participants depending on the sign-ups. A total of 102 students, none of whom had any previous experience on our experiment, were recruited as participants, of whom 56 participated in the treatment O while the others in the treatment R.

In each session, participants were randomly paired up in a group at the very beginning and remained with the same partner until the end of the experiment. This fixed matching protocol facilitates the emergence of artificial languages in a limited number of interactions in the laboratory. For each treatment, each group interacted for 30 rounds plus the abovementioned unforeseen bonus round at the end. For each session, we also conducted two practice rounds before the official rounds in order to ensure participants' understanding of the instructions.

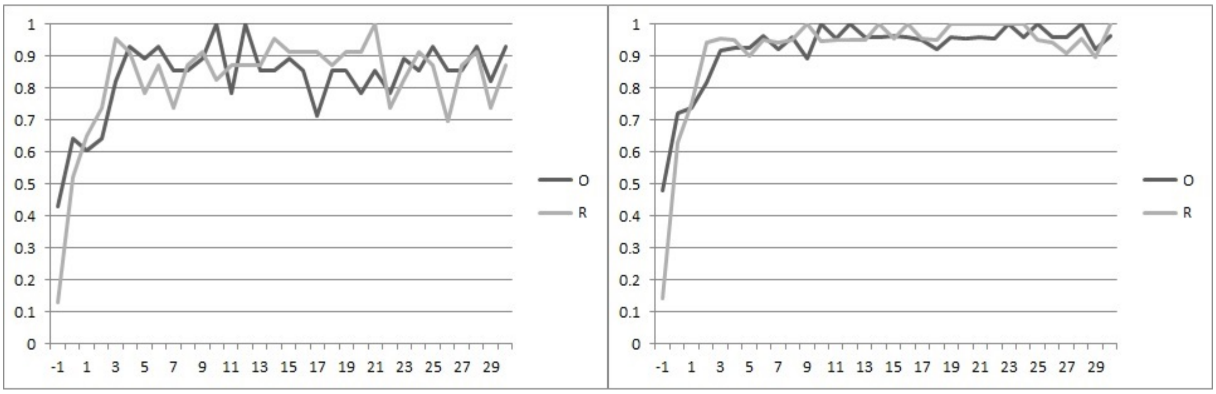
The cash payments were calculated using the following formula with every 3 Experimental Currency Units (ECU) converted to 1 Renminbi Yuan. For each participant, the income in ECU is determined by

$$[3 \times \#(\text{successful communication}) + 15 \times 1_{\{\text{Success in Bonus Stage}\}}] \text{ ECU},$$

where #(successful communication) means the number of rounds with successful communication in the 30 rounds, and $1_{\{\text{Success in Bonus Stage}\}}$ is an indicator function equal to 1 if the group has successful coordination in the bonus stage and 0 otherwise. On top of this, each participant received a show-up fee of 5 Yuan. On average a participant received 33.6 Renminbi Yuan (≈US$5).[16]

4 Experimental Results

In both treatments, participants develop languages that achieve efficient communication. Figure 2(a) and Figure 2(b) report time trends for the average success rate of communication including both treatments for all figures and non-rare figures respectively.[17] The increasing trends suggest how languages in their communication emerge and evolve over time. While the frequencies of successful communication are increasing, the volatilities have been alleviated over time. In particular, for non-rare figures, the trend is quite stable after 10 rounds.



(a) Time Trends for All Figures (b) Time Trends for Non-rare Figures

Figure 2: Frequencies of Successful Communication

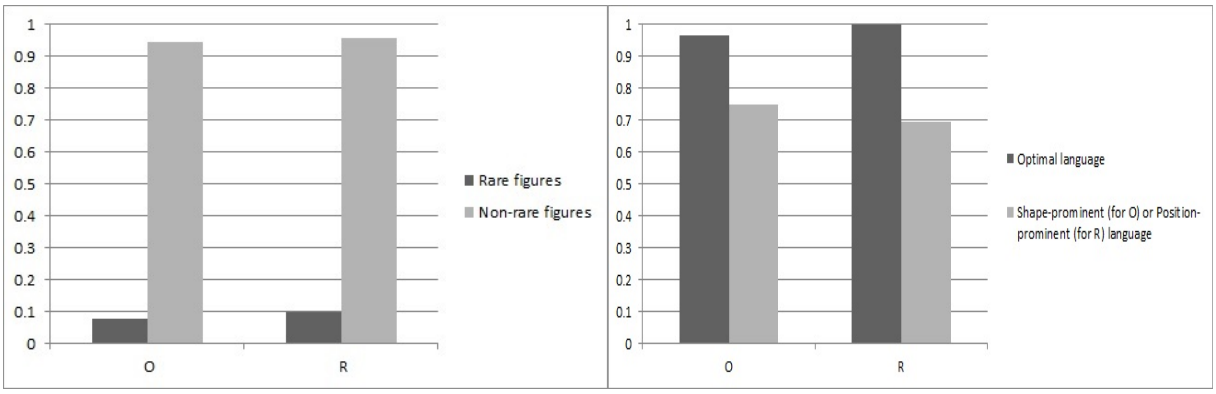
The optimality of language suggests that communication should be more successful for non-rare figures than rare figures. The average success rate for rare figures is 0.09 varying between 0.08 for treatment O and 0.1 for treatment R, while the average success rate is 0.95 for non-rare figures and no lower than 0.94 for both treatments, as depicted in Figure 3(a). Using data aggregated at the session level, Wilcoxon signed-rank tests show that there is a significant difference in terms of success rate between rare figures and non-rare figures, for both treatments (p value=0.068 for treatment O,

[16] Although the average payment is smaller than the standard amount paid to subjects in developed countries, the amount is sufficient to motivate participants from Wuhan University. A regular meal in the university canteen costs approximately US$ 1 only.

[17] Periods -1 and 0 are the two practice rounds before the official rounds. While the time trends in Figure 2 include the practice rounds, in the analysis below we focus on official rounds in which the subjects were incentivized.

and p value=0.043 for treatment R). However, Mann-Whitney tests show that there is significant difference in terms of success rate between the treatments O and R for neither rare figures nor non-rare figures (p values>0.45). Moreover, in 22 out of the 28 groups in treatment O and 18 out of the 23 groups in treatment R, the average success rate for rare figures is 0, and in 15 groups in treatment O and 10 groups in treatment R, the average success rate for non-rare figures is 100%, consistent with the theoretical prediction that the non-rare (rare) states will (not) be communicated in optimal languages.[18] Taken together, we have the following result lending support to our Hypothesis 1.

Result 1 (Optimality) *The success rates for non-rare figures are significantly higher than those for rare figures in both treatments.*



(a) Success Rate of Rare or Non-rare Figures (b) Optimality and Shape/Position-Prominence

Figure 3: Emergence of Optimal and Shape/Position-Prominent Languages

Result 1 also explains the higher volatility of the average success rate for all figures relative to that of non-rare figures as shown in Figure 2. Since the average success rate for rare figures is very low, due to different number of occurrences of rare figures in each period, the average success rate for all figures displays a larger volatility across time.

Table 1 in the Online Appendix B shows the sender's mappings from figures to messages for each group in the last 20 rounds. Figure 3(b) reports the percentages

[18]The 100% success rate for non-rare figures in those groups suggests that the players learnt very fast in the beginning and developed stable common codes at the later stage. After 2 practice rounds, they quickly converged to the optimal languages.

of groups developing optimal languages in both treatments, the percentage of groups developing shape-prominent languages for treatment O and that of groups developing position-prominent languages for treatment R. A group is said to have developed an optimal language if messages are used to distinguish the non-rare figures for all of the last 20 rounds. A group is said to have developed a shape-prominent language if messages are used to distinguish $\triangle$ and $\bigcirc$ in the last 20 rounds, and a group is said to have developed a position-prominent language if messages are used to distinguish the vertical relation and the horizontal relation in the last 20 rounds. The fact that the time trends in Figure 2 become more stable after the 10th round, especially for non-rare figures, suggests that the last 20 rounds can be used to represent the convergence of behavior.

In the treatment O, 27 out of the 28 groups developed optimal languages, and 21 of these groups developed shape-prominent languages; in the treatment R, all of the 23 groups developed optimal languages and 16 out of these groups developed position-prominent languages. None of the groups in treatment R developed a shape-prominent language and none of the groups in treatment O developed a position-prominent language.

Fisher's exact test confirms that there is no significant difference between treatments O and R in terms of the frequency of developing optimal languages (p value≈ 1); meanwhile, within those groups with optimal languages, there is no significant difference between treatments O and R in terms of the frequency of developing languages with attribute-based categorization (p value$= 0.5$). Confirming Hypothesis 2, we have the following result (with p values from Fisher's exact test both lower than 0.0001).

Result 2 (Shape/Position Prominence) *Shape-prominent languages emerge significantly more frequently in the treatment O than in the treatment R. Similarly, position-prominent languages emerge significantly more frequently in the treatment R than in the treatment O.*

We then conduct a regression analysis to look into the determinants of the communication outcomes, using the group-period level data. Table 4 reports *odds ratios* from logit regressions, with a binary variable indicating communication success as the dependent variable. We create several dummy variables: R, which indicates treatment R, $Rare$, equal to 1 if the figure to be communicated is a rare figure and 0 otherwise, $Optimal$, which equals 1 if the group developed an optimal language according to the above classification and 0 otherwise, and *Attribute-based Categorization*, which equals 1 if the group developed a language with attribute-based categorization according to the above classification and 0 otherwise. We also create another dummy variable, *Stable*, which is equal to 1 if from the current period to the last period the sender's mapping from figures to messages does not change and 0 otherwise. Therefore, for any group, the pattern for *Stable* would display a pattern like 0, .., 0, 1, ..., 1, across periods. This dummy variable, if equal to 1, indicates that the sender has converged to a stable language that maps figures to messages, and does not change the mapping in any period afterwards. In 38 out of the 51 groups, *Stable* = 1 for all the periods, implying that the sender set a stable language as soon as the official periods started. However, we have *Stable* = 29 for the group that did not develop an optimal language, suggesting that the sender never came up with a stable mapping from figures to messages.

The first three columns of Table 4 makes use of the whole sample. Column (1) regresses the communication outcome on the above five dummy variables, controlling for session fixed effects, with robust standard errors clustered at the group level. Column (2) further includes period dummy variables, while Column (3) replaces the period dummy variables by a variable, *Period*, indicating the period of interaction, to account for the possible time trends. We find that in all of the three columns, the coefficients of R are not statistically significant, implying that the subjects were not different in their likelihood of successful communication between the treatments. The effects of $Rare$ are statistically significant (with odds ratios$<$1), implying that it is less likely to successfully communicate a rare figure than a non-rare figure, consistent to our Result 1. Meanwhile, developing a stable and optimal language significantly increases the chance of successful communication (the odds ratios of $Optimal$ and *Stable* are both much higher than 1 and statistically significant). However, the coefficients of *Attribute-based Categorization* are statistically insignificant, which seems to suggest that having a language with certain attribute-based categorization does not significantly increases the chance of successful communication. Finally, in Column (3), the effect of *Period* is not significant either.

Section 2 suggests that the value of developing a language with attribute-based categorization comes from the (dynamic) learning efficiency, which, in our setting, would happen in the very beginning periods of interactions between the subjects. Figure 2 shows that the subjects indeed learnt very fast, leading to a sharp increase in the average success rate of communication in the first periods, especially for non-rare figures; the time trend then keeps relatively stable after the beginning periods. Therefore, the effect of *Attribute-based Categorization* on learning and the effect of the experience in playing the game with a particular partner (as represented by *Period*) might be diluted if we look at the entire dataset. Columns (4)-(6) of Table 4 thus repeated the regressions in Columns (1)-(3), using the data in the first 3 periods. Note that our discussion of the (dynamic) efficiency improvement from *Attribute-based Categorization* is based on optimal languages that satisfy static efficiency. To focus on the effects on learning efficiency, we thus excluded the only group without an optimal language in the regressions reported in Column (4)-(6), and therefore the dummy variable *Optimal* is dropped. We find that in Columns (4)-(6), the effects of *Rare* and *Stable* are still statistically significant, with odds ratios lower and higher than 1 respectively. Moreover, the odds ratios of *Attribute-based Categorization* are higher than 1 and statistically significant in all the last three columns, that is, shape-prominent or position-prominent languages lead to higher chance of successful communication in the beginning periods for the groups with optimal languages, implying that attribute-based categorization enhances learning efficiency. Meanwhile, the odds ratio of *Period* in Column (6) is higher than 1 and statistically significant. This implies that the previous experience of interacting with the partner is helpful for communication in the beginning periods, suggesting a learning effect. Overall, these results suggest that the significance of the effects of *Attribute-based Categorization* and *Period* in the first periods and the insignificance of the effects when we look at the entire interaction may be due to the fact that the subjects learnt very fast as shown in Figure 2. The following result summarizes our findings from the regressions.

Result 3 *The sender's stable and optimal mapping from figures to messages signif-*

Table 4: Logit Regression Results on Communication Outcome

	(1)	(2)	(3)	(4)	(5)	(6)
R	2.006	2.108	2.022	0.3724	0.2829	0.2837
	(1.201)	(1.195)	(1.228)	(0.5313)	(0.3513)	(0.3610)
Rare	0.0025***	0.0013***	0.0024***	0.0029***	0.0016***	0.0016***
	(0.0012)	(0.0006)	(0.0012)	(0.0049)	(0.0028)	(0.0028)
Optimal	20.80***	31.35***	21.10***			
	(8.311)	(14.61)	(8.273)			
Attribute-based Categorization	0.9261	0.8671	0.9200	3.189*	3.423*	3.429*
	(0.2711)	(0.2952)	(0.2692)	(2.067)	(2.240)	(2.255)
Stable	152.5***	159.2***	129.4***	16.39***	14.66***	14.70***
	(75.19)	(66.96)	(66.87)	(12.96)	(10.65)	(10.61)
Period			1.015			3.454***
			(0.022)			(1.480)
Period Dummies Included	No	Yes	No	No	Yes	No
Sample		Whole Sample			Optimal Groups, First 3 Periods	
Pseudo R^2	0.615	0.649	0.615	0.544	0.600	0.600
No. of Observations	1530	1530	1530	150	150	150

Note: This table reports odds ratios from logit regressions on communication outcomes, controlling for session fixed effects. Robust standard errors clustered at the group level are reported in parentheses. *** for p <0.01, ** for p <0.05, and * for p <0.1.

icantly increases the likelihood of successful communication. Meanwhile, for groups with optimal languages, a language with attribute-based categorization increases the likelihood of successful communication in the beginning periods of interaction.

At the end of the each session without prior warning, participants faced a bonus round, in which they were asked to describe a never-before-seen figure $\bullet\ \bigcirc$ by either $\overset{\bullet}{\bigcirc}$ or $\bullet\ \triangle$. If members of the group choose the same figure, the coordination is successful and both receive a bonus.[19] Figure 4(a) reports the percentages of participants choosing $\overset{\bullet}{\bigcirc}$ for the two treatments. 34 out of 56 participants in the treatment O and 19 out of 46 participants in the treatment R chose $\overset{\bullet}{\bigcirc}$. Fisher's exact test suggests that participants in the treatment O were significantly more likely to choose $\overset{\bullet}{\bigcirc}$ than participants in the treatment R ($p = 0.07$).

This finding provides an opportunity for us to examine whether subjects "speaking" different languages would behave differently in the bonus stage. Figure 4(b)

[19]The frequency of successful coordination in this bonus stage is 0.6.

reports the percentages of participants choosing $\overset{\bullet}{\bigcirc}$ for the groups developing shape-prominent languages, the groups developing position-prominent languages, and the other groups. 29 out of 42 participants in groups developing shape-prominent languages and 9 out of 32 participants in groups developing position-prominent languages chose $\overset{\bullet}{\bigcirc}$, while in groups developing neither shape-prominent nor position-prominent languages, around one half (15 out of 28) participants chose $\overset{\bullet}{\bigcirc}$. Fisher's exact tests show that participants in groups with shape-prominent languages chose $\overset{\bullet}{\bigcirc}$ significantly more often than groups with position-prominent languages (p value<0.001), and insignificantly more often than groups with neither shape-prominent nor position-prominent languages (p value=0.2); meanwhile, participants in groups with position-prominent languages chose $\bullet\ \triangle$ significantly more often than both groups with shape-prominent languages and groups with neither shape-prominent nor position-prominent languages (p value<0.001 and p value=0.065 respectively). These results suggest that participants "speaking" position-prominent languages are more likely to focus on the dimension R when describing the novel state, and vice versa for participants with shape-prominent languages.

In the above tests, we use the subjects' choice data for the novel state across different treatments/environments. We then conduct the following additional tests controlling for the environment in which the subjects interact. Figures 4(c) and 4(d) break down Figure 4(b) for treatments O and R respectively. We find that controlling for treatment R, participants in groups with position-prominent languages are significantly less likely to choose $\overset{\bullet}{\bigcirc}$ to describe the novel figure, than those in the other groups (Fisher's exact tests, p value<0.01). Meanwhile, controlling for treatment O, participants in groups with shape-prominent languages are significantly more likely to choose $\overset{\bullet}{\bigcirc}$, than those in the other groups (Fisher's exact tests, p value=0.055). These statistical tests, which control for the treatment, suggest that the effects in Figure 4(b) are not purely caused by the environment in which the players interacted, but at least partially driven by the languages that the players "spoke".

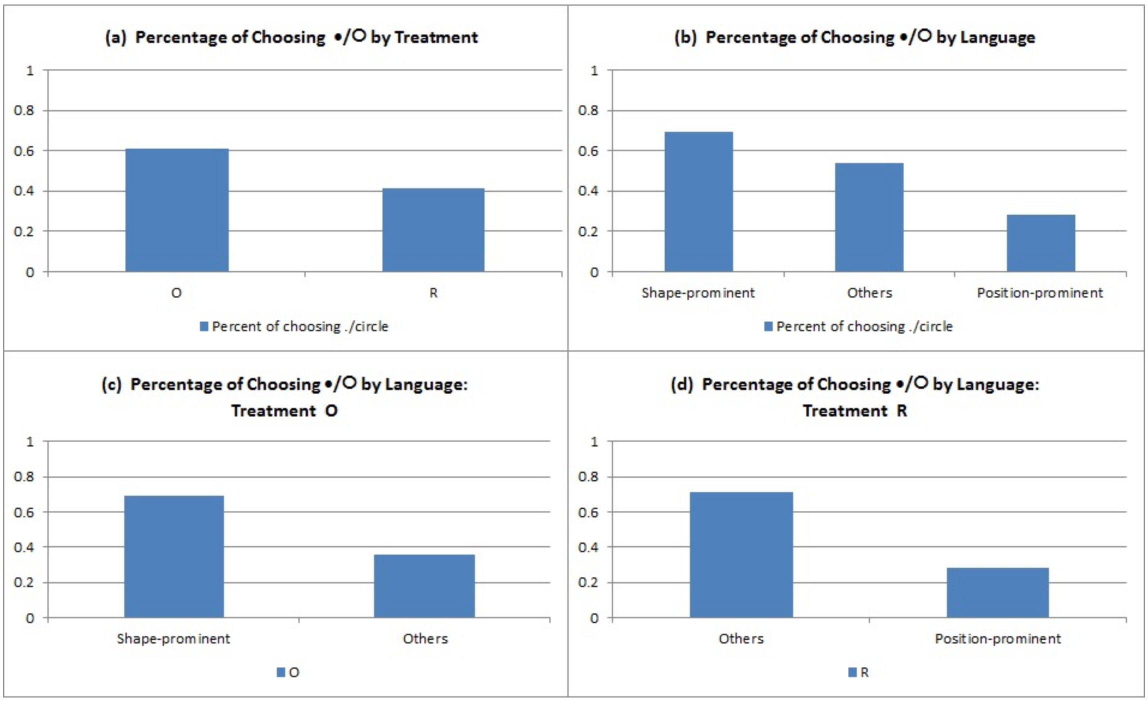


Figure 4: Proportion of groups choosing $\overset{\bullet}{\bigcirc}$ in the bonus round

The findings are summarized in the following result, which is consistent to our Hypothesis 3.

Result 4 (Novel State) *1) Confronted with the novel figure* $\bullet \bigcirc$*, participants in the treatment O were significantly more likely to choose* $\overset{\bullet}{\bigcirc}$ *than participants in the treatment R. 2) Confronted with the novel figure* $\bullet \bigcirc$*, participants in the groups developing shape-prominent languages are more likely to choose* $\overset{\bullet}{\bigcirc}$*, while participants in the groups developing position-prominent languages are more likely to choose* $\bullet \triangle$*.*

Our findings reveal that after "speaking" an artificial language that discriminates positions for a sufficient number of rounds, subjects tend to choose the figure sharing the same position with the novel state, and after "speaking" an artificial language that discriminates shapes, subjects are more likely to choose the figure sharing the same shape with the novel state. That is, the figure sharing the same attribute that the language stresses is more likely to be the focal point for the coordination in the bonus stage. Therefore, our findings suggest that the artificial languages that players developed in the laboratory could facilitate the players to identify a focal point in subsequent coordination.

This experimental result echoes the economics literature on the power of precedents in coordination (see, e.g. Devetag and Ortmann (2007) for a review). Crawford and Haller (1990) theoretically show that precedents could be used as focal points in coordination. Van Huyck, Battalio and Beil (1991) report results from one of the earliest experimental investigations on historical precedents in coordination. Knez and Camerer (2000) and Devetag (2005) study cross-game transfer of historical precedents of cooperation. In our setting, the artificial languages the subjects previously developed play the role of precedents in the related (but different) coordination game in the bonus stage, and guide how they coordinate on the multiple equilibria.

5 Discussion

In the above sections, the model and our experiment are context-free, where we only literally reported the settings and the results. In this section, we discuss possible interpretations of our setup and findings, and relate them to broader literature in psychology, linguistics and economic history.

In the simple model in Section 2, if s represents a subject, say "Alice", a and b represent objects, say, "tea" and "coffee" respectively, and α and β represent two relations, say, "drink" and "buy" respectively, then the states could be interpreted as events; for example, $(s)\alpha a$ could be interpreted as "Alice drinks tea". When $p_{\alpha o}>p_{\beta a}>p_{\beta b}= 0$ for any $o \in O$ (where the sender and the receiver interact in an environment in which objects are more variable relative to relations), in an optimal and learning efficient language, the binary messages will be used to represent the object dimension, distinguishing between (mainly drinking) "coffee" and "tea". On the other hand, when $p_{ra}>p_{\alpha b}>p_{\beta b}= 0$ for any $r \in R$ so that relations are more variable relative to objects, a language distinguishing drinking and buying (mainly tea) is optimal and learning-efficient. In other words, languages emerging from an environment with more variable relations tend to use a limited set of symbols to represent relations, whereas languages emerging from an environment with more variable objects tend to discriminate among objects. In terms of *parts of speech*, the term in the former language is more of a noun than a verb, while that in the latter language is more of a verb than a noun.[20]

Moreover, our experimental study in the bonus stage may be related to a well-known but debatable hypothesis called the "principle of linguistic relativity" or the "Sapir-Whorf Hypothesis" (e.g., Whorf, 1956; Lucy, 1992; Boroditsky, 2001) in cognitive linguistics. The hypothesis predicts that language affects the ways its speakers view the world. There is a huge literature on the Sapir-Whorf hypothesis in cognitive linguistics, which we will not review here.[21] In the economics literature, Chen (2013) finds empirical evidence on how the ways languages partition time affect saving, smoking and dieting behavior. While our study does not aim to test this hypothesis, we find that the languages in artificial codes developed in the laboratory may facilitate players to identify a focal point in their subsequent coordination.

The rest of this section is devoted to discussing the following issues. First, we review the evidence from the linguistic and psychological literature regarding the linguistic and cultural differences in line with the relation/object differential in natural languages. Second, we discuss our conjecture that social or organizational environments where people interact might be one of the factors that account for the structural differences in natural languages. We also provide a caveat for our results.

Linguists and psychologists have paid considerable attention to differences in languages and provided well-documented evidence on the systematic and structural differences in natural languages, for instance, English and Chinese (e.g. Nisbett, 2003). In general, Chinese belongs to the class of "pro-drop" languages in which certain classes of pronouns may be omitted when they are pragmatically inferable, while English is not a pro-drop language (Bresnan, 1982). Among major languages, Japanese

[20]The interpretation here is motivated by the following example from Nisbett (2003): Suppose that at a dinner, one asks another if he or she wants to drink more tea. In Chinese the question is usually "drink more?", while in English the question would be "more tea?"

[21]Experimental and empirical research on the Sapir-Whorf hypothesis has mainly examined the following two issues: the metaphorical relationship between space and time, and color perception (see, e.g., Boroditsky, 2011 for a discussion of the literature).

and Chinese exhibit frequent pro-drop features. Remarkably, non-pro-drop is an areal feature of standard average European languages including French, German, and English (Haspelmath, 2001). For instance, there is a subject "it" even in a sentence like "it is raining" in English while in Chinese one simply says "xià yǔ le" (Raining). The pro-drop property of Chinese allows the omission of sentence subjects and objects, leaving verbs to frequently occupy initial or end positions in sentences and, therefore, to come across as perceptually salient to a listener (Chan et al, 2011).[22] In his well-known book "The Geography of Thought", Nisbett (2003) compares English and Chinese and illustrates the vivid example of "Drink more?" vs. "More tea?"[23] In a recent paper, He and Riyanto (2016) explore the possible economic implications of the pro-drop property, e.g. on social preferences.

Infants and young children have much more limited symbolic resources compared to adults. With this constraint, Chinese-learning and English-learning children exhibit more prominent difference when they learn and speak languages. In developmental psychology, Gentner (1982) finds that American children learn nouns much more rapidly than they learn verbs. However, this is not the case for East-Asians. Chinese children learn verbs at the same rate or even faster than they learn nouns (Tardif, 1996; Chan et al, 2011). Tardif, Shatz, and Naigles (1997) examine caregivers' naturalistic speech to their toddlers and find that the speech of English-speaking caregivers emphasized nouns over verbs, whereas that of Mandarin-speaking caregivers emphasized verbs over nouns; for child-directed speech in Chinese, both sentence-initial and sentence-final positions were more often occupied by verbs than by nouns. Ma et al (2009) find that Chinese verbs' higher imageability, the ability of a word to produce a mental image, relative to English verbs, partially accounts for a portion of the variance in age of acquisition of verb learning in Chinese and English.

In cultural psychology, Chiu (1972) and Ji, Zhang and Nisbett (2004) show that American children have a preference for grouping objects on the basis of "taxonomic" category, e.g., pandas and monkeys, whereas Chinese children show a preference for grouping on the basis of relations, e.g. monkeys and bananas (as monkeys eat ba-

[22]Verbs in Korean, which are also salient, tend to come at the end of the sentences. See Tardif (1996).

[23]See Footnote 20.

nanas). Notably, Ji, Zhang and Nisbett (2004) show that mainland and Taiwanese Chinese are much less likely to group things together on the basis of relationships when tested in English instead of Chinese.

In cultural psychology, the complexity of social interactions has attracted much attention as one reason for the structural differences between English and Chinese (e.g. Nisbett, 2003). The economics literature has shown that pre-modern China and Europe have distinct epitomizing social structures, i.e., the clan and the city, that enforce cooperation (Greif and Tabellini, 2010). In a traditional Chinese society, ordinary people live in a society of acquaintances (Fei, 1992) and do not interact with a large number of people. But because the clan is a kinship-based hierarchical organization, social relationships in China are highly complicated. In Medieval Europe, by contrast, the main example of a cooperative organization is the city, an open society where people tend to interact with a lot of others (Greif and Tabellini, 2010, 2012).[24] In a nutshell, it could be considered that pre-modern China entails greater variability of relations while in Europe the "objects" of interactions are more various.[25]

To conclude, the existing evidence in linguistics, and cultural and developmental psychology suggests that Chinese seems more "relation-prominent" than English. Meanwhile, the pre-modern Chinese society had a different epitomizing social structure than Medieval Europe, where relation played a predominant role. Our experimental finding that codes emerging from an environment with more variable positions (shapes) tend to discriminate among positions (shapes), together with historical accounts on the different social structures, may provide a new angle to examine these differences. This characteristic of the social environment deserves our attention, as it could be one of the factors affecting the emergence and evolution of languages.[26]

Of course, it is important to note that distinct structural differences between the

[24]Cities in pre-modern China were not units of cooperation, and urbanization rate was constantly low. In Medieval Europe, rural settlements were organized as cities which are neither composed nor governed by kinship lines (Greif and Tabellini, 2012).

[25]For instance, jià and qŭ in Chinese correspond to different relations in marriage. The statements that A jià B and that C qŭ D, roughly speaking, imply that B and C are more dominant in the marriage relationships. For another example, while there is only one term "uncle" in English, there are so many different terms in corresponding Chinese, representing different kinship relations of uncles.

[26]In this respect, closest to our work is Dessi and Zhao (2015) who theoretically study how differences in the social and economic environment can give rise to differences in psychological traits such as overconfidence, supported by evidence from 38 countries.

Chinese language and the English language should result from a variety of distinct causes, and that our study is too stylized to explain these differences. In this paper, we only demonstrate the validity of our findings for the case of the emergence of simple artificial languages, which do not explain the causes shaping differences in natural languages.

6 Concluding Remarks

In economics, Rubinstein (1996) is the first to study the optimal semantic properties (or word-thing mapping). He provides a rationale for the existing color terms in the natural language such as "green", "blue" but not "grue". Selten and Warglien's (2007) experiment firstly studies grammar-like language structures like compositionality in artificial languages. While Rubinstein (1996) and Selten and Warglien (2007) focus more on common properties of languages, we provide a perspective to examine certain language differences, as highlighted in the vivid example of "Drink more?" vs. "More tea?" illustrated in Nisbett (2003).

In this paper, while we investigate artificial languages, we hold a broad view of languages including organizational codes as examined in Cremer et al (2007) and Weber and Camerer (2003). We are interested in how players in an organization optimize in their communication under different environments and how this leads to difference in their communication codes. Our experiment concisely endogenizes a language difference under different environments. If the pool of states entails more heterogenous spatial relations than geometric shapes, in order to optimize communication and learning efficiency, *optimality* and *attribute-based categorization* will guide individuals to use a limited set of symbols to represent spatial relations, and vice versa. Our study is consistent with a basic idea in the economics of language: As language is a tool of communication, certain optimal linguistic properties are valid for all languages. Moreover, we highlight the important role of the environment in which players interact, when combined with those universal linguistic rules, in driving the language differences we observe.

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