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An Agent-based Concept to Analyze Elite-Athletes' Doping Behavior

Daniel Westmattelmann, Marcel Goelden, Gerhard Schewe
Chair of Organization, Human Resource Management and Innovation, University of Münster, Universitätsstr. 14-16, 48143 Münster,
GERMANY
Email:
{daniel.westmattelmann, marcel.goelden, orga}@uni-muenster.de

Sascha Hokamp
Research Unit Sustainability and Global Change, Center of Earth System Research and Sustainability, KlimaCampus, University of Hamburg, Grindelberg 7, 20144 Hamburg, GERMANY
Email: sascha.hokamp@zmaw.de

***Abstract* — A seemingly endless series of scandals has focused increasing public attention on the issue of doping among elite athletes. But we still do not know how many elite athletes really make use of banned drugs. In addition, we recognize the literature suffers a lack of appropriate game theory models for complex social interactions related to doping. Therefore, we think that an agent-based approach may allow doping behavior patterns in professional sports to be explored and elucidated. We conceptualize an agent-based model on three interacting objectives, namely (i) elite athletes, (ii) anti-doping laboratory and (iii) anti-doping agency. The latter agency announces anti-doping rules and imposes penalties; the anti-doping laboratory executes doping controls and elite athletes compete for income. In particular, we focus on presenting an agent-based concept to analyze elite athletes' doping behavior. Using such an agent-based framework and computational simulations may lead in the future to policy recommendations for the fight against doping.**

I. Introduction

AS LONG as competitive professional sports exist the phenomenon of using illicit methods like doping will remain. However, in modern times doping has gained more and more public attention since the astonishing death of cyclist Knud Jensen at the Olympic Games of 1960. The World Anti-Doping Agency (WADA) has shown the rate of Adverse Analytical Findings is approximately 1% in recent years [1]. But banned substances and methods may not be detectable and effective doping controls may not be feasible, e.g. because of their enormous costs in economic terms. Therefore, we believe, in line with [2]-[3], that [1] underestimates the true extent of doping behavior in elite sports. Recent research activities in this field are based on various methods to approximate the extent of doping but estimates differ widely. To begin with, [4] make use of projection-methods and estimate the extent of doping as approximately 72%. Applying a forensic approach, [5] analyze 7,289 blood samples collected from 2,737 athletes. The authors detect abnormal blood profiles and calculate the extent of blood doping as approximately 14% [5]. In a world wide web survey, [6] ask 448 German elite athletes about their doping behavior, making use of a randomized response technique to ensure that answers are anonymous. The authors present a lower interval limit of 25.8% and an upper limit of 48.1% for the use of banned substances or methods by German elite athletes [6]. Also applying a randomized response technique, [7] conduct a study of 1,394 international top athletes and find the extent of doping is approximately 6.8%. To sum up, we find in the literature estimations for extents of doping in a range of 1% to 72% [1]-[7]. Further investigations also differ in the extent of doping estimated, which supports our notion that identifying the real extent of doping is a complex problem [8]-[13].

To address this problem of complexity in professional sports doping researchers have developed various game theory models based on rational choice theory [14]-[17]. A common feature of these models is to depict doping behavior patterns in professional sports. But we think that these models exhibit a low degree of complexity because of analytical solvability.

Therefore, the main purpose of the paper is to address the complexity problem by presenting an agent-based concept to analyze elite athletes' doping behavior. If we have no clue what the real extent of doping may be how can we provide reliable policy recommendations? An agent-based approach might allow determining detected as well as undetected dopers within populations of elite athletes under varying environmental conditions. We describe below an agent-based framework that may serve in the future as a basis for generating simulation results and follow-up contributions. For instance, we incorporate elite athletes' decisions that affect more than one time period; an issue frequently neglected in the literature and which allows the investigation of lapse-of-time effects.

The paper is organized as follows. The next section presents a brief literature overview of game theory models that describe doping behavior patterns in professional sports, with a focus on strategic and inspection games. The third section proposes an agent-based concept to analyze elite athletes' doping behavior. The final section discusses implications and provides an outlook.

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II. Literature Overview of Game Theory Models

A. Strategic Games

In this subsection we survey briefly a series of game theory models that make use of strategic interactions based on rational choice theory to elucidate doping behavior patterns in sports. The seminal paper [14] appeared in 1987 and by a simple and simultaneous game theory model similar to a prisoner's dilemma situation describes an athlete's doping decision. The authors' so-called 'doping dilemma' consists of two rational-acting athletes endowed with identical characteristics who have to decide independently from each other to dope or not to dope. To do so, the athletes make use of an expected utility maximization approach as follows. An athlete decides to dope if her expected utility is higher in the case of doping abuse compared to the abandonment of doping. Therefore, athletes take benefits and costs of doping into account. The author concludes that without an anti-doping control, checked in turn by an international inspection procedure, the doping problem cannot be eliminated. In the case such a strategy does not work within a few years the legalization of doping is the only solution.

To our best knowledge [18] implements for the very first time a doping-control-scheme in strategic games to verify if athletes act rule-consistently so that detected doping athletes may be punished. Two interacting athletes make use of a linear expected utility function concerning whether to take banned substances or not. Although the authors invent a novel doping-control-scheme, their focus is on strategic interactions among athletes because of controls conducted at random and not on the basis of a specific decision-making process. The authors find that, beyond the investments made in the dope-testing system, other factors, such as prevention measures, the number of events and the prizes offered, have a non-negligible effect on doping behavior in elite sports.

Contrary to the assumption in both strategic games above, [19] assumes that athletes do not have an identical chance to win a competition. Hence, the author creates two artificial athletes endowed with heterogeneous characteristics and, therefore, having an unequal probability to win a competition even under identical conditions. The result is that ranking-based punishments are less costly and more effective than the regulations announced by the International Olympic Committee. Further, based on [19], 'unpublished' [20] develop an evolutionary doping game considering more than one time period. The authors find situations where, in theory, all athletes either break anti-doping rules or act totally rule-consistently. Furthermore, the authors provide evidence that highly talented athletes are more likely to dope than athletes with a lower degree of talent.

Reference [16] evolves a symmetric strategic game that takes two athletes into account who are endowed with homogeneous characteristica. The author aims to determine the influences of prize-money distributions and likelihoods to detect doping behavior. As an extension, [21] examines up to four athletes and focuses on comparisons between linear and non-linear prize-money distributions. While linear prize-money distributions lead to situations in which all athletes act (non-) rule-compliantly, non-linear prize-money distributions lead to more complex situations. Reference [22] refers to [16] as well as [21] and implements so-called 'fair play norms' like pre-play communication about doping and formal anti-doping agreements, which may induce higher compliance levels with anti-doping rules.

Reference [23] evolves an asymmetric strategic game within athletes' performance that depends on individual talent, or rather, constitution. An athlete may make use of legal activities like training or may resort to banned and illicit substances. In consequence athletes can enhance their performance and thereby improve their competition result. The author examines effective strength of doping substances, doping costs, and income effects with respect to the influence on an athlete's decision to dope or not to dope. The author identifies costs, likelihoods and base-salary effects that deviate athletes from doping abandonment.

Reference 'unpublished' [24] provides an asymmetric strategic game appropriate to consider any desired number of athletes. The author models a 'winner-takes-all' effect, i.e. only the winner of a competition receives prize-money. Such an extreme prize-money distribution seems to be responsible for the finding that incentives to dope decrease if the number of athletes in competition increases. In addition, 'unpublished' [24] deduces an optimal – in the sense of economic costs – quantum of doping controls if athletes are selected at random for testing.

B. Inspection Games

In this subsection we overview briefly inspection games applied to doping behavior, a recent development in game theory that [15] launched in 2002. It is important to distinguish between strategic and inspection games insofar as inspection games feature an institution which conducts doping controls on the basis of specific decision-making processes. After interactions among athletes in competition have taken place, an institution conducts doping controls. Thus, inspection games focus mainly on interactions between athletes and a doping-control institution whereas strategic games illuminate interactions among athletes. In the seminal paper on inspection games [15] shows that increasing fines leads to a higher level of rule-compliance.

Reference 'unpublished' [25] models characteristica very similar to those modeled in [15] and presents an institution that conducts doping controls as facing two kinds of error. On the one hand a doped athlete is not detected despite being tested (error of the first kind) and on the other hand a clean athlete may be erroneously found guilty of taking banned substances (error of the second kind). The author finds that an athlete's optimal choice – with respect to maximization of expected payoffs – depends on the preferences of the institution in terms of how to conduct dope controls and on the quality of those controls.

Reference [17] extends [19] with respect to a doping-control institution that decides subsequently to the competition whether to test the winner or not. Hence, the authors extend a strategic game to obtain an inspection game. Recall that the basic model, i.e. [19], consists of two athletes; a winner and a looser. Among other things, the doping-control institution takes information into account from the losing athlete, the so-called 'whistleblower' [17]. The authors conclude that whistleblowing reduces economic costs of doping controls, since testing athletes is costly.

Reference 'unpublished' [26] provides an extension of an inspection game model. The authors model three steps, which are, (i) competitions among athletes, (ii) doping controls, and (iii) decisions of customers or sponsors. The latter step is innovative and concerns in particular customers or sponsors' point of view with respect to their option to withdraw their financial support after a doping scandal. The authors find that doping controls should be carried out by an independent institution. A doping-control institution that depends on the financial support of customers or sponsors has no incentive to detect doping athletes.

To summarize, we surveyed briefly more than ten contributions to game theory models of doping behavior patterns. We find that the strategic and inspection models above often consider fewer than four athletes; a feature far from reality in professional sports. Reference 'unpublished' [24] is an exception that allows any desired number of athletes to be considered. However, game theory models applied to doping have a low degree of complexity. Therefore, we propose in the following section an agent-based concept to analyze an elite athletes' doping behavior.

III. Agent-based Concept

A. Aims and Basics

In line with the literature we think that agent-based modeling has potential as a 'third way' of doing social science in addition to argumentation and formalization [27]. Reference [28] provides a toolkit for agent-based modeling and computational economics. Reference [29] overviews agent-based modeling applied to economic problems and social dilemmas. Reference [30] presents recent advances in computational econophysics including agent-based econophysics. Making use of agent-based modeling we are able to formalize theories on complex social processes like doping behavior patterns in professional sports. Thus, modeling a high degree of complexity is an essential advantage of an agent-based approach compared to game theory models.

Note that we do not aim to present an agent-based model of doping behavior for the purpose of estimating or predicting the real extent of doping in professional sports. Instead, we intend to model a complex social system to test how parameters – e.g. bans, fines, prize-money distributions and subjective detection probabilities – may influence elite athletes' doping behavior and how policymakers may fight against doping.

Our multi-period agent-based doping concept is based on three interacting objectives, namely, (i) elite athletes, (ii) an anti-doping laboratory, and (iii) an anti-doping agency. The agency announces anti-doping rules and imposes fines as well as bans. Anti-doping laboratory executes doping controls whereby control frequency and efficiency are imperfect, so that not every doped and tested elite athlete is detected as a dope user. In each time period any elite athlete competes for income in a rank-order tournament. We assume that using dope increases an elite athlete's chance of success in rank-order tournaments in the short term but such an illegal practice causes an adverse reaction in the long term. To put it differently, in the long term the harm caused to elite athletes by doping is higher than the benefits. We justify such an adverse reaction to doping in terms of potential health risks. However, in the following subsections we introduce key parameters and explain in detail our three interacting objectives (i) elite athletes, (ii) anti-doping laboratory, and (iii) anti-doping agency.

B. Anti-doping Agency

We create an 'artificial' anti-doping agency within our agent-based concept to reflect the 'real world' institution, i.e. the WADA. The anti-doping agency announces anti-doping rules the elite athletes have to comply with. Hence, the anti-doping agency sets a Complexity of Anti-doping Rules (CAR). Furthermore, the anti-doping agency determines pecuniary levels of FINes (FIN) and states BANs (BAN). Thus, detected dope-taking athletes face a system of punishment that consists of fines paid in Tokens and bans with respect to time periods an elite athlete is forbidden to participate in rank-order tournaments. The maximum number of time periods applied, i.e. the maximum ban (maxban), depends on minimum and maximum age (minage, maxage) within a population of elite athletes. Table I provides characteristica of parameters and attributes used in our agent-based doping concept.

At the end of any time period the anti-doping agency publishes statistics on doping. In particular, we aim at calculating figures like the Share of DEtected elite athletes (SDE), the Share of DOped elite athletes (SDO) and the Share of Detected and Doped elite athletes (SDD).

TABLE I.
AGENT-BASED DOPING MODEL: CHARACTERISTICA OF PARAMETERS AND ATTRIBUTES

Parameter / Attribute	**Abbreviation**	**Characteristica**	
Anti-doping Agency			
Complexity of Anti-doping Rules	CAR	[0;1]	Exogenous
FINes	FIN	[0; ∞]	Exogenous
BAN	BAN	[0; maxban]	Exogenous
Anti-doping Laboratory			
Number of Tested elite Athletes	NTA	[0; N]	Exogenous
Number of Preannounced-tested elite Athletes	NPA	[0; N]	Exogenous
Number of Randomly-tested elite Athletes	NRA	NTA-NPA	Exogenous
Control EFficiency	CEF	[0; 1]	Exogenous
Number of Controlled Periods	NCP	[1; ∞]	Exogenous
Share of DEtected elite athletes	SDE	[0; 1]	Endogenous
Share of DOped elite athletes	SDO	[0; 1]	Endogenous
Share of Detected and Doped elite athletes	SDD	[0; 1]	Endogenous
Elite Athletes			
Population of elite athletes	N	[1, ∞]	Exogenous
Identification number	I	[1, N]	Exogenous
AGe	AG	[minage; maxage]	Endogenous
Behavioral-Type	BT	[A; B; C; D]	Exogenous
PErformance	PE	[0, maxperformance]	Endogenous
FItness	FI	[0; 100]	Endogenous
COnstitution	CO	[0; 100]	Endogenous
DIsturbance	DI	[0; 100]	Endogenous
INcome	IN	[-∞; maxprize]	Endogenous
Income due to Detected doping	ID	[-∞; maxprize]	Endogenous
Income due to Undetected doping	IU	[-DC; maxprize]	Endogenous
Doping Decision	DD	[+; -]	Endogenous
Realized Rank in tournament	RR	[0; N]	Endogenous
Doping Costs	DC	[0; ∞]	Exogenous
Doping Efficiency	DE	[0; 1]	Exogenous
Doping Harm	DH	[0; 1]	Exogenous
Prize-Money	PM	[0; maxprize]	Endogenous
Weighting of Fitness	WF	[0; 1]	Exogenous
Weighting of Constitution	WC	[0; 1]	Exogenous
Weighting of Disturbance	WD	[0; 1]	Exogenous
Time index	T	[0; ∞]	Endogenous
Weighting of doping Efficiency	WE	[0; 1]	Exogenous
Weighting of doping Harm	WH	[0; 1]	Exogenous
Expected Utility	EU	[0; 1]	Endogenous
Subjective detection Probability	SP	[0; 1]	Endogenous
Risk Perception	RP	[0; 1]	Endogenous
Size of an elite athletes' social Network	SN	[1; N]	Exogenous
Number of periods an elite athlete has to act Rule-compliant	NR	[0; maxage-minage]	Exogenous

Note: Table I offers an overview of characteristica used within the agent-based concept sorted according to (i) anti-doping agency, (ii) anti-doping laboratory, and (iii) elite athletes. The first column displays the parameters or attributes; the second column shows related abbreviations, and the last column presents characteristica with respect to the domain and whether the parameter or attribute is determined endogenous or exogenous.

C. Anti-doping Laboratory

We suppose an 'artificial' anti-doping laboratory that conducts doping controls according to anti-doping rules announced by the anti-doping agency for the whole population of N elite athletes. In each time period doping controls are carried out as follows. Immediately after a rank-order tournament some participants are selected for testing so that we obtain a Number of Tested elite Athletes (NTA). Note that the number of tested elite athletes is made up of two terms. First, we assume a Number of Preannounced-tested elite Athletes (NPA) in the sense that participants are always tested if they achieve preannounced placements in a rank-order tournament – usually placements near the winner, for instance, winners of medals at the Olympic Games are always tested. Second, we suppose a Number of Randomly-tested elite Athletes (NRA), reflecting doping controls at random to ensure that doped elite athletes face the risk of being caught and punished regardless of their placement in the rank-order tournament. Equation (1) guarantees some randomly tested elite athletes will be selected, since otherwise a feasible strategy for doped participants is to achieve placement NPA +1 so that any risk of being tested and caught is circumvented. Thus, Equation (1) is necessary and sufficient to generate deterrence of the use of banned substances.

$$NRA = NTA - NPA > 0 \qquad (1)$$

Numbers of tested and preannounced-tested elite athletes can be freely selected according to Equation (1) before executing the source code to obtain simulation results. Eventually, in analogy with the literature of game theory models, we assume that doped and tested elite athletes will not be detected as doping athletes for sure in this time period because of imperfect Control EFficiency (CEF).

Regarding time periods, we suppose two treatments concerning how to conduct doping controls. First, in the `baseline treatment` we require that elite athletes face doping controls in the actual time period only. Obviously, the Number of Controlled Periods (NCP) then equals one. Further, an objective likelihood of being caught in the baseline treatment depends on control efficiency, placements in rank-order tournaments, and numbers of tested and preannounced-tested elite athletes. Second, in the `back-controlling treatment` we postulate that elite athletes are tested in the actual time period as well as for some time periods in the past. Thus, the number of controlled periods is now greater than one. Further, the objective likelihood of being caught in the back-controlling treatment depends on the number of controlled periods in addition to control efficiency, placements in rank-order tournaments, and numbers of tested and preannounced-tested elite athletes.

Finally, at the end of any time period the anti-doping laboratory and the anti-doping agency exchange information on doping rules, the number of tested elite athletes (i.e. executed doping controls), Share of DEtected elite athletes (SDE), Share of DOped elite athletes (SDO) as well as Share of Detected and Doped elite athletes (SDD). Based on that information the anti-doping agency regularly publishes doping statistics and assigns fines and bans to elite athletes. Among other things, we describe in the following subsection how punishment of detected and doped elite athletes might take place.

D. Elite Athletes

We create 'artificial' elite athletes endowed with heterogeneous attributes to populate our agent-based framework. In particular, among the population of N elite athletes each one has ten attributes at any specific Time index (T), namely Identification number (I), AGe (AG), INcome (IN), Doping Decision (DD), Realized Rank (RR), PErformance (PE), FItness (FI), COnstitution (CO), DIsturbance (DI), and Behavioral-Type (BT).

Identification numbers are allotted in the initial time period and remain constant for all future periods to identify elite athletes in computational simulations. For simplicity, we drop abbreviations I, N, and T whenever possible.

An elite athlete's age is assigned, also in the initial time period, to an integer between minimum and maximum age but in every period the population grows one period older. As a consequence elite athletes retire mandatorily after reaching the maximum age, i.e. their career in professional sports ends. Retired elite athletes are replaced by newcomers at the minimum age. During replacement all other attributes of newcomers are set to the initial values of retired elite athletes. Note that such a procedure of replacement ensures that the distribution of elite athletes' attributes like Behavioral-Type (BT) remains identical over time and, therefore, allows for observing age-effects under `ceteris paribus` conditions.

In each time period elite athletes compete for income in a rank-order tournament [31]. In such a rank-order tournament the income depends on elite athletes' relative performance. Rank externalities in combination with the so-called 'superstar effect' may result in a situation where small variations in performance lead to strong differences in the distribution of income [32]. Thus, we assume a prize-money distribution as follows. Winners of a rank-order tournament get a maximum prize of 1,000 Tokens and the next-highest finishers until rank 99 get a positive amount of Tokens – but less than each finisher's predecessor. If elite athletes realize rank 100 or worse they earn nothing in this time period. Table II presents a non-linear prize-money distribution intended to be used for theoretical considerations and computational simulations. In particular, we make use of this prize-money distribution to provide a numerical example in the course of the paper. Nevertheless, to allow for a higher degree of generality we introduce a parameter for the maximum prize (maxprize) available.

TABLE II.
EXAMPLE: PRIZE-MONEY DISTRIBUTION OF RANK-ORDER TOURNAMENT IN TIME PERIOD T

Realized Rank	Prize-Money in Tokens	Realized Rank	Prize-Money in Tokens	Realized Rank	Prize-Money in Tokens	Realized Rank	Prize-Money in Tokens
1	1,000	**26**	135	**51**	63	**76**	24
2	700	**27**	130	**52**	61	**77**	23
3	500	**28**	125	**53**	59	**78**	22
4	400	**29**	120	**54**	57	**79**	21
5	350	**30**	115	**55**	55	**80**	20
6	310	**31**	112	**56**	53	**81**	19
7	280	**32**	109	**57**	51	**82**	18
8	260	**33**	106	**58**	49	**83**	17
9	250	**34**	103	**59**	47	**84**	16
10	240	**35**	100	**60**	45	**85**	15
11	230	**36**	97	**61**	43	**86**	14
12	220	**37**	94	**62**	41	**87**	13
13	210	**38**	91	**63**	39	**88**	12
14	200	**39**	88	**64**	37	**89**	11
15	190	**40**	85	**65**	35	**90**	10
16	185	**41**	83	**66**	34	**91**	9
17	180	**42**	81	**67**	33	**92**	8
18	175	**43**	79	**68**	32	**93**	7
19	170	**44**	77	**69**	31	**94**	6
20	165	**45**	75	**70**	30	**95**	5
21	160	**46**	73	**71**	29	**96**	4
22	155	**47**	71	**72**	28	**97**	3
23	150	**48**	69	**73**	27	**98**	2
24	145	**49**	67	**74**	26	**99**	1
25	140	**50**	65	**75**	25	**100**	0

Note: Table II shows a regressive non-linear prize-money distribution used within the agent-based concept. We assign each realized rank a specific amount of prize-money in Tokens due to an elite athlete's placement in the rank-order tournament. Note that if elite athletes achieve rank 100 or worse they receive a prize-money of zero.

An elite athlete's income in a time period is calculated as follows. We suppose elite athletes have only one source of earnings, which is prize-money earned from successful competition in rank-order tournaments. Depending on Realized Rank (RR), any participant can earn a non-negative amount of Prize-Money (PM) according to Table II. An elite athlete's spending depends on the individuals' Doping Decision (DD), Doping Costs (DC) and proposed FINe (FIN) in the case of detection. Note that doping decisions are binary. We explain how elite athletes make their doping decision in the behavioral-type paragraph later on in this subsection. However, subscript '+' indicates that an elite athlete uses dope and subscript '–' indicates an elite athlete does not use dope. Thus, we obtain Equation (2) presenting three cases with respect to feasible income.

$$IN = \begin{cases} IU = PM_{+} - DC \\ ID = -DC - FIN \\ PM_{-} \end{cases} \tag{2}$$

First, an elite athlete dopes and remains undetected for whatever reason. Then, she has to pay her doping costs (DC) from her prize-money (PM_+) so that she obtains an Income due to Undetected doping (IU). Second, a doped elite athlete is detected and as a consequence she earns no prize-money and has to pay a fine (FIN) in addition to her doping costs (DC), which leads to a non-positive Income due to Detected doping (ID). Third, an elite athlete does not make use of doping so that she can enjoy her prize-money (PM_-) for certain. Note that we implement an error of the first kind if and only if control efficiency of the anti-doping laboratory is less than one. Further, we do not model an error of the second kind. To put it differently, we may find in our agent-based framework a dope-using elite athlete who is not detected despite being tested but a clean elite athlete cannot erroneously be found guilty of taking banned substances. We adhere to this feature since an accused and innocent elite athlete may go to court and we are confident that she will get justice sooner or later. Moreover, intuition may favor the notion that prize-money is always higher when making use of doping than not. Note that this notion is not true since an elite athlete's placement depends on her performance in

TABLE III.
EXAMPLE: SHORT- AND LONG-TERM EFFECTS OF DOPING IN TIME PERIOD T

Parameter	Weighting of Doping Efficiency (Short-term Effects)	Weighting of Doping Harm (Long-term Effects)
Period T	WE_0=1	WH_0 = 0
Period T+1	WE_1=0.5	WH_1=0.25
Period T+2	WE_2=0.25	WH_2=0.5
Period T+3	WE_3=0	WH_3=0.75
Period T+4	WE_4=0	WH_4=1
Period T+5	WE_5=0	WH_5=0.75
Period T+6	WE_6=0	WH_6=0.5
Period T+7	WE_7=0	WH_7=0.25
Period T+8	WE_8=0	WH_8=0

Note: Table III contrasts doping efficiency and doping harm over time. While doping has a decreasing positive effect over three periods, the negative effect of doping increases from time period T+1 to T+4 and declines afterwards until it becomes zero in time period T+8.

rank-order tournaments and includes randomly allotted disturbance-effects.

In this paragraph we explain an elite athlete's PErformance (PE) used to model rank-order tournaments in the presence of doping behavior. Performance takes into account an individual's FItness (FI), COnstitution (CO), and DIsturbance (DI). In addition, we need to introduce three related figures as real numbers between zero and unity. These numbers are Weighting of Fitness (WF), Constitution (WC), and Disturbance (WD). If a weighting factor is zero, performance is not influenced by the respective attribute. An increase in the weight of a factors leads to higher influence of respective attributes; maximum influence is reached at unity. To ensure that clean elite athletes can get only a preannounced maximum performance (maxperformance) we suppose that weighting factors sum up to unity. Equation (3) formalizes this weighting-condition.

$$WF + WC + WD = 1 \tag{3}$$

Further, we assume Equation (4) represents an elite athlete's performance.

$$PE = WF \cdot FI + WC \cdot CO + WD \cdot DI \tag{4}$$

In the initial time period an individual's FItness (FI), COnstitution (CO), and DIsturbance (DI) are randomly allotted between zero and 100. Thereafter, we suppose that disturbance is calculated each time period randomly, whereas physical fitness and constitution change due only to doping. Thus, a clean elite athlete can reach only a maximum performance of 100. COnstitution reflects an elite athlete's physique in terms of long-term effects. For instance, we assume that Doping Harm (DH) affects constitution as follows. Effects of doping harm increase over time, reach a maximum, and then need some time periods to vanish. Fitness represents an elite athlete's physique regarding short-term effects. Thus, Doping Efficiency (DE) affects fitness as follows. Effects of doping efficiency occur immediately at a high positive level and then need some time periods to vanish (see Table III). Finally, disturbance may reproduce an elite athlete's fortune or misfortune in competition. Realized rank depends on an individual's performance; in each period the highest value of performance wins the rank-order tournament.

To provide an example, we assume that an elite athlete makes use of doping in time period T only. Further doping has positive effects on fitness for three time periods whereas such an illegal practice has negative effects on constitution for seven periods. Regarding strength of effects we introduce two related figures as real numbers between zero and one. These are Weighting of Doping Efficiency (WE), and Doping Harm (WH). Furthermore, we assign in Table III numerical values to these weighting factors. For a sequence of time periods we obtain then Equations (5) and (6), which describe effects on constitution and fitness, respectively, if an elite athlete makes use of doping in time period T

$$CO_{T+at} = CO \cdot \prod_{t=0}^{at} \left(1 - WH_t \cdot DH\right), at \in \{0;...;8\} \tag{5}$$

and

$$FI_{T+at} = FI \cdot \prod_{t=0}^{at} \left(1 + WE_t \cdot DE\right), at \in \{0;...;8\} \tag{6}$$

Of course, we have to adjust Equations (5) and (6) if elite athletes make use of doping in more than one time period to incorporate overlapping-effects. However, in the following paragraph we describe how elite athletes may behave with respect to making their multi-period doping decisions.

We postulate four Behavioral-Types (BT) of elite athletes, namely, (i) rational-acting A-types, (ii) suggestible B-types, (iii) compliant C-types, and (iv) erratic D-types. Rational-acting A-type elite athletes might make use of doping substances with respect to an expected utility maximizing approach. A suggestible B-type elite athlete is influenced strongly by doping behavior committed in her social network. A compliant C-type elite athlete accepts and follows strict announced anti-doping rules. An erratic D-type elite athlete wants to act rule-consistently but may commit doping unintentionally because of her ignorance of announced anti-doping rules or other misbehaviors. Note that these proposed behavioral-types stem originally from agent-based tax evasion models [33]-[39]. For instance, [33] makes use of an exponential utility function to model expected-utility-maximization behavior of rational-acting taxpayers. Thus, we transfer recent advances in tax compliance research to doping behavior patterns.

Rational-acting A-type elite athletes constrain their doping decision based on whether taking banned substances increases their Expected Utility (EU) or not. Thus, we make use of an exponential utility function displayed in Equation (7). Distinguishing the doping use and doping abandonment cases, we aim to model expected-utility-maximization behavior of rational-acting elite athletes, that is

$$EU(IN) = \begin{cases} \mathrm{EU}_{+} = \mathrm{SP}(1-\mathrm{e}^{-\mathrm{RP}\cdot\mathrm{ID}}) + (1-\mathrm{SP})(1-\mathrm{e}^{-\mathrm{RP}\cdot\mathrm{IU}}) \\ \mathrm{EU}_{-} = \qquad 1-\mathrm{e}^{-\mathrm{RP}\cdot\mathrm{PM}_{-}} \end{cases} \quad (7)$$

In order to maximize their expected utility, A-type elite athletes take Income due to Detected doping (ID) and Income due to Undetected doping (IU) into account. Further, we introduce a Subjective detection Probability (SP) that reflects an A-type elite athlete's perception of being caught as a doped participant. In the course of the paper we provide a numerical example of the maximizing procedure. However, note that the subjective detection probability may differ from an objective detection probability given by the anti-doping laboratory and the anti-doping agency. Furthermore, A-type elite athletes are endowed with a subjective Risk Perception (RP) to reflect their attitude to uncertainty. Subjective risk perception takes values between zero and unity whereby risk-seeking athletes have a value close to zero and risk-averse athletes have a value of nearly unity. According to [40] elite athletes become more risk seeking over time because of increasing opportunity costs in the course of their biographical fixation. While young elite athletes have more opportunities to find employment beyond professional sports, older elite athletes have often to persist in the system. A-type elite athletes are assigned to one out of four risk groups appropriate to their age. Table IV provides details with respect to classification of A-type elite athletes in risk perception groups. Risk perception is randomly allotted to elite athletes between the upper and lower threshold of their respective risk group. However, A-type elite athletes make use of doping if expected utility is higher in the case of doping abuse (EU_+) than in the case of anti-doping rule compliance (EU_-).

B-type elite athletes are suggestible and therefore their doping behavior depends on the doping behavior committed in their social networks. Therefore, B-type elite athletes decide to dope if at least one athlete in her social network dopes but none is caught as a doped participant. The size of the elite athletes' Social Network (SN) is equal for all athletes. For simplicity we assume a ring-world structure so that an elite athletes' I social network includes athletes with the identification numbers I+1, …, I+SN. If N is reached the social network includes elite athlete I=1 and so on until SN athletes are chosen. Note that [33] have used such a ring-world structure to investigate tax evasion behavior in a society of heterogeneous agents. Reference [37] examine various social network structures and find that Erdös-Rényi and Power-law-distributed networks influence taxpaying behavior particularly strongly. However, in line with the literature we assume that a convicted B-type elite athlete has to act for a designated Number of periods Rule-compliantly (NR).

Compliant C-type elite athletes act always and deliberately in a rule-compliant manner. That is why C-type elite athletes do not make use of a specific decision-making calculation.

Erratic D-type elite athletes also want to act in compliance with anti-doping rules but may break these rules unintentionally because of a lack of knowledge about anti-doping rules in force. The probability for such misbehavior depends on the Complexity of Anti-doping Rules (CAR) set by the anti-doping agency. For instance, CAR=1 corresponds to anti-doping rules with the highest level of complexity. In this case D-type elite athletes are more likely to act against anti-doping rules. Contrarily, CAR=0 displays anti-doping rules with the lowest level of complexity so that

TABLE IV.
CLASSIFICATION OF RATIONAL-ACTING A-TYPE ELITE ATHLETES IN RISK PERCEPTION GROUPS

Age (AG)	**Subjective Risk Perception (RP)**
minage ≤ AG < minage + (maxage-minage)·0.25	[0.75;1]
minage+ (maxage-minage)·0.25 ≤ AG < minage + (maxage-minage)·0.5	[0.50;0.75]
minage + (maxage-minage)·0.5 ≤ AG < minage + (maxage-minage)·0.75	[0.25;0.50]
minage + (maxage-minage)·0.75 ≤ AG < maxage	[0;0.25]

Note: Table IV displays classification of rational-acting A-type elite athletes into four risk perception groups with equal intervals. The first column illustrates age intervals and the second column is associated with the related subjective risk perception interval.

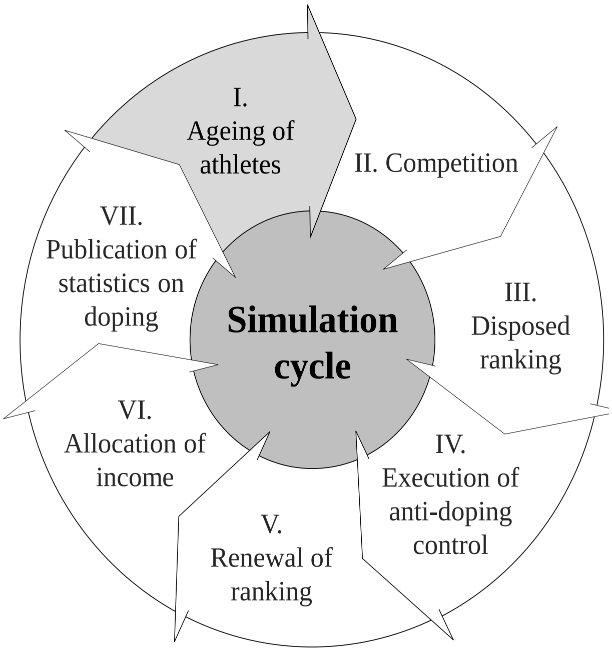

Fig 1. Graphical Illustration of Simulation Process

all D-type elite athletes are able to follow anti-doping rules. In the latter case D-type agents behave like compliant C-type agents.

E. Simulation Process

Above we have described three interacting objects. The aim of this subsection is to depict the simulation process within which these objects interact. After running some initial rounds to create objects and to generate initial information we repeat a simulation cycle as often as required. Fig. 1 illustrates this simulation cycle and its seven steps.

As a first step, in each time period any elite athlete grows one time period older until reaching maximum age (maxage). On reaching maximum age an elite athlete retires and is replaced by an agent at minimum age (minage), all of whose other attributes are set to the initial values of the retired elite athlete to allow for investigations under ceteris paribus conditions.

Subsequently, elite athletes make their doping decision on the basis of their behavioral-type specific decision calculus described above. Using the information concerning doping decisions a rank-order tournament takes place (step II). In the third step, a disposed ranking is drawn up. According to the rank-order tournament, all elite athletes are sorted according to their performance in competition. Both clean and doped elite athletes are listed on this disposed ranking.

Afterwards an anti-doping laboratory executes an anti-doping control (step IV) in which the preannounced-tested elite athletes are chosen on the basis of the disposed ranking and additional athletes are selected at random. Note that since doping test efficiency and frequency is imperfect not every doped athlete will be caught. Convicted dopers are noted and are punished by the anti-doping agency.

In the fifth step, convicted dopers are removed from the disposed ranking and a renewed ranking is created. The next step is to distribute income to clean elite athletes and undetected dopers based on the renewed ranking (step VI). Thus, we make use of the prize-money distribution described in Table II. In the seventh and last step, the anti-doping agency announces detected and undetected extent of doping and other statistics. This information is used in subsequent periods e.g. elite athletes base their doping decisions on them.

F. Illustration of Doping Decision

We describe in this subsection the decision-making calculus of a rational-acting A-type elite athlete in the course of a rank-order tournament as an example. In this example, parameters and attributes are set to values as follows.
N = 100; WF = 0.5; WC = 0.4; WD = 0.1; DC = 100; FIN = 200. Furthermore, let us assume we are considering elite athlete 23 (I = 23) and suppose parameter values in the first period (T = 1) are as follows. $AG_{23;1} = 37$; $FI_{23;1} = 86.4$; $CO_{23;1} = 78.5$; $DI_{23;1} = 95.0$; $RP_{23;1} = 0.01$; $SP_{23;1} = 0.002$. Inserting these values in Equation (4) leads to Equation (8).

$$PE_{23;1} = 0.5 \cdot 86.4 + 0.4 \cdot 78.5 + 0.1 \cdot 95.0 = 84.1 \qquad (8)$$

Moreover, we assume that elite athlete 23 achieves rank eight ($RR_{23;1} = 8$) with respect to her performance ($PE_{23;1} = 84.1$). Using the prize-money distribution described in Table II, she earns 260 Tokens if acting rule-compliantly.

Elite athlete 23 may increase her $FI_{23;1}$ value in the short term by 30 percent (DE = 0.3) through the use of banned substances. In this case her $FI_{23;1}$ may increase to 112.32 and, therefore, her $PE_{23;1}$ to 97.06. If her doping abuse remains undetected, let us assume she achieves second place in the rank-order tournament and earns 700 Tokens, but has to pay 100 Tokens for doping substances, so that 600 Tokens ($IU_{23;1} = 600$) remains. If elite athlete 23 is detected her loss amounts 300 Tokens ($ID_{23;1} = -300$). Inserting $IU_{23;1}$, $ID_{23;1}$, $RP_{23;1}$, and $SP_{23;1}$ in Equation (7) leads to Equation (9).

$$EU_{23;1+} \begin{array}{l} = 0.002\,(1-e^{(-0.01)\cdot(-300)}) + (1-0.002)\,(1-e^{(-0.01)\cdot(600)}) \\ \approx 0.957 \end{array} \qquad (9)$$

In the case of doping abandonment, elite athlete 23 earns 260 Tokens for certain, so that IN = 260 is inserted in Equation (7) leading to Equation (10)

$$EU_{23;1-} = 1 - e^{(-0.01)\cdot(260)} \approx 0.926 \qquad (10)$$

Since elite athlete 23 is rational and an expected-utility-maximizer she decides to dope ($EU_{23;1+} > EU_{23;1-}$).

IV. DISCUSSION AND OUTLOOK

To our best knowledge we have proposed in this paper for the very first time an agent-based concept to analyze elite athletes' doping behavior. Varying parameters for various kinds of sport can be selected. Currently the computational simulation is in a preliminary state so that simulation results are not yet available. However, a benefit of such an agent-based modeling approach is that doping behavior patterns may be investigated in a more realistic manner than with other methods like traditional game theory approaches.

In theory we expect our basic concept to show that back-controlling, i.e. doping controls with respect to competitions years ago, influences an elite athlete's decision to dope or not to dope particularly strongly. Note that lapse-of-time effects with respect to doping behavior are frequently neglected in the literature. We think that such an agent-based approach may provide new insights concerning lapse-of-time effects. For instance, deterrence effects that lengthen time spans regarding storage of necessary materials to conduct doping controls, e.g. blood and urine samples of elite athletes, are important. Moreover, interaction processes among elite athletes in competition may influence the effectiveness of lengthening storage time spans depending on behavioral type distributions in artificial populations.

After generating simulation results, the next step in our research project might allow the sensitivity of various anti-doping measures to be determined by varying the latter `ceteris paribus`. Based on simulation results we may provide policy recommendations to the WADA such as an optimal budget allocation for prevention policies. This will be very useful for future practice of doping prevention. In 2014 a budget of 26 million US Dollar is available to the WADA, but the contributions of several anti-doping measures are still unknown [41]. Using an agent-based modeling approach, their efficiency and effectiveness can be estimated for the first time.

With respect to extensions, we plan to implement a fixed budget for the anti-doping agency that finances various activities, e.g. control (delegated to anti-doping laboratories), education and prevention of doping behavior patterns. Within such an extended framework we can examine economic costs of doping controls and investigate optimal allocations of resources. In addition, several doping substances may be distinguished. The latter feature would lead to different detection probabilities and doping costs. Furthermore, consultants, e.g. team-managers or doctors, with an own advisor utility function could be implemented since consultants seem to play a main role in professional sports. Both outlook and extensions delineate a rather rich agenda for research activities in the future.

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REFERENCES

[1] World Anti-Doping Agency, "2012 Anti-doping testing-figures report", 2013, available online http://www.wada-ama.org/Documents/Resources/Testing-Figures/WADA-2012-Anti-Doping-Testing-Figures-Report-EN.pdf [last retrieval: 19.12.2013].

[2] H. Striegel, R. Ulrich, and P. Simon, "Randomized response estimates for doping and illicit drug use in elite athletes," in *Drug and Alcohol Dependence*, vol.106, no 2-3, pp. 230–232, 2010.

[3] A. Petróczi and K. K. Haugen "The doping self-reporting game: The paradox of a 'false-telling' mechanism and its potential research and policy implications," in *Sport Management Review*, vol. 15, no. 4, pp. 513–517, 2012.

[4] M. H. Anshel "A survey of elite athletes on the perceived causes of using banned drugs in sport" in *Journal of Sport Behavior*, vol. 14, pp. 283-308, 1991.

[5] H.-E. Sottas, N. Robinson, G. Fischetto, G. Dolle, J. M. Alonso, and M. Saugy, "Prevalence of blood doping in samples collected from elite track and field athletes," in *Clinical Chemistry*, vol. 57, no. 5, pp. 762–769, 2011.

[6] W. Pitsch, E. Emirch, and M. Klein, "Doping in elite sports in Germany: results of a www survey," in *European Journal for Sport and Society*, vol. 4, no. 2, pp. 89–102, 2007.

[7] H. Striegel, R. Ulrich, and P. Simon, "Randomized response estimates for doping and illicit drug use in elite athletes," in *Drug and Alcohol Dependence*, vol. 106, no. 2-3, pp. 230–232, 2010

[8] H. Plessner and J. Musch, "[How much doping is commited in elite sports? A www-questionnaire making use of randomized response technique] Wie verbreitet ist Doping im Leistungssport? Eine www-Umfrage mit Hilfe der Randomized-Response-Technik," in *Expertise im Sport*, 1st Ed., B. Strauß, M.Tietjens, N. Hagemann, A. Stachelhaus (Eds.) Cologne, Sport und Buch Strauß, 2002, pp. 78–79.

[9] C. Breuer and K. Hallmann, [Dysfunction in high-performance sports: Doping, match-fixing and health risks from population's and athlete's point of view] Dysfunktionen des Spitzensports: Doping, Match-Fixing und Gesundheitsgefährdungen aus Sicht von Bevölkerung und Athleten," edited by Stiftung Deutsche Sporthilfe, DSHS Cologne, 2013

[10] I. Waddington, "Drug use in English professional football – Commentary," in *British Journal of Sports Medicine*, vol. 39 no. 4, pp. 18–23, 2005.

[11] A. Petróczi, J. Mazanov, T. Nepusz, S.H. Backhouse, and D. P. Naughton, "Comfort in big numbers: Does over-estimation of doping prevalence in others indicate self-involvement?," in *Journal of Occupational Medicine and Toxicology*, vol. 3 no. 1, pp. 19−27, 2008.

[12] M. Uvacsek, T. Nepusz, D. P. Naughton, J. Mazanov, M. Z. Ránky, and A. Petróczi, "Self-admitted behavior and perceived use of performance-enhancing vs. psychoactive drugs among competitive athletes," in *Scandinavian Journal of Medicine & Science in Sports*, vol. 21, no. 2, pp. 224–234, 2011.

[13] R. A. James, T. Nepusz, D.P. Naughton, and A. Petróczi, "A potential inflating effect in estimation models: Cautionary evidence from comparing performance enhancing drug and herbal hormonal supplement use estimates," in *Psychology of Sport and Exercise*, vol. 14, no.1, pp. 84–96, 2013.

[14] G. Breivik, "The doping dilemma," in *Sportwissenschaft*. vol. 17, pp. 83–94, 1987.

[15] W. Maennig, "On the economics of doping and corruption in international sports," in *Journal of Sports Economics*, vol. 3, no. 1, pp. 61–89, 2002.

[16] K. K. Haugen, "The performance-enhancing drug game," in *Journal of Sports Economics*, vol. 5, no. 1, pp. 67–86, 2004.

[17] A. Berentsen, E. Brügger, and S. Lörtscher, "On cheating, doping and whistleblowing," in *European Journal of Political Economy*, vol. 24, pp. 415–436, 2008.

[18] N. Eber and J. Thépot, "Doping in sport and competition design," in *Louvain Economic Review*, vol. 65, pp. 435–446, 1999.

[19] A. Berentsen, "The economics of doping", in *European Journal of Political Economy*, vol. 18, pp. 109-127, 2002.

[20] A. Berentsen and Y. Lengwiler, "Fraudulent accounting and other doping games," working paper no. 175, 2003, University of Zurich.

[21] K. K. Haugen, T. Nepusz, A. Petróczi, and R. Huerta-Quintanilla, "The multi-player performance-enhancing drug game," in *PLOS ONE*, vol. 8, no.5, pp. 1-7, 2013.

[22] N. Eber, "The performance-enhancing drug game reconsidered: A fair play approach," in *Journal of Sports Economics*, vol. 9, no. 3, pp.318-327, 2008.

[23] M. Kräkel, "Doping and cheating in contest-like situations," in *European Journal of Political Economy*, vol. 23, no. 4, pp. 988–1006, 2007.

[24] D. Ryvkin, "Contests with doping", 2009, available online ftp://econpapers.fsu.edu/RePEc/fsu/wpaper/wp2009_06_01.pdf [last retrieval: 13.09.2013].

[25] R. Kirstein, "Doping, the inspection game, and Bayesian monitoring," working paper no. 36, 2009, Otto-von-Guericke University Magdeburg.

[26] B. Buechel, E. Emrich, and S. Pohlkamp, "Nobody's innocent – The role of customers in the doping dilemma," 2013, available http://mpra.ub.uni-muenchen.de/44627/1/MPRA_paper_44627.pdf [last retrieval: 13.09.2013].

[27] N. Gilbert and P. Terna, "How to build and use agent-based models in social science", in *Mind & Society*, vol. 1, no. 1, pp. 57-72, 2000.

[28] J. M. Epstein and R. Axtell, "*Growing artificial societies*," Cambridge, MA: The MIT Press, 1996.

[29] G. D. Garson, "Computerized simulation in the social sciences - A survey and evaluation." in *Simulation and Gaming*, vol. 20, no. 2, pp. 267–279, 2009.

[30] C. Schinckus, "Between complexity of modelling and modelling of complexity: An essay on econophysics," in *Physica A*, vol. 392, no. 13, pp. 3654-3665, 2013.

[31] E. P. Lazear and S. Rosen, "Rank-order tournaments as optimum labor contracts." in *NBER working paper series*, no. 401, 1979.

[32] S. Rosen, "The economics of superstars", in *The American Scholar*, vol. 52, no. 4, pp. 449-460, 1983.

[33] S. Hokamp and M. Pickhardt, "Income tax evasion in a society of heterogeneous agents – Evidence from an agent-based model," in *International Economic Journal*, vol. 24, no. 4, pp. 541–553, 2010.

[34] K. M. Bloomquist, "Tax compliance as an evolutionary coordination game: An agent-based approach," in *Public Finance Review*, vol. 39 no. 1, pp. 25-49, 2011.

[35] G. Seibold and M. Pickhardt, "Lapse of time effects on tax evasion in an agent-based econophysics model" in *Physica A*, vol. 392, no. 9, pp. 2079-2087, 2013.

[36] S. Hokamp and G. Seibold, "How much rationality tolerates the shadow economy? An agent-based econophysics approach" in *Advances in Social Simulation*, Proceedings of the 9th Conference of the European Social Simulation Association, B. Kamiński, G. Koloch (Eds.) *Advances in Intelligent Systems and Computing*, J. Kacprzyk (Series Editor), Heidelberg New York Dordrecht London: Springer, vol. 229, pp. 119-128.

[37] A. L. Andrei, K. Comer, and M. Koehler, "An agent-based model of network effects on tax compliance and evasion," in *Journal of Economic Psychology*, vol. 40, pp.119-133, 2014.

[38] M. Pickhardt and G. Seibold, "Income tax evasion dynamics: Evidence from an agent-based econophysics model," in *Journal of Economic Psychology*, vol. 40, pp.147-160, 2014.

[39] S. Hokamp, "Dynamics of tax evasion with back auditing, social norm updating, and public goods provision – An agent-based simulation," in *Journal of Economic Psychology*, vol. 40, pp.187-199, 2014.

[40] T. Haug, "[Doping – Dilemma of competitive sport] Doping – Dilemma des Leistungssports", Hamburg, Merus Verlag, 2006.

[41] World Anti-Doping Agency, "Contributions to WADA's budget 2014", 2014, available online http://www.wada-ama.org/PageFiles/21130/WADA_Contributions_2014_update_EN.pdf [last retrieval: 07.06.2014].