Embedded Agency in Institutional Fields: Developing Theory from a Matching Game

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Abstract

We apply a formal model to understand the effects of the relative learning rates of embedded agents and the institutional field on organizational outcomes. Applying the principle of reinforcement learning in a repeated game of matching, we generate hypotheses for specific configurations of agents and fields. We contribute to the theory on embedded agency in institutional fields with a nuanced and dynamic view of the role of the relative rates of learning in achieving matching outcomes in organizations.

Keywords:

Embedded Agency, Agent Based Modeling, Reinforcement Learning

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Our understanding of institutional phenomena has come a long way since Selznick (1957) made the observation that organizations adopted new goals suited to existing structures instead of changing the structures that may have outlived their utility. One of the most significant adaptations to our understanding seems to have occurred when the misinterpretation of the 'iron cage' metaphor from DiMaggio and Powell (1983) precipitated the introduction of the notion of agency in institutional theory in the form of institutional entrepreneurship in DiMaggio (1988). Since then, organizational theorists have grappled with understanding the nature of interaction between embedded actors within the institutional field and the institutional field itself. Selznick (1996) suggested that formal structure should be ideally seen as an adaptive product, responsive to environmental influences, including cultural definitions of propriety and legitimacy. Institutional theory has therefore now come to recognize as important, the notion that embedded actors can attain their goals by intentionally constructing and/or altering the institutional structures in which they are embedded (Phillips and Tracey, 2009).

A rigorous yet nuanced understanding of embedded agency has seemed elusive and hard to theorize, however. One part of problem may be that the role of agency may have been carried too far. As Suddaby (2010) suggests succinctly, research in institutional theory is plagued with the problem of organizations now being presented as 'hypermuscular supermen' as compared to the 'passive cultural dopes' they were characterized as earlier. There is clearly a need for more integrative institutional theory that can inform how organizations operating in their respective institutional fields straddle this continuum between the characterizations of 'hypermuscular supermen' on the one extreme, suggesting high levels of agency to that of 'passive cultural dopes', suggesting high levels of structuration of institutional fields.

We attempt to contribute to this conversation by generating hypotheses developed from a formal model of agent-field learning through repeated interaction. Scholars have recognized that formal and computational models provide a creative and fertile approach to aid in the development of theories of organizations (Puranam et al., 2015). A few points of those points deserve to be highlighted again for the current context. First, by allowing the researcher the flexibility to control the variables that change, computational models allow for focussed and crisp hypotheses concerning specific aspects of the phenomenon under study. Second, formal models allow for easier comparison between competing models. This allows for theory building as an indirect outcome. Finally, computational models allow for more complex models to be built on top of earlier models, thus aggregating the knowledge base in an area over time. We note, however that such a method of theory generation is no substitute for empirical research. Formal and computational models and empirical research are sometimes viewed as being complementary, with the former being an aid to developing theory while the latter being one to test theory. However as (Puranam et al., 2015, p. 376) recognize, empirical literature may be somewhat limited in the scope of their task environments. This has implications for the boundaries and environments where formal models may be taken to be tested in empirical settings. The objective of this article, however is to use a formal computational model to generate hypotheses that may inform further empirical work. Any arguments about the feasibility of such empirical work however, will remain outside the scope of this article.

In this article, we apply a simple matching game model to understand the dynamics of the interaction between embedded agents and the institutional field. Despite the simplicity of the model (it models the institutional field and the embedded agent as two players), our model provides us with the opportunity to propose hypotheses that would be difficult to explicate cleanly in a typical empirical setting.

The rest of this article is organized as follows. In the following section, we summarize the key constructs and definitions in institutional theory that we build upon in this article. We then present the assumptions and the formal definitions for the model. A subset of our initial results from the computer simulations of the model are then presented in the following section. We propose hypotheses on the dynamics of embedded agency and their institutional fields based on our findings from our computer simulation. We conclude with a call for continuing this path for theory development, and for empirical studies to use the theoretical frames developed here for both conceptual synthesis and empirical validity of the hypotheses proposed. The Python code used for this modeling work is provided in the appendix section.

BACKGROUND

Prior to describing our formal model, we discuss here some of the salient constructs within institutional theory that provide both the motivation as well as the vocabulary appropriate to our discussion. Scott (1995) visualized institutional fields as a community of organizations that partakes of a common meaning system and whose participants interact more frequently and fatefully with one another than with actors outside the field. This definition is similar to that of DiMaggio and Powell (1983) who defined institutional fields as those organizations that in the aggregate constitute a recognized area of institutional life: key suppliers, resource and product consumers, regulatory agencies, and other organizations that produce similar services or products.

Scholars have suggested that legitimacy is an important aspect of the institutional setup and that it is achieved primarily through isomorphism (Kostova et al., 2008), where organizations become similar to other organizations in their institutional field. However, little seems to have been understood about the processes of legitimation (Harmon et al., 2015).

On the other hand, organizations seem to engage in ceremonial adoption of institutionalized structures and practices while at the same time decoupling themselves from the environment by actually using different structures and practices they view as more economically efficient (Kostova et al., 2008). Recent rhetorical theory has emphasized the role of audience in affecting the way rhetoric shapes social action. Further, the paradox of embedded agency draws attention to the following tension: how can organizations or individuals innovate if their beliefs and actions are determined by the institutional environment they wish to change (Scott, 1987)?

A common thread across the arguments for legitimacy, decoupling, rhetoric and the paradox of embedded agency is that the mechanism that explains the agent-field dynamic is unclear. Our work in this article is addressed toward this gap in our theoretical understanding. We propose to do so by modeling heterogeneity in the relative rates of learning of the agent and the field in an environment of frequent interaction. The relative rates of learning, we propose is a plausible mechanism driving the dynamic of the embedded agent - institutional field relationship toward determining organizational outcomes.

MODEL

We develop a simple model consisting of two players who participate in a repeated game of matching

Insert TABLE 1 about here.

At the end of round t, both the institutional field F and the embedded agent A update their respective probabilities $p^0_{t+1,F}$ and $p^0_{t+1,A}$ based on their prior probabilities ($p^0_{t,F}$ and $p^0_{t,A}$) and their respective learning rates ϕ_F and ϕ_A. We expect the institutional field F and embedded agent A to update their prior probabilities along the lines of the theory on reinforcement learning. We define ϕ as the learning rate function that may take any value between 0 and 1. A ϕ value of 0 indicates no learning, while a ϕ value of 1 indicates perfect learning. The institutional field F and the embedded agent A both update their prior probabilities based on their respective learning rates ϕ_F and ϕ_A respectively. The rules used to update prior probabilities are laid out in the matrix in Table 2.

Insert TABLE 2 about here.

The intuition behind this way of thinking about our assumptions is that both players win when they are aligned on the decision. The specific configuration of the alignment does not impact the payoffs beyond their being the same. Therefore (0,0) would be just as good an outcome as (1,1). The intuition behind the updating of prior probabilities in Table 2 is that both agents and the institutional fields learn to understand the other's preferences over multiple interactions based on their inherent learning rates. Since the payoffs exist only when there is agreement on the outcome, we would expect that either player would, at their given rate of learning try to adjust to the other.

For the purposes of this paper, we assume that the rates of learning ϕ_F and ϕ_A remain constant for entire duration of the game[1]. However, the application of the learning rate to prior probabilities opens the opportunity for the respective probabilities p_F and p_A to change from one time period to another. The model described above was coded in a Python program and analyzed using Stata. The Python code has been shared in the appendix section.

From prior sections, we understand prior probabilities $p^0_{t,F}$ and $p^0_{t,A}$ as the probability with which the field F and the agent A choose the outcome 0 in time period t. We understand that these probabilities are computed for each time period after taking into account both the choice made in the previous period, and the learning rate ϕ defined for each of F and A.

To help improve the intuition in the analysis, we define a few categories. For the learning rate ϕ, we define three categories: Slow ($\phi <= 0.05$), Medium ($0.05 < \phi <= 0.3$) and Fast ($0.3 < \phi <= 0.7$). In the models to follow, we additionally assume that agents may have learning rates of Slow, Medium and Fast, while Fields may have learning rates of Slow and Medium. The determination is made building on the assumption that the institutional field may learn at a rate no faster than that of any of its constituent embedded agents. $choice(t)$ is either 0 or 1 for each player, with 0 being picked with a probability of $p^0_{t,F}$ by the field F and 0 being picked with a probability of $p^0_{t,A}$ by the agent A. We now define the following categories to assist in referring to prior probabilities of player choice.

Field Start Position

The Field Start Position is a characterization of the choice preference of the institutional field at the start of the interaction. The institutional field may chose an outcome 0 with probability $p^0_{0,F}$. We visualize the institutional field's initial preference as being Left (L) when $p^0_{0,F}$ takes a value

[1] While outside the scope of the current article, it seems reasonable that boundedly rational agents could also update their rates of learning in response to the payoffs. It would be an interesting extension of the current work to consider the impact of making this assumption

between zero and 0.1, as Left of Center (LC) when $p^0_{0,F}$ takes a value between 0.1 and 0.35, as Center (C) when $p^0_{0,F}$ takes a value between 0.35 and 0.65, as Right of Center (RC) when $p^0_{0,F}$ takes a value between 0.65 and 0.9, and as Right (R) when $p^0_{0,F}$ takes a value between 0.9 and 1. For the analysis in this article however, we restrict ourselves to only two of the five Field Start Positions, viz: Right of Center (RC) and Right (R). We do so since the scale is symmetric across the Center (C), any initial mapping of Left (L) and Left of Center (LC) can be mapped onto an equivalent Right (R) or Right of Center (RC) configuration. The Center (C) configuration may be an interesting one to consider, but has had to be dropped here to stay focussed on environments where the institutional fields have a clear directional preference to start with.

Agent Start Position

We define three categories for the Agent Start Position, as a function dependent on the starting prior probability of the embedded agent relative to the starting prior probability of the institutional field. First, the agent start position is said to be **Aligned** if $p^0_{0,A}$ is 0.95, to be **Agnostic** if $p^0_{0,A}$ is 0.5 and to be **Adversarial** if $p^0_{0,A}$ is 0.05. This definition of the Agent Start Position relative to a Right (R) or a Right of Center (RC) orientation for the institutional field allows us to capture the effects of alignment in initial preferences between the institutional field and the embedded agent.

Aligned

An agent start position of 'Aligned ' suggests that both the field F and the agent A have a higher starting prior probability of picking 0 (Note from the previous section that under configurations R and RC that we have restricted our experiments to, institutional field F is more likely to pick 0 in all conditions).

Adversarial

An agent start position of 'adversarial ' suggests that the institutional field F and the embedded agent A have opposite orientations toward picking 0 as the outcome at the start (i.e., this would mean $p^0_{0,A} = 0.05$ for both R and RC configurations of the field F).

Agnostic

An agent start position of 'Agnostic ' suggests that the embedded agent A starts off without preferring outcome 0 over outcome 1, therefore with $p^0_{0,A} = 0.5$.

The prior probabilities of the institutional field F (captured by R, or RC), of the embedded agent A (captured by Aligned, Agnostic, or Adversarial) and the relative rates of learning (Slow, Medium, Fast) are the mechanisms that we model to demonstrate the dynamic in the interaction between the embedded agent and the institutional field. The following section discusses the results of the simulation experiments that were run on 1000 pairs of agents over 100 periods. While we ran experiments on 54 unique configurations, we limit our current discussion to the configurations defined above.

Insert FIGURE 1 about here.

Insert FIGURE 2 about here.

DISCUSSION

Having laid out the formal model and having described the assumptions and classifications made in the previous section, we now consider if the model described above is a reasonable abstraction of the phenomenon that we wish to theorize upon. We consider this in the current section.

We use an example to illustrate our argument. In the arena of international business, the decision making behavior of the Multi-National Corporation (MNC) subsidiary is considered a classical case in the institutional theory argument. The institutional field of the MNC subsidiary consists of the MNC parent firm, the legal and intellectual property regimes in the host country, and other organizations such as compatriot MNC subsidiaries in the same region, other firms in the supply chain and host country human resource attributes. Scholars have demonstrated that such MNC subsidiaries have significant autonomy in decision making due to the varied nature of stakeholders that have to managed in the smooth functioning of the MNC subsidiaries.

It is therefore reasonable to model the embedded agent (the MNC subsidiary in this case) as one with the three varied positions at the start: Aligned, where the MNC subsidiary's prior preferences are aligned to that of its institutional field (the host government and the MNC parent are all aligned on the same outcomes, say a higher quantum of offshoring of work from the MNC parent to the MNC subsidiary); Agnostic, where it may not be clear to the MNC subsidiary if it should or should not take up a decision, say of say launching a consulting division of the business. A situation like this may arise because the MNC subsidiary sees both advantages and disadvantages from such a move owing to their understanding of the local characteristics and idiosyncracies while the MNC parent or the government or the workforce at large may be glossing over potential scaling or integration issues; and finally Adversarial, where the MNC subsidiary's initial position is at odds with that of the MNC parent or the larger institutional field.

Having addressed the classification of initial preferences for the agent, we now consider the classification proposed for the institutional field. Given that an institutional field is a complex multitude of several organizations, the question that comes up is if the institutional field should be modeled to reflect the complexity of its underlying constituents, or if it should be modeled based on how it is perceived by the embedded agent. Clearly there are advantages and disadvantages to both approaches. We chose the latter approach in the current study for the simplicity in characterization and modeling[2].

In summary, our model assumes that the institutional field's priors are either one where it favors an outcome of 0 with a 0.95 probability (the configuration that we describe as 'Right' for the lack of a more meaningful alternative), or one where it favors an outcome of 0 with a 0.75 probability (the configuration that we describe as 'Right of Center' in keeping with our Left-Center-Right

[2]Computational models can get quite complex easily, and the judgment of the modeler is often called upon in making such decision. We expect that despite the simplifying assumptions, the current approach is likely to generate insightful behavioral patterns.

terminology). Our conception of an institutional field with a right orientation is one that has a strong initial preference for one set of outcomes, and when associated with a slow rate of learning, equivalent to the structuration resembling the iron cage as described in the literature. A 'Right' initial orientation with a medium rate of learning and a 'Right of Center' initial orientation with a slow rate of learning capture the classic tradeoff between starting position and adaptation capacity. Finally, the 'Right of Center' initial orientation coupled with slow learning is one that captures the rather complex pulls and pushes of the various stake holders in the institutional field who are unable to move the field to any strong consensus in any reasonable period of time. Between the four combinations of characterizations for the institutional field, we have captured the salient aspects of complex interaction as well as coordinated harmony in institutional fields.

A question may arise about the appropriateness of the matching mechanism for studying the dynamics of agent-field interactions. Clearly, the payouts are not in perfect alignment or in perfect misalignment in real embedded agent-institutional field interactions in the real world. Second, most embedded agent- institutional field interactions are not settled at every time period, nor is it necessary or appropriate that these agents pursue a single objective at a point of time. Indeed, as suggested by Kostova et al. (2008), it is quite common for agents to engage in decoupling behavior with ceremonial adoption of institutionalized structures along side the pursuit of specific economically efficient practices. We are sympathetic to these concerns, and believe that these must at some stage be incorporated into computational models. However, it seemed overly ambitious to take those up in this study, and were hence left out.

Finally, it is worth noting two other points. First, that while the embedded agents are allowed three learning rates: slow, medium and fast; institutional fields are allowed only two: slow and medium. This is just an outcome of the complexity assumption, that highly complex organizational forms may not adapt as quickly as less complex organizational forms. Second, because of our classification of initial position of the agent as one in contrast to that of the field, we did not require to consider data from our experiments where the institutional field's starting orientation was 'Left' or 'Left of Center' . This is so because a field orientation of 'Left' , and an agent orientation of agnostic would be no different from a field orientation of 'Right' and an agent orientation of agnostic. A similar argument could be made for 'Left, Adversarial' and being no different from 'Right, Adversarial' . However, we do drop the 'Center' orientation of the institutional field as a simplification for the current study. It is conceivable that a 'Center' initial orientation and slow learning disposition may capture the highest strain of conflict in the institutional field, but it was left out of this study so as to focus more on the configurations in the middle where the answers to appropriate agent action are not particularly obvious.

INTERPRETATION OF MODEL RESULTS

In order to understand the effect of each change on the outcome, we proceed to understand the effects of field configuration and agent configuration on overall outcome one change at a time. Figure 1 lays out the average score charts for four agent-field combinations while enforcing the field to start in Right of Center (this is the same as saying $p^0_{0,F} = 0.75$). Figure 1 demonstrates that an adversarial agent with a slow rate of learning ($\phi_A = 0.05$) is likely to get stuck at a peak average performance of around 0.5, whereas one in medium learning rate field is likely to reach a peak average performance of close to 0.8 (This is the comparison of the two dotted lines graphs in blue and green).

On the other hand, we notice that agnostic agents do similarly despite changes in the rate of learning of the field F. The interesting result from Figure 1 is that though adversarial agents start off with contradictory preferences to the field, they end up with a higher average score than the agnostic agents who start off with a better alignment (0.5 is more aligned to 0.95 than is 0.05). The logic for this result is that the adversarial agent is actually adapted by the field F due to its relatively higher learning rate. In the case of the adversarial agent in the (Slow, Slow) configuration, the agent was stuck with $p^0_{t,A}$ closer to 0.5 with the field F unable to pull that agent A up quickly enough due to it's slow rate of learning. This (adversarial agent in a (Slow, Slow)) configuration is therefore a good candidate for a change in setting.

Insert FIGURE 3 about here.

In moving from Figure 1 to Figure 2, we shift the initial preference of the institutional field from Right of Center, to Right. This effectively increases the initial divergence in the preferences between agents and the institutional field. We observe that the peak average score for the slow learning adversarial agent is lower as compared to the peak average score of the slow learning adversarial agent in Figure 1. This result is to be expected because of the increased burden on the institutional field to bridge a wider gap in initial preferences.

Hypothesis 1a: When the institutional field is open to influence, slow learning adversarial agents will raise overall performance higher than slow learning agents with a neutral orientation

Hypothesis 1b: For the same rate of learning for the institutional field, slow learning adversarial agents will raise overall performance less with a larger divergence between the initial preferences between agents and the institutional field

Insert FIGURE 4 about here.

In moving from Figure 2 to Figure 3, we raise the agent learning rate from slow to medium for all configurations while keeping everything else constant. We observe here that the increased learning rate increases the overall performance in all configurations, but the greatest gains are made in configurations with agnostic agents. The effect that we had observed in Figure 1 and Figure 2 may therefore be confirmed to be due to the differential rate of learning of the agents with respect to the institutional field. Once agents were allowed to increase their rate of learning, the adversarial agents are no longer better than agnostic agents. Indeed, Figure 3 demonstrates that the agnostic agents who begin being neutral to either outcome are able to use their superior learning rates to achieve a higher level of overall performance. This trend is confirmed further in Figure 4 where the learning rates of agents are increased even further to 'Fast'.

Hypothesis 2a: For the same initial outcome preferences, the overall performance score varies curvilinearly with difference in the rates of learning of the agent and the institutional field

Hypothesis 2b: For the same initial outcome preferences, the overall performance score drops as the difference in the rates of learning of the agent and the institutional field drops

Insert FIGURE 5 about here.

Our next experiment studies the effect of increasing the initial level of openness of the institutional field while retaining the learning rates of the agents at 'Fast'. We notice from comparing Figure 5 with Figure 4 that a performance gap opens up between the slow learning institutional field and the medium learning institutional field. This leads us to an interesting insight that increasing the learning rate differential between the institutional field and the agent is useful up to a point, after which a large divergence in learning ability results in a lower level of overall outcome.

Insert FIGURE 6 about here.

Figure 6 illustrates the effect of reducing the rate of learning of the fast learning agents to medium, keeping all else the same. We notice that the average overall performance drops as a result. The trends from Figure 4, Figure 5, and Figure 6 suggest that the outcomes may initially increase with increased difference in learning abilities and then drop. This trend is confirmed in Figure 7 where we drop the learning rate of one set of agents all the way to slow. Clearly this result is hardly surprising, as one would expect fast learning agents to contribute higher to overall outcomes than slow learning ones.

Hypothesis 3: An increase in the openness of an institutional field does not raise overall performance when agents have a neutral orientation with a slow rate of learning

Insert FIGURE 7 about here.

LIMITATIONS AND FUTURE WORK

The formal computational modeling approach to theorizing organizational phenomena comes across as being both valuable and challenging simultaneously. While the fine grained control and possibility of step by step changes in experiments allows for a detailed understanding of micro phenomena, the very flexibility also creates a problem of plenty. However, with the appropriate priorities this should be a good problem to have.

The larger question relevant for institutional theory applications is how to model the institutional field. A potential alternative to the current simplifying assumption coming from an agent view of the institutional field is to develop independent models of the institutional field with its associated components, and to possibly use the outcomes from such models to inform our model of the institutional field. Clearly, there is much further to go on this question before anything may be applied to the practice of research.

We would like to highlight three specific points that can be developed upon in future work. First, it seems unrealistic to assume that either agents or institutional fields have a constant rate of learning for all time. An interesting experiment would be to allow for both phases of inspiration (a higher rate of learning) and phases of boredom (lower or counter productive learning) while maintaining some average learning rate. Second, decoupling seems to an important phenomenon in practice that is has also been hard to formalize using traditional empirical methods. It seems like modeling embedded agency with decoupling could lead to very interesting opportunities to theorize organizational phenomena. Finally, the inclusion of decoupling could possibly suggest relooking the assumption of the matching game. As was noted earlier in the article, agents and fields are probably updating their priors less often, and with less perfect information that has been assumed in the current model. Allowing for some flexibility there could help us capture the nuances of the agent field interaction in greater depth.

CONCLUSION

We started out attempting to improve our understanding of the mechanisms behind the embedded agent - institutional field engagement. We captured the dynamics of the embedded agent - institutional field relationship as a function of their relative learning rates over repeated encounters in a game of matching. Despite focusing on a sub-set of potential states, we were able to demonstrate multiple situations where seemingly counter-intuitive priors lead to better outcomes. Our work here contributes to a nuanced and deeper understanding of the dynamics of the embedded agent - institutional field relationship, and a potential mechanism by which changes in this setting may affect organizational outcomes.

In addition to helping develop theory further, our approach has also identified a number of simplifying assumptions, that when relaxed can help generate richer theory. We expect that much additional theoretical understanding of dynamic organizational phenomena may ensue by the application of formal computing models in the years ahead. In that respect, the current article remains very much a snapshot of a larger work-in-progress project.

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SIMULATION CODE

```
# Using reinforcement learning to a game of repeated matching
# Modified from a version obtained from Phanish Puranam

import random
import numpy as np
import csv

def choice(attraction,t):
    retval=random.random() # this picks a random number between 0 and 1
    if attraction[t]>retval: # compare to the agent's prior
        retval= 0
    else:
        retval= 1
    return retval

def learning(phi):
    if (phi < 0 or phi > 1):
        return "LearnUndef"
    if phi <= 0.05:
        return "Slow"
    if phi <= 0.3:
        return "Medium"
    if phi <= 0.7:
        return "Fast"
    return "Rapid"

def position(p):
    if (p < 0 or p > 1):
        return "PositionUndef"
    if p <= 0.10:
        return "L"
    if p <= 0.35:
        return "LC"
    if p <= 0.65:
        return "C"
    if p < 0.9:
        return "RC"
    return "R"

num_periods=100 #number of periods to simulate the model
num_pairs=1000 #number of pairs of agents
```

```
pAs=[0.5, 0.75, 0.95]
pBs=[0.05, 0.5, 0.95]
phiAs=[0.05, 0.3]
phiBs=[0.05, 0.3, 0.7]
models = []
for pB in pBs:
    for phiB in phiBs:
        for pA in pAs:
            for phiA in phiAs:
                modelName="F["+position(pA)+"-"+learning(phiA)+"] U["+
                    position(pB)+"-"+learning(phiB)+"]"
                models.append([modelName, pA, phiA, pB, phiB])

allResults = np.zeros((num_periods,len(models)))
iteration = 0
for current in models:
    phi1 = current[2]
    phi2 = current[4]
    prefA=np.zeros((num_periods+1,1))
    prefB=np.zeros((num_periods+1,1))
    prefA[0] = current[1]
    prefB[0] = current[3]

    org_perf=np.zeros((num_periods,num_pairs)) # fill zeors for all time
    org_cumperf=np.zeros((num_periods,num_pairs)) # cumulative performance
        over time for each pair of agents
    result=np.zeros((num_periods,3)) # this stores the aggregated results
        which we will show on graphs

    #mapoff matrix
    R=np.zeros((2,2)) # 2 by 2 matrix full of zeroes
    R[0][0]=1 # Payoff = 1 when both agents chose 0
    R[1][1]=1 # Payoff = 1 when both agents chose 1


    for a in range(num_pairs): # for each pair of agent

        for t in range(num_periods): # for each period
            choice1=choice(prefA,t) # agent 1 choice at t
            choice2=choice(prefB,t) # agent 2 choice at t
            payoff=R[choice1][choice2]

            org_perf[t][a]=payoff # this payoff constitutes the org's
                performance at time t...
            # ... and contributes to the org's cumulative performance:
```

```
            if t>0:
                org_cumperf[t][a]=org_cumperf[t-1][a]+payoff
            else:
                org_cumperf[t][a]=payoff

            # The 2 agents update their priors based on what the payoff was
            if payoff==1:
                if choice1==0:
                    prefA[t+1]=prefA[t]+phi1*(1-prefA[t])
                else:
                    prefA[t+1]=prefA[t]-phi1*prefA[t]
                if choice2==0:
                    prefB[t+1]=prefB[t]+phi2*(1-prefB[t])
                else:
                    prefB[t+1]=prefB[t]-phi2*prefB[t]
            if payoff==0:
                if choice1==0:
                    prefA[t+1]=prefA[t]-phi1*prefA[t]
                else:
                    prefA[t+1]=prefA[t]+phi1*(1-prefA[t])
                if choice2==0:
                    prefB[t+1]=prefB[t]-phi2*prefB[t]
                else:
                    prefB[t+1]=prefB[t]+phi2*(1-prefB[t])


    for t in range(num_periods):
        result[t][0]=t+1
        result[t][1]=float(np.sum(org_perf[t,:]))/num_pairs
        result[t][2]=float(np.sum(org_cumperf[t,:]))/num_pairs
        allResults[t][iteration] = result[t][1]

    iteration += 1

results = open('embeddedAgency.csv', 'w')
writer = csv.writer(results)
header = []
header.append('period')
for model in models:
    header.append(model[0])
writer.writerow(header)
iteration=1
for values in allResults:
    row = [iteration]
    row.extend(values)
```

```
    writer.writerow(row)
    iteration += 1
results.close()
```

FIGURE 1

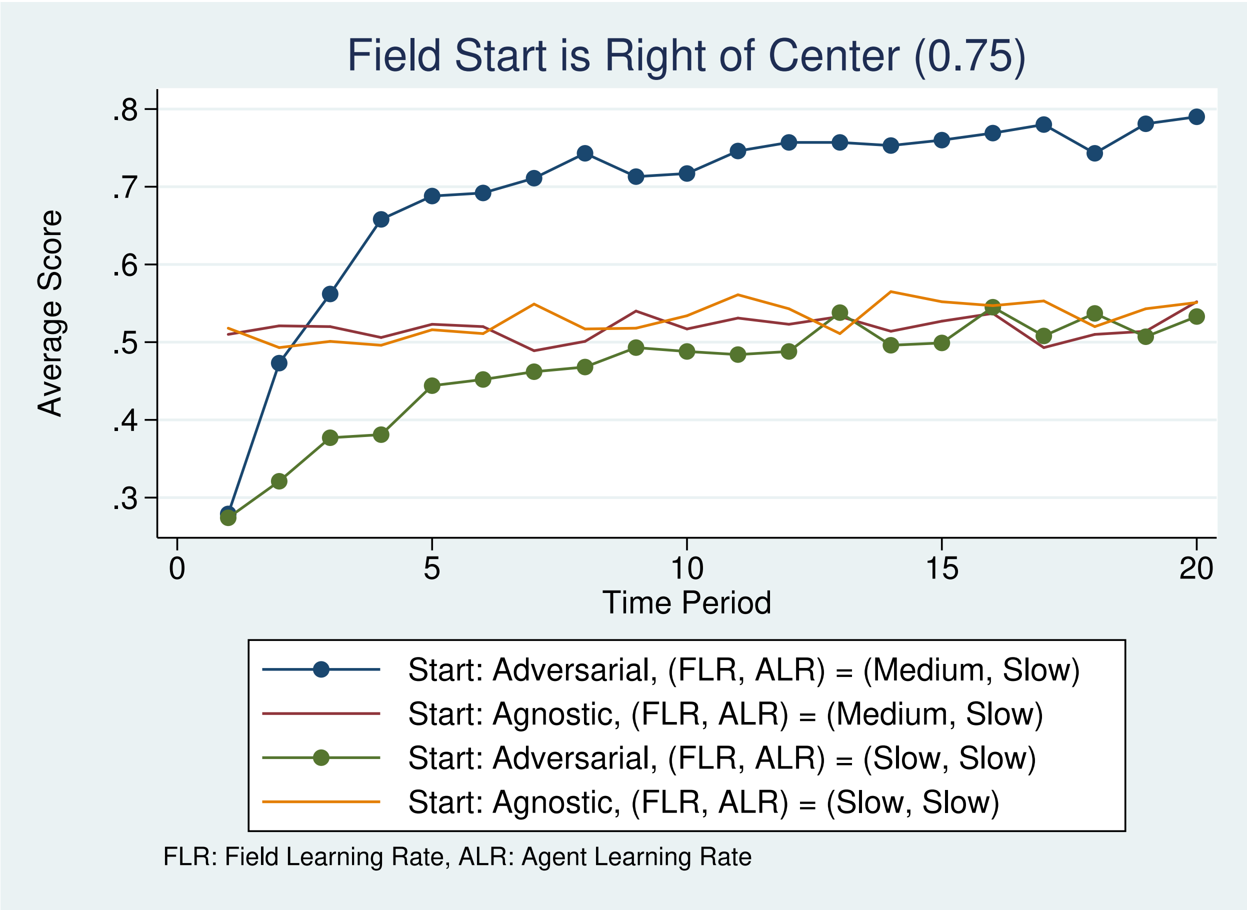
Field Start is Right of Center (0.75)
Average Score
.8
.7
.6
.5
.4
.3
0
5
10
15
20
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Slow)
Start: Agnostic, (FLR, ALR) = (Medium, Slow)
Start: Adversarial, (FLR, ALR) = (Slow, Slow)
Start: Agnostic, (FLR, ALR) = (Slow, Slow)
FLR: Field Learning Rate, ALR: Agent Learning Rate

FIGURE 2

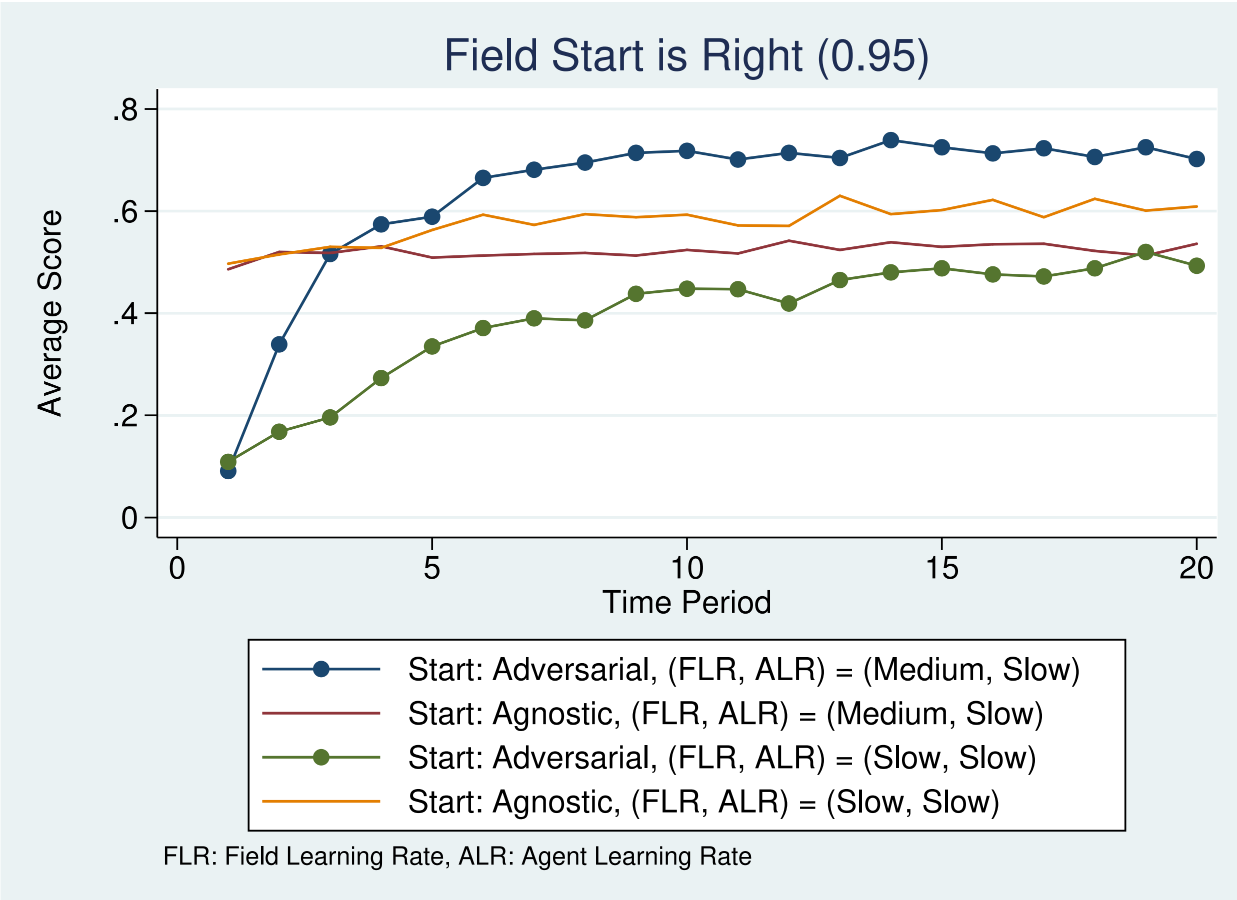
Field Start is Right (0.95)
Average Score
.8
.6
.4
.2
0
0
5
10
15
20
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Slow)
Start: Agnostic, (FLR, ALR) = (Medium, Slow)
Start: Adversarial, (FLR, ALR) = (Slow, Slow)
Start: Agnostic, (FLR, ALR) = (Slow, Slow)
FLR: Field Learning Rate, ALR: Agent Learning Rate

FIGURE 3

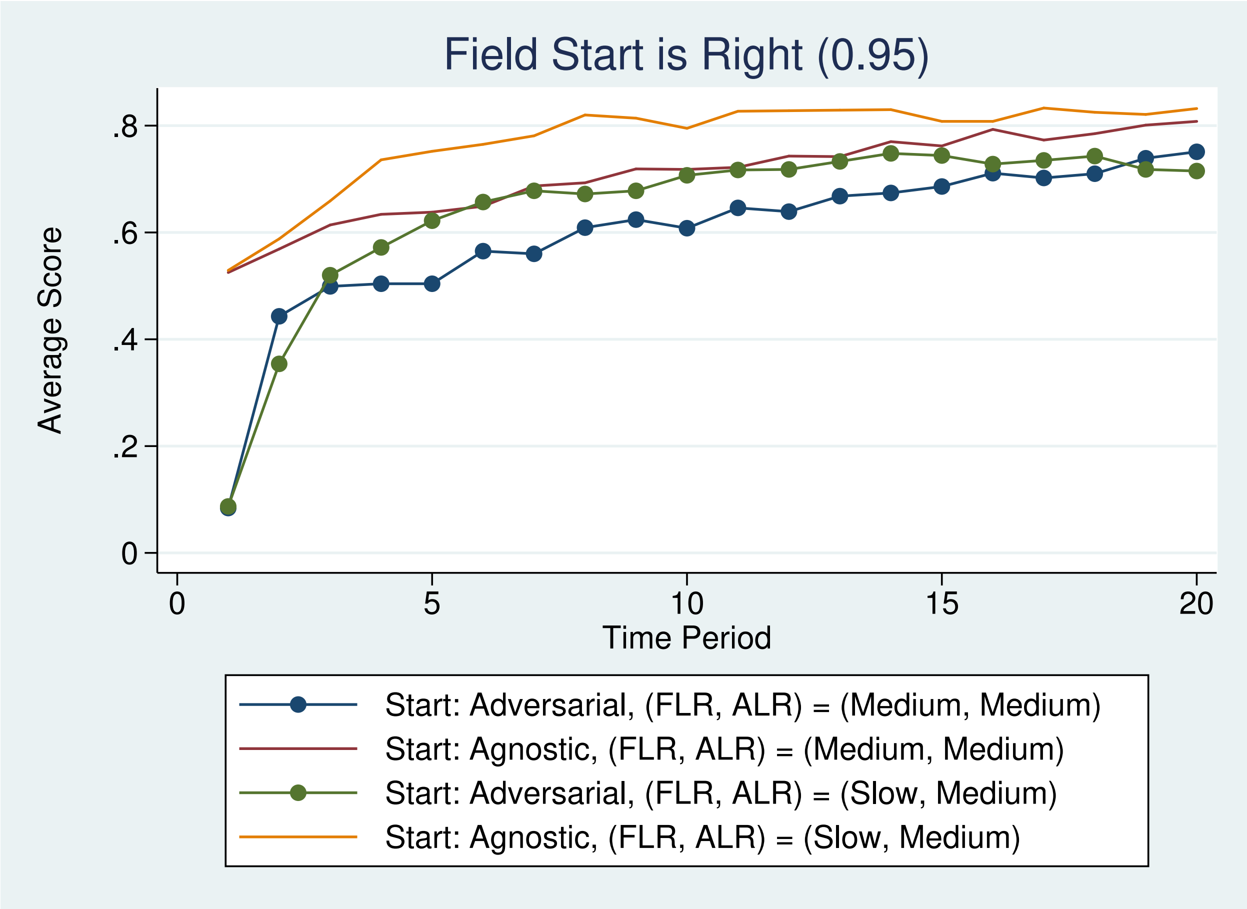
Field Start is Right (0.95)
Average Score
0
.2
.4
.6
.8
0
5
10
15
20
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Medium)
Start: Agnostic, (FLR, ALR) = (Medium, Medium)
Start: Adversarial, (FLR, ALR) = (Slow, Medium)
Start: Agnostic, (FLR, ALR) = (Slow, Medium)

FIGURE 4

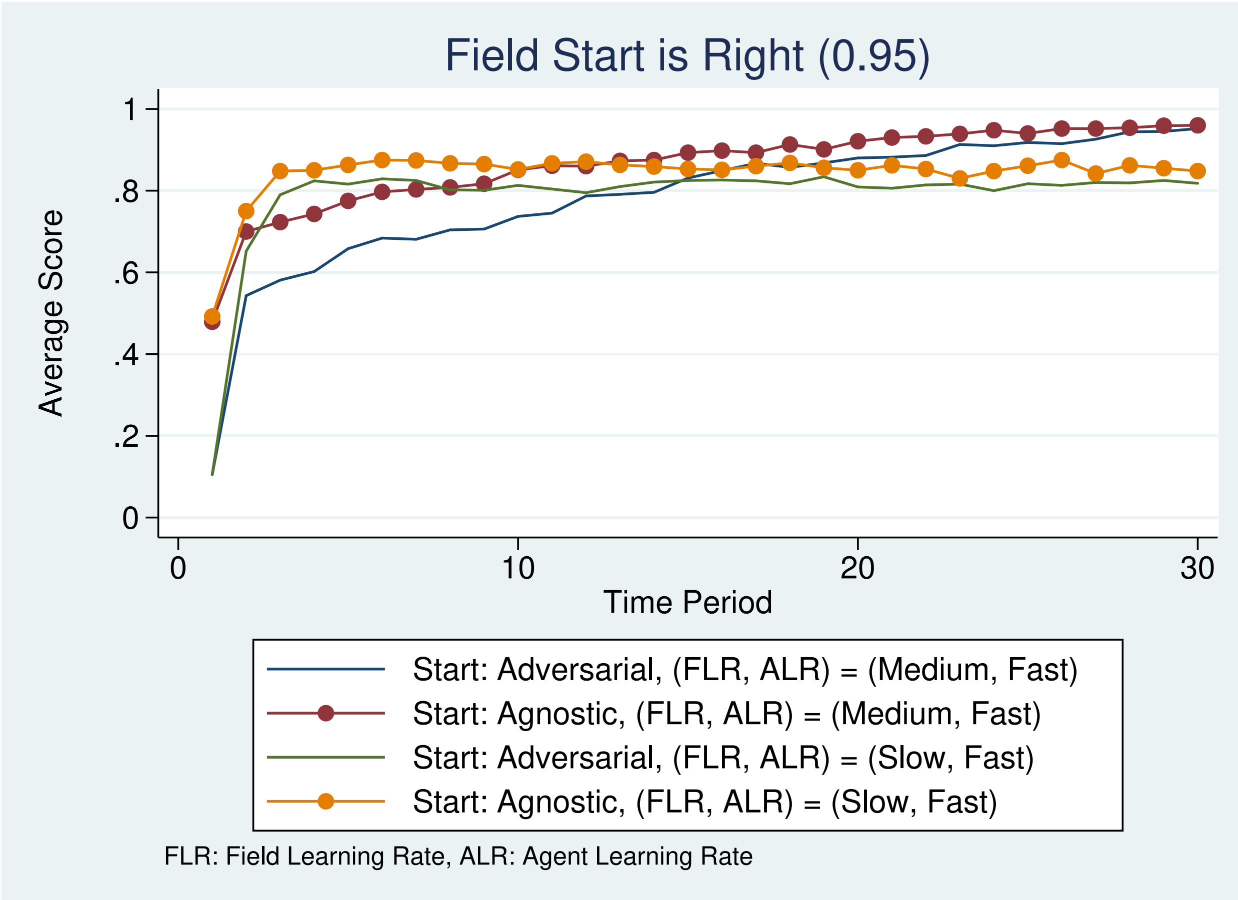
Field Start is Right (0.95)
Average Score
0
.2
.4
.6
.8
1
0
10
20
30
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Fast)
Start: Agnostic, (FLR, ALR) = (Medium, Fast)
Start: Adversarial, (FLR, ALR) = (Slow, Fast)
Start: Agnostic, (FLR, ALR) = (Slow, Fast)
FLR: Field Learning Rate, ALR: Agent Learning Rate

FIGURE 5

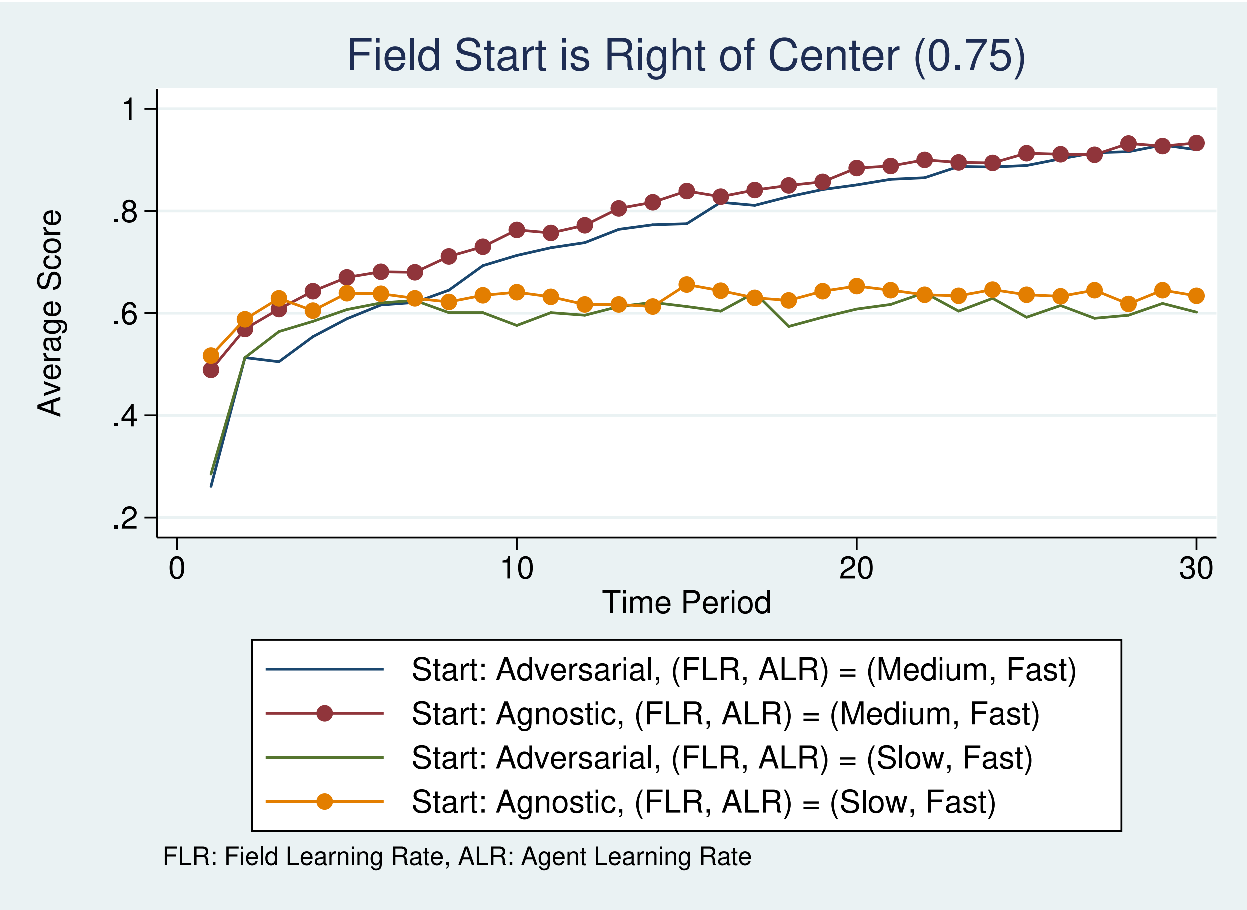
Field Start is Right of Center (0.75)
Average Score
1
.8
.6
.4
.2
0
10
20
30
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Fast)
Start: Agnostic, (FLR, ALR) = (Medium, Fast)
Start: Adversarial, (FLR, ALR) = (Slow, Fast)
Start: Agnostic, (FLR, ALR) = (Slow, Fast)
FLR: Field Learning Rate, ALR: Agent Learning Rate

FIGURE 6

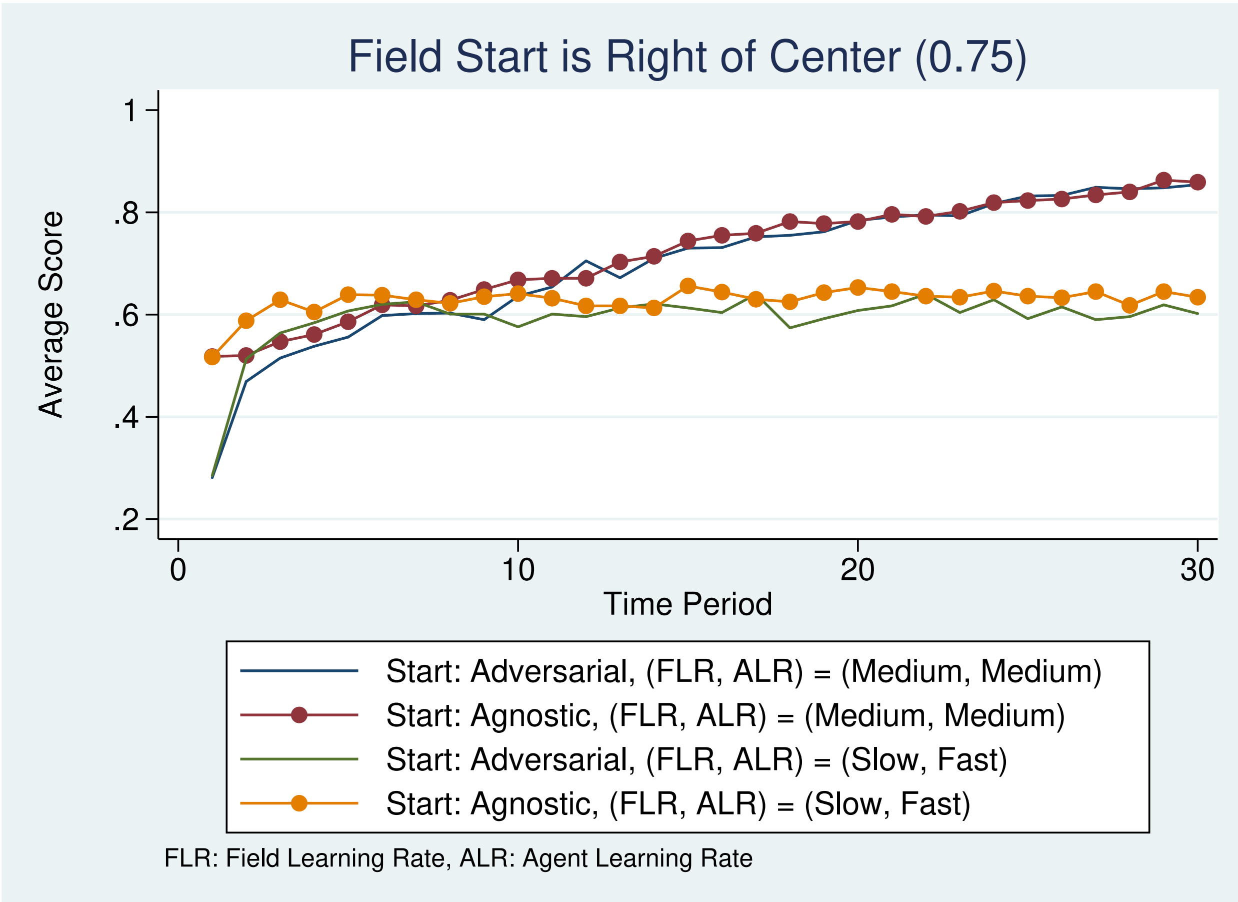
Field Start is Right of Center (0.75)
Average Score
1
.8
.6
.4
.2
0
10
20
30
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Medium)
Start: Agnostic, (FLR, ALR) = (Medium, Medium)
Start: Adversarial, (FLR, ALR) = (Slow, Fast)
Start: Agnostic, (FLR, ALR) = (Slow, Fast)
FLR: Field Learning Rate, ALR: Agent Learning Rate

FIGURE 7

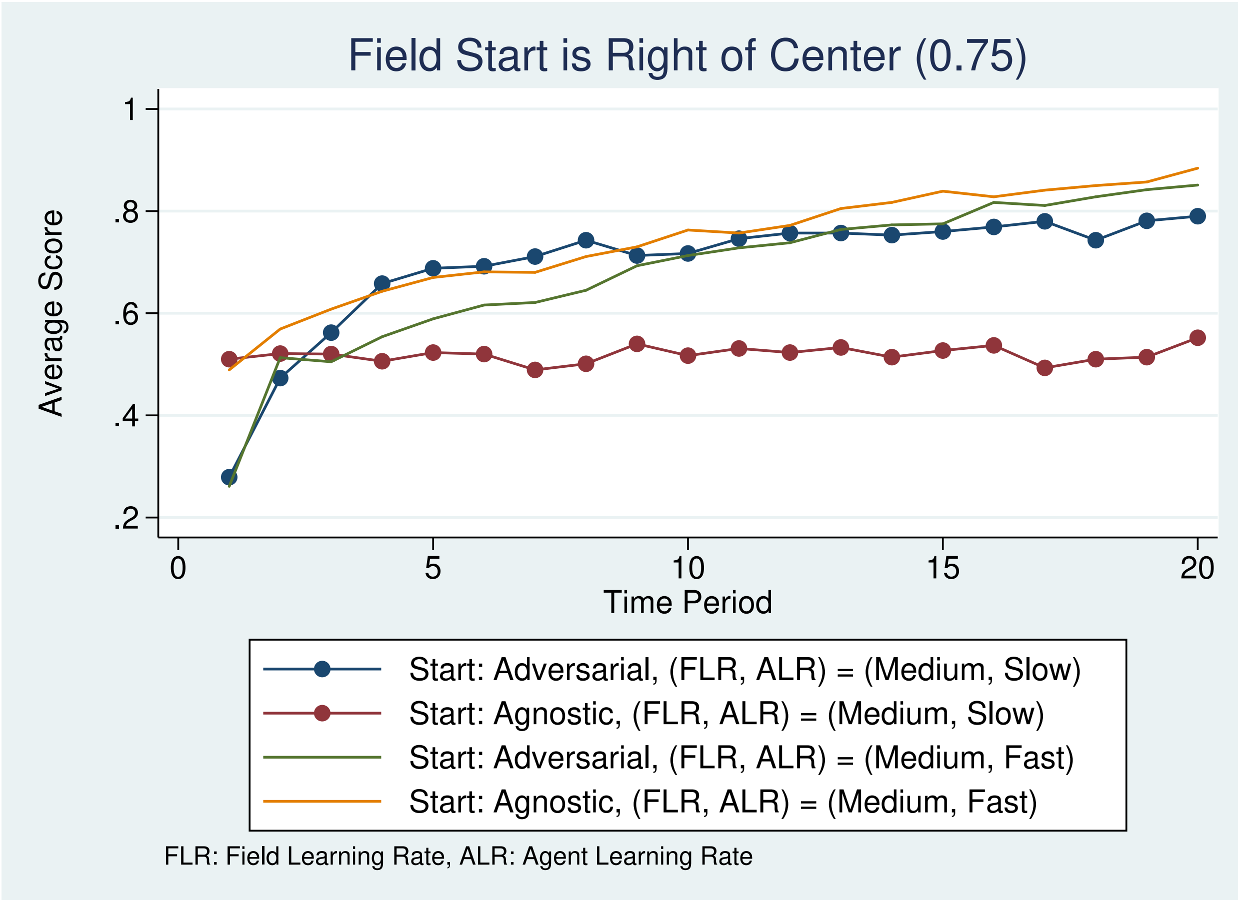
Field Start is Right of Center (0.75)
Average Score
1
.8
.6
.4
.2
0
5
10
15
20
Time Period
Start: Adversarial, (FLR, ALR) = (Medium, Slow)
Start: Agnostic, (FLR, ALR) = (Medium, Slow)
Start: Adversarial, (FLR, ALR) = (Medium, Fast)
Start: Agnostic, (FLR, ALR) = (Medium, Fast)
FLR: Field Learning Rate, ALR: Agent Learning Rate

TABLE 1: Payoff Matrix

	$choice_F(t) = 0$	$choice_F(t) = 1$
$choice_A(t) = 0$	$[payoff_F(t), payoff_A(t)] = [1,1]$	$[payoff_F(t), payoff_A(t)] = [0,0]$
$choice_A(t) = 1$	$[payoff_F(t), payoff_A(t)] = [0,0]$	$[payoff_F(t), payoff_A(t)] = [1,1]$

TABLE 2: Matrix of Rules for Updating Prior Probabilities

	$payoff(t) = 1$	$payoff(t) = 0$
$choice(t) = 0$	$p^0_{t+1} = p^0_t + \phi(1 - p^0_t)$	$p^0_{t+1} = p^0_t - \phi(p^0_t)$
$choice(t) = 1$	$p^0_{t+1} = p^0_t - \phi(p^0_t)$	$p^0_{t+1} = p^0_t + \phi(1 - p^0_t)$