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„Sanctions vs. Convictions:
Heterogeneous Anti-Doping Legislation in the
Performance-Enhancing Drug Game"

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Abstract

The *International Convention against Doping in Sport* of the UNESCO does not specifiy, whether governments should implement the principles of the *World Anti-Doping Code* through legislation, regulation or administrative practices. Consequently, some governments enforce them through harsh anti-doping laws, while others impose sanctions without criminal repercussions. As most athletes train in their home country, this heterogeneity of policies is especially evident concerning potential out-of-competition doping. This thesis aims to analyze the effects of these legal differences through extending the *Performance-Enhancing Drug Game* of Haugen (2004) to asymmetric payoff functions and incomplete information concerning potential competitors. Results of the game suggest that athletes from countries with specific anti-doping laws have lower incentives to use forbidden practices than their international peers.

In the second part of the analysis, these insights are combined with findings of Ulrich (2017), which verify that doping is considerably more common than indicated by standard testing-mechanisms. As a result, the adoption of anti-doping laws can be linked to decreased peak-performances of domestic athletes at a statistically significant level. The empirical analysis indicates that heterogeneous anti-doping policies constitute a competitive advantage for athletes from countries without legislation targeting the use of banned substances.

This thesis is among the first scientific works to incorporate incomplete information to the strategic problem of doping, while also deriving specific hypotheses and testing them on empirical data of sporting competitions.

Key words: anti-doping, policy, game theory, incomplete information, competitive advantage

Zusammenfassung

Im *Internationalen Übereinkommen gegen Doping im Sport* der UNESCO ist nicht festgelegt, ob Regierungen die Grundsätze des *Welt-Anti-Doping-Codes* durch Gesetzgebungen, Regulierungen oder etwaige andere Verwaltungspraktiken implementieren sollen. Infolgedessen setzen einzelne Staaten die Grundsätze mittels strengen Anti-Doping-Gesetzen um, wohingegen ein Großteil der Länder Sanktionen ohne strafrechtliche Konsequenzen verhängen. Da die meisten AthletInnen in ihren Heimatländern trainieren, wirken sich diese zwischenstaatlichen Unterschiede besonders stark auf Doping in der wettkampffreien Zeit aus. Diese Masterarbeit zielt darauf ab, die Auswirkungen dieser Heterogenität in der Gesetzgebung auf die individuellen Doping-Anreize der AthletInnen auszumachen. Im ersten Schritt der Analyse wird das *Performance-Enhancing Drug Game* von Haugen (2004) auf asymmetrische Auszahlungsfunktionen und unvollständige Informationen hinsichtlich potenzieller GegnerInnen erweitert. Die Ergebnisse deuten daraufhin, dass AthletInnen aus Ländern mit Anti-Doping-Gesetzen niedrigere Anreize haben leistungssteigernde Substanzen zu verwenden als jene aus Staaten ohne entsprechender Gesetzeslage.

In weiterer Folge werden die Erkenntnisse mit jenen von Ulrich (2017) kombiniert. Diese zeigen, dass Doping im Spitzensport deutlich stärker verbreitet ist, als Statistiken standardisierter Doping-Kontrollen vermuten lassen. Schließlich ist es möglich einen statistisch signifikanten Zusammenhang zwischen den Anti-Doping-Gesetzen in den Heimatländern der AthletInnen und verminderter Spitzenleistung der jeweiligen SportlerInnen herzustellen. Die Analyse legt daher nahe, dass heterogene Anti-Doping-Maßnahmen einen Wettbewerbsvorteil für jene SportlerInnen darstellen, die keinen spezifischen Anti-Doping-Gesetzen unterliegen.

Diese wissenschaftliche Arbeit gehört zu den ersten, die das Konzept unvollständiger Informationen in das strategische Problem des Dopings miteinbeziehen, spezifische Hypothesen ableiten sowie diese anhand empirischer Daten aus sportlichen Wettkämpfen überprüfen.

Stichwörter: Anti-Doping, Gesetzgebung, Spieltheorie, Unvollständige Information, Wettbewerbsvorteil

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1 Introduction

Developing effective anti-doping policies is not an easy task. Experts from multiple fields participate in the quest for insights to understand athletes' environments and ultimately prevent the use of performance-enhancing drugs. While research suggests that it can be difficult to detect whether an athlete has indeed violated the rules, it seems almost impossible to truly evaluate the policies that should have prevented the violation in the first place. Though on the surface, the notion of gaining an unfair advantage seems to be condemned by athletes, officials and politicians alike, its flourishing existence suggests that the development of effective anti-doping policies still requires vast consideration.

1.1 Motivation

It is easy to observe that the public tends to place enormous expectations on professional athletes yet being equally ruthless when their "national heroes" explore every option to fulfill this promise. While blaming positive doping-tests on contaminated nutritional supplements is often discredited as a petty excuse, contemporary research still identifies it as a serious problem (Martínez-Sanz et al., 2017; Tsarouhas et al., 2018). Consequently, anti-doping policies generally offer room for leniency if those affected can comprehensibly explain unwitting behaviour. Unfortunately, in many other cases, athletes are well aware what stands between their current performance and fulfilling all expectations. To comprehend one's incentives for doping, it is crucial to understand that many forbidden practices simply enable athletes to train harder or more frequent than their bodies would naturally allow them to. Any athlete knows that the "extra-mile" in training makes the difference in competition, but what if the "extra-mile" is not enough?

It seems indisputable that doping is unfair to those who are committed to clean competitions. But, could it be that doping is also unfair among athletes who have taken equal decisions concerning the use of forbidden substances? Clearly, noone wants to be regarded as a cheater, but it seems that, still, many athletes find themselves in the unfortunate situation that risking public humiliation seems to be their best option. However, as some countries enforce anti-doping laws, it is one thing to be considered a cheater, but another to be considered a criminal. Thus, regardless of the belief which terminology is more fitting, it is worthwhile to examine the effect this seemingly subtle difference has on actual deterrence from using forbidden practices.

1.2 Context and background

Founded in 1999, the World Anti-Doping Agency (WADA) serves as the main governing body to "promote, coordinate and monitor the fight against drugs in sports". Since its inception in 2004, their *World Anti-Doping Code* (WADC) aims to harmonize anti-doping regulations worldwide and the contained rules have been accepted by most sports-related organizations around the globe. Yet, as the WADC is a non-governmental document, it is not legally binding, and governments could only give a moral commitment by supporting the *Copenhagen Declaration on Anti-Doping and Sport*. Hence, in 2005, the UNESCO drafted the *International Convention against Doping in Sport*, which came into effect in February 2007. It contains obligations for governments to take appropriate measures in implementing the principles of the WADC (Figure 1.1 outlines some the key points of the convention). However, in the face of all harmonization efforts, the convention does not specify whether countries shall fulfill these obligations by adopting legislation, regulation or administrative practices. Thus, some governments have taken harsher steps than others, including the criminalization of doping-offenders and the use of forensic intelligence to expose otherwise undetected perpetrators.

Initially only present in Italy (since 2000), governments of Austria (2007), France (2008), Australia (2013) and Germany (2015) have adopted similar legislation, leading to a situation in which doping entails substantially different consequences on an athlete's career and post-career life, depending on one's home country. As an example, prior convictions due to doping violations (self-induced or not) may disqualify athletes for specific professions in the public or medical field, and therefore potentially entail long-lasting economic and psychological consequences. To be clear, the lifes of athletes from countries without judicial repercussions may also be strongly affected by a positive doping test, but punishments rarely spill over to long-lasting consequences after athletes have already ended their sporting career.

Key points of the International Convention against Doping in Sport (2005):

- Facilitating doping controls and supporting national testing-programmes
- Encouraging the establishment of "best practices" concerning labelling, marketing, and distribution of products that might contain prohibited substances
- Withholding financial support from those who engage in or support doping
- Taking measures against manufacturing and trafficking of forbidden substances
- Encouraging the establishment of "codes of conduct" for sport and anti-doping related professions
- Funding education and research on drugs in sports

Figure 1.1 Key points of the International Convention against Doping in Sport

While the detailed judicial landscape concerning international anti-doping laws is much more complex, this thesis aims to focus on the impact of deviating from the envisionend homogeneity of the *World Anti-Doping Code*. My analysis should yield insights on how athlete-centered anti-doping legislation changes individual incentives to use performance-enhancing drugs and, eventually, has the potential to influence the outcome of athletic competitions.

1.3 Structure of the thesis

Firstly, I will give a brief overview on how economists have attempted to contribute to understanding athletes' incentives before focussing on one particular way of modeling individual decision-making: The *Performance-Enhancing Drug Game* of Haugen (2004). After discussing the various ways of how the game has already been modified by other authors in the literature, I perform an additional extension to account for the differences in athletes' expected costs of doping depending on their domestic legal structure. By incorporating the aspect of incomplete information concerning other athletes' payoff functions, I solve the game from the perspective of athletes from countries with and without anti-doping laws. Eventually, I aim to derive insights on how different kinds of policies influence the incentives to use performance-enhancing drugs. Following this procedure, it is possible to conclude that universally increased sanctions have the potential to deter all athletes from using performance-enhancing drugs, while not systematically disadvantaging some groups of athletes. Conversely, heterogeneous policies based on partially implemented anti-doping laws seem to create exactly such competitive advantage for athletes that are not immediately affected by them.

In the second part of the thesis, I combine results from the game theoretic analysis with findings from other research quantifying the real prevalence of doping in sports. As a result, I intend to determine how anti-doping laws and universally increased sanctions relate to individual athletes' peak-performances. To assess the resulting deterrence effects, I develop an econometric model that predicts personal best-times of male and female long-track speed skaters based on individual and socioeconomic parameters. Deriving these results should assist in validating the insights of the game theoretic analysis. Evaluating the empirical model suggests that both kinds of policy changes (adoption of anti-doping law and increasing sanctions for all athletes) have a negative effect on athletes' peak-performances. As anti-doping laws only affects a certain group of participants, it is sensible to suspect that these differences lead to a competitive advantage for those who are not directly affected by such legislation.

2 Literature Review

In the early literature until the late 1990s, the strategic problem of doping in sports was generally considered to be a prisoner's dilemma (Breivik, 1987; Wagner, 1993; Bird and Wagner, 1997). Conversely, Berentsen (2002) explains that this is true only if the players have equal prospects of winning. Concerning competitions with unequally talented participants, he discovers that the athlete with higher success probability is ultimately more likely to use performance-enhancing drugs than his less-talented competitor. Yet, the more talented athlete is less likely to win the competition in the presence of doping opportunities than if no doping is available. Berentsen (2002) aims to describe the effects of so-called "race-day drugs" (taken immediately before a contest) and introduces a rank-based punishment scheme that is less costly to implent. However, as the paper was developed before the legislative changes in 2007, the analysis does not take into consideration unequal cost structures or potential differences in anti-doping policies.

2.1 The *Performance-Enhancing Drug Game* – Haugen (2004)

Concerning the field of game theory, another essential contribution to understanding the role of policies was the *Performance-Enhancing Drug Game* of Haugen (2004). Several extensions have since been developed to model different aspects concerning an athlete's decision to use forbidden substances. The original model considers a sporting event between two, equally strong athletes in which both athletes can choose to take one available performance-enhancing drug. Assuming the expected gain of doping to exceed the expected costs, the game again unfolds as a prisoner's dilemma with a unique Nash Equilibrium in which both athletes dope. Considering differences in strength, another possible case emerges, in which both athletes choose a mixed strategy, in other words, choose to dope with a certain probability. Only when relaxing the assumption about the effectiveness of the drug, a scenario becomes possible in which staying clean for both athletes is the optimal action. Hence, the paper concludes that as long as athletes believe strongly enough in the effectiveness of a drug, doping cannot be fought.

2.2 Previous modifications

As the extension of the *Performance-Enhancing Drug Game* to heterogeneous anti-doping policies is the center of this thesis, it is necessary to examine what other modifications are already present in the existing literature:

2.2.1 Eber (2008)

By adding fair-play characteristics in the form of resentment- and guilt-factors to the individual payoffs, Eber (2008) transformes the structure of the game from a prisoner's dilemma to a coordination game ("stag hunt"). As a result, two Nash Equilibria in pure strategies are possible: Firstly, a risk-dominant equilibrium in which both athletes choose to dope and, secondly, a pay-off dominant equilibrium, in which both participants abstain from taking performance-enhancing drugs. Eber argues that, which of the two equilibria will eventually be reached depends largely on the beliefs of individual athletes about the intentions of their opponent. Hence, one main issue among competitors is to coordinate their true intentions. The author proposes that formal agreements through anti-doping charters could constitute such a credible signalling device for athletes.

2.2.2 Haugen, Nepusz, Petróczi (2013)

Haugen, Nepusz, Petróczi (2013) expands the original game to multiple participants and introduces different prize functions to the agents' payoff structures. The authors show that in the case of linear prize functions, results of the n-player game are identical to those of the 2-player game. However, as soon as prize money is awarded non-linearly (which is generally the case in real-world competitions), they discovered a rapidly increasing complexity with regards to the structure of Nash Equilibria already in an initial expansion from two to three players. Ultimately, the authors abort further examination of the case of four players due to the overwhelming complexity of case distinctions. They cautiously conclude that keeping the number of athletes in individual competitions relatively low would reduce the region of unpredictable outcomes and, in return, also reduce the required complexity of effective anti-doping policies. The authors question their necessary assumption of complete information and suggest solving the game under incomplete information as a candidate for further research.

2.2.3 Hirschmann (2015)

Hirschmann (2015) changes the structure of the game from a one-shot to a two-stage game with n participants. At first, athletes have to choose whether they want to enter the competition or not, and only in the second stage, they need to decide about the use of performance-enhancing drugs. The author examines whether an increase in sanctions could eventually discourage athletes to enter the competition. In terms of payoffs, linear prize function and equal costs of being revealed as an offender are assumed for both athletes. As a result, it can be shown that if sanctions are initially relatively low, a mild increase in severity of punishment can deter senior as well as unexperienced athletes from entering the competition. By raising doping sanctions even further, ultimately, entering the competition becomes more attractive again. Consequently, Hirschmann argues that the overall participation barrier for athletes is minimized if the anti-doping agency can guarantee a “doping-free competition” through imposing harsh punishments on potential doping offenders.

2.2.4 Cartwright (2019)

Cartwright (2019) revisits the *Performance-Enhancing Drug Game* in the light of psychological game theory and adds reciprocity and guilt-aversion to the athletes’ payoffs. He argues that reciprocity mainly affects first-order beliefs of athletes about the prevalence of doping in their respective sport and would require a coordinated effort to establish a norm of clean competitions to change the individuals’ behaviour. On the other hand, athletes’ individual guilt-aversion mainly affects second-order beliefs and could potentially propel competitors to “stay clean” even if their opponents decide to use performance-enhancing drugs.

2.3 Further research concerning anti-doping policies

In addition to the previously discussed papers, research in many other fields has been conducted to understand potential forces that propel athletes towards doping. On the one hand, theoretical work like Sumner (2017) or Marclay, Mangin, Margot & Saugy (2013) support the criminalization of doping-offenses to ensure justice and trustworthiness of professional sports. Conversely, research of Strelan & Boeckmann (2006) or Aubel & Ohl (2014) proposes a more ethics-oriented position in addressing the issue doping, highlighting the role of morality in an athlete’s decision to use forbidden substances. These papers introduce multiple different perspectives concerning athletes’ incentives for doping, which enabled me to better integrate certain subtleties into the development of the game theoretic and empirical model in this thesis.

3 Extension of the *Performance-Enhancing Drug Game*

Based on the original setup by Haugen (2004), I start extending the game by defining potentially different expected costs of doping for each athlete. By altering the game's sequence and introducing certain policy changes, I eventually incorporate the aspect of incomplete information about other athletes' payoff functions.

3.1 Game description

Consider a population of professional athletes (e.g. active long-track speed skaters). Each athlete i of the population will compete against another athlete j in a single sporting event, and each winner of her competition will receive the reward a (e.g. prize money, fame). All athletes can decide to use a performance-enhancing drug (D) or to stay clean (N). All athletes are assumed to be of equal strength. Hence, if both athletes in a competition decided to stay clean, each one wins the competition with success probability $p = \frac{1}{2}$ (i.e. talent, skill). There is only one available drug, which is 100% effective. If one of the competing athletes takes the drug and the other one does not, the former wins with certainty and receives the entire reward (a) while the latter is left empty-handed (0). The drug has an equal effect on all athletes, hence, if both athletes in a competition take it, the initial success probabilities remain unchanged. Should athletes choose to take the drug, however, they are detected with probability r_i (or r_j) and face negative consequences c_i (or c_j).

Initially, all athletes in the population are of type L, meaning that all are subject to the same testing procedures and sanctions outlined in the *World Anti-Doping Code* (homogeneous policies). However, there are two possible kinds of policy changes: Firstly, a universal increase in sanctions for all athletes and, secondly, a partial introduction of anti-doping laws. After the first kind of policy change, all athletes in the population remain of the same type but are subject to increased expected costs of doping. The second kind of policy change transforms some athletes from type L to type H, where athletes of type H are subject to criminal prosecution and are exposed to the use of forensic intelligence in detecting doping offenders. Hence, $r_H > r_L$ and $c_H > c_L$ (heterogeneous policies).

After the second kind of policy change, all athletes know their own type, but they do not know what type of athlete they will meet in competition. When deciding about whether or not to take the performance-enhancing drug, with probability $m \in (0,1)$ athletes believe their opponent to be an athlete of type L and with probability $1 - m$ to be an athlete of type H. Athletes learn the type of their opponent at the time of competition, all other information is considered to be common knowledge. All athletes must decide before the competition ("simultaneously") whether to use the drug or not and the decision is made only once ("one-shot").

As every athlete in the population has equal chances to represent either i or j, it is sufficient to solve the game for a pair of generic athletes, called **athlete i** and **athlete j**. Table 3.1 illustrates the general game in normal form:

		Athlete j D		*Athlete j* N	
Athlete i	D	$\frac{a}{2} - r_i c_i$	$\frac{a}{2} - r_j c_j$	$a - r_i c_i$	0
Athlete i	N	0	$a - r_j c_j$	$\frac{a}{2}$	$\frac{a}{2}$

Table 3.1 Extension of the *Performance-Enhancing Drug Game* in normal form

3.2 Relevance of the policy changes

As the aim of the *World Anti-Doping Code* (WADC) is to harmonize anti-doping policies across all countries, I initially assume an "optimal" situation in which only athletes of type L exist. In this situation of homogeneous policies there is no uncertainty among athletes about their opponent's type and $r_i c_i = r_j c_j = r_L c_L$.

3.2.1 Homogeneous policies with increased sanctions

The first kind of policy change resembles a situation like the 2015 revision[1] of the WADC in which sanctions were universally increased from c_L to c_M, such that $c_M > c_L$. Despite this increase, all athletes remain of the same type and the existing structure of the game persists. Hence, it is still appropriate to refer to both athletes as type L, but with elevated expected costs $r_i c_i = r_j c_j = r_L c_M$.

3.2.2 Transition to heterogeneous policies

The second kind of policy change relates to the decision of some countries (e.g. Austria, France, Germany) to adopt specific anti-doping legislation to fulfill the principles of the WADC. Thus, a portion of all athletes changes to type H, while the rest remains of type L. As athletes at the time of decision-making do not know whether their opponent in competition will be an athlete of type L or type H, this policy change transforms the game to a **game of incomplete information**. To determine

[1] In 2015, some countries already enforced national anti-doping laws. For simplistic reasons, I assume the increase in sanctions to happen without the presence of anti-doping laws.

the impact this policy change has on the optimal actions of each type, I will solve the game from the perspectives of two separate athletes (one of type L, the other of type H), each competing against a generic competitor called athlete i, whose type is unknown.

3.3 Objectives of the game:

As mentioned, the aim is to analyze how different kinds of anti-doping polices affect individual athletes' incentives to use performance-enhancing drugs.

Abiding the necessary case distinctions with regards to a, $r_i c_i$ and $r_j c_j$, and deriving respective Nash Equilibria, it is possible to define optimal actions in equilibrium for all athletes in the population. Hence, comparing optimal actions before and after each policy change may yield insights about how these policies affect athletes' incentives for doping and possibly alter results of the competitions.

The objectives of the analysis revolve around the following questions:

(1) Given that an athlete remains of type L after a change to heterogenous policies, how does the arising uncertainty about her opponent's type influence her incentives to dope?

(2) Conversely, for athletes transitioning to type H, do expectations about the type of her opponent have an impact on her optimal decision?

(3) How is the effect of anti-doping laws different from a universal increase in sanctions?

3.4 Further assumptions and considerations

(I) Reward a and success probability p are independent of an athlete's type.

(II) It must be that $a > r_H c_H$, otherwise doping would never occur.

(III) All athletes are risk-neutral and have identical utility structures.

(IV) If an athlete is indifferent between doping and staying clean, she chooses to stay clean.

3.5 Solution process

3.5.1 Homogeneous policies

Analogous to Haugen (2004), I firstly examine the situation of homogeneous policies in which the population only consists of athletes of type L. Hence, the game is of the following structure:

Type spaces :	$\theta_i \in \{ L \}$
	$\theta_j \in \{ L \}$
Action spaces :	$A_i \in \{ D, N \}$
	$A_j \in \{ D, N \}$
Strategies :	$s_i : \{ L \} \rightarrow \{ D, N \}$
	$s_j : \{ L \} \rightarrow \{ D, N \}$

3.5.1.1 Game in normal form

While only athletes of type L exist, it is possible to write expected costs of doping for both generic athletes as $r_i c_i = r_j c_j = r_L c_L$ and the payoffs of the game in normal form look as follows:

		Athlete j $(\theta_j = L)$	
		D	**N**
Athlete i $(\theta_i = L)$	**D**	$\frac{a}{2} - r_L c_L$, $\frac{a}{2} - r_L c_L$	$a - r_L c_L$, 0
	N	0 , $a - r_L c_L$	$\frac{a}{2}$, $\frac{a}{2}$

Table 3.2 Expected payoffs in the situation of homogeneous policies

3.5.1.2 Case distinctions

To determine all Nash Equilibria, it is necessary to consider the following case distinctions:

(1.1) $\frac{a}{2} > r_L c_L$

(1.2) $r_L c_L \geq \frac{a}{2}$

3.5.1.3 Nash Equilibria in pure strategies

(1.1) If for both athletes, the expected reward from winning the competition is **strictly larger** than the expected cost of doping $r_L c_L$, **(D , D)** is a unique Nash Equilibrium.

(1.2) If for both athletes, the expected reward from winning the competition is **smaller than or equal to** the expected cost of doping $r_L c_L$, **(N , N)** is a unique Nash Equilibrium.

3.5.2 Homogeneous policies – Increased sanctions

To analyze the effect of a universal increase in sanctions, I introduce medium costs c_M, such that $c_i = c_j = c_M$ and $c_H > c_M > c_L$. Leaving detection probabilities r_L unchanged, it is possible to write expected costs of doping for both generic athletes as $r_L c_M$.

3.5.2.1 Game in normal form

Inserting increased costs c_M into the expected payoffs, the game in normal form looks as follows:

Athlete j $(\theta_j = L)$

		D	N
Athlete i $(\theta_i = L)$	**D**	$\frac{a}{2} - r_L c_M$, $\frac{a}{2} - r_L c_M$	$a - r_L c_M$, 0
	N	0 , $a - r_L c_M$	$\frac{a}{2}$, $\frac{a}{2}$

Table 3.3 Expected payoffs in the situation of homogeneous policies and elevated sanctions c_M

3.5.2.2 Case distinctions

To determine all Nash Equilibria, it is necessary to consider the following case distinctions:

(1.3) $\frac{a}{2} > r_L c_M$

(1.4) $r_L c_M \geq \frac{a}{2}$

3.5.2.3 Nash Equilibria in pure strategies

(1.3) If for both athletes, the expected reward from winning the competition is **strictly larger** than the expected cost of doping $r_L c_M$, **(D , D)** is a unique Nash Equilibrium.

(1.4) If for both athletes, the expected reward from winning the competition is **smaller than or equal to** the expected cost of doping $r_L c_M$, **(N , N)** is a unique Nash Equilibrium.

At first sight, the resulting Nash Equlibria appear to be identical compared to those before the increase in sanctions. In section 3.6.1, I elaborate on the potential consequences of universally increased sanctions concerning individual doping incentives.

3.5.3 Heterogeneous policies (type L's perspective)

As mentioned, i and j represent two generic competitors, and all athletes in the population are equally likely to eventually act as i or j. Therefore, it is sufficient to only solve the game from the perspective of one athlete from the population who takes the position of such a generic competitor. In this section, I assume an athlete who remained of **type L** after the second kind of policy change to take the spot of generic athlete j and I solve the game from j's perspective. To reiterate, athlete j knows that she is of type L, but she does not know whether her opponent in the competition will be an athlete of type L or H. With probability m, athlete j believes to compete against an athlete of type L, and with probability $1-m$ to meet an athlete of type H. In other words, with probability m she expects the left, and with $1-m$ the right game to manifest:

$\boldsymbol{m}$	
Type spaces :	$\theta_i \in \{L\}$
	$\theta_j \in \{L\}$
Action spaces :	$A_i \in \{D, N\}$
	$A_j \in \{D, N\}$
Strategies :	$s_i : \{L\} \rightarrow \{D, N\}$
	$s_j : \{L\} \rightarrow \{D, N\}$

$\boldsymbol{1-m}$	
Type spaces :	$\theta_i \in \{H\}$
	$\theta_j \in \{L\}$
Action spaces :	$A_i \in \{D, N\}$
	$A_j \in \{D, N\}$
Strategies :	$s_i : \{H\} \rightarrow \{D, N\}$
	$s_j : \{L\} \rightarrow \{D, N\}$

3.5.3.1 Game in normal form

Hence, from athlete j's perspective, the possible games in normal form materialize as follows:

$\boldsymbol{m}$

		Athlete j $(\theta_j = L)$	
		D	**N**
Athlete i $(\theta_i = L)$	**D**	$\frac{a}{2} - r_L c_L$, $\frac{a}{2} - r_L c_L$	$a - r_L c_L$, 0
	N	0 , $a - r_L c_L$	$\frac{a}{2}$, $\frac{a}{2}$

$\boldsymbol{1-m}$

		Athlete j $(\theta_j = L)$	
		D	**N**
Athlete i $(\theta_i = H)$	**D**	$\frac{a}{2} - r_H c_H$, $\frac{a}{2} - r_L c_L$	$a - r_H c_H$, 0
	N	0 , $a - r_L c_L$	$\frac{a}{2}$, $\frac{a}{2}$

Table 3.4 Games in normal form in the situation of heterogeneous policies and $\boldsymbol{\theta_j = L}$

3.5.3.2 Strategies and actions

From athlete j's perspective, her opponent (athlete i) could follow four different strategies[2]:

(a) $\mathbf{D}$ if $\theta_i = L$, $\mathbf{D}$ if $\theta_i = H$

(b) $\mathbf{D}$ if $\theta_i = L$, $\mathbf{N}$ if $\theta_i = H$

(c) $\mathbf{N}$ if $\theta_i = L$, $\mathbf{D}$ if $\theta_i = H$

(d) $\mathbf{N}$ if $\theta_i = L$, $\mathbf{N}$ if $\theta_i = H$

Conversely, athlete j can either choose D or N.

3.5.3.3 Case distinction

Solving the game, it is necessary to consider the following case distinctions:

(2.1) $\frac{a}{2} > r_H c_H > r_L c_L$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$

(2.3) $r_H c_H > r_L c_L > \frac{a}{2}$

3.5.3.4 Solving for Nash Equilibria

To determine all resulting Nash Equilibria, it is best to start by eliminating strictly dominated strategies for athlete i. After, I determine athlete j's optimal response to the remaining strategies, given her beliefs m about which game will be played. Though the setup looks very similar to a Bayesian Game, it lacks the initial random draw of nature determining athlete i's type. Instead of one athlete for which nature determines her type, athlete i reprents two (possibly) different athletes of the population, each being of a distinct type. Yet, I still use similar steps in the solution process as I would in solving a Baysian Game. It offers the benefit to determine j's optimal action depending on her belief m by solving only one single inequality accounting for both potential games. Applying the described procedure, the games have the following Nash Equilibria per case.

A detailed solution process can be found in Appendix A.

[2] In this context, the term "strategy" is not entirely correct as $\theta_i = L$ and $\theta_i = H$ represent the types of two *different* athletes that could take the spot of generic athlete i. However, lacking a better description, I continue to use the term "strategy" for the rest of the thesis. One could also rationalize a strategy of athlete i as "what would the opponent of athlete j do, given that she is either an athlete of type L or type H?"

Nash Equilibria[3]**:**

(2.1) $\frac{a}{2} > r_H c_H > r_L c_L$ $\quad$ $[(\mathbf{D\ if\ \theta_i = L\ ,D\ if\ \theta_i = H}),\mathbf{D}]$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$ $\quad$ $[(\mathbf{D\ if\ \theta_i = L\ ,N\ if\ \theta_i = H}),\mathbf{D}]$

(2.3) $r_H c_H > r_L c_L > \frac{a}{2}$ $\quad$ $[(\mathbf{N\ if\ \theta_i = L\ ,N\ if\ \theta_i = H}),\mathbf{N}]$

3.5.4 Heterogeneous policies (type H's perspective)

Analogous to 3.5.3, the game is again considered from the perspective of athlete j. However, in this section, j is assumed to represent an athlete who transitioned to be of **type H** after the second kind of policy change. Again, with probability m, athlete j believes to compete against an athlete of type L, and with probability $1 - m$ to meet an athlete of type H in competition. In other words, with probability m she beliefs the left, and with $1 - m$ the right game to manifest:

$\boldsymbol{m}$		
Type spaces :	$\Theta_i \in \{ L \}$	
	$\Theta_j \in \{ H \}$	
Action spaces :	$A_i \in \{ D, N \}$	
	$A_j \in \{ D, N \}$	
Strategies :	$s_i : \{ L \} \rightarrow \{ D, N \}$	
	$s_j : \{ H \} \rightarrow \{ D, N \}$	

$\boldsymbol{1 - m}$		
Type spaces :	$\Theta_i \in \{ H \}$	
	$\Theta_j \in \{ H \}$	
Action spaces :	$A_i \in \{ D, N \}$	
	$A_j \in \{ D, N \}$	
Strategies :	$s_i : \{ H \} \rightarrow \{ D, N \}$	
	$s_j : \{ H \} \rightarrow \{ D, N \}$	

3.5.4.1 Game in normal form

From athlete j's perspective, the possible games in normal form materialize as follows:

$\boldsymbol{m}$		*Athlete j* $(\theta_j = H)$	
		D	**N**
Athlete i $(\theta_i = L)$	**D**	$\frac{a}{2} - r_L c_L$, $\frac{a}{2} - r_H c_H$	$a - r_L c_L$, 0
	N	0 , $a - r_H c_H$	$\frac{a}{2}$, $\frac{a}{2}$

[3] Syntax of Nash Equilibria: $[(\ \boldsymbol{a}_i^*(\boldsymbol{\theta}_i = \mathbf{L}),\ \boldsymbol{a}_i^*(\boldsymbol{\theta}_i = \mathbf{H})\ )\ ,\ \boldsymbol{a}_j^*(\boldsymbol{\theta}_j = \mathbf{L})]$:

$\mathbf{1-m}$		*Athlete j* $(\theta_j = H)$	
		D	**N**
Athlete i $(\theta_i = H)$	**D**	$\frac{a}{2} - r_H c_H$, $\frac{a}{2} - r_H c_H$	$a - r_H c_H$, 0
	N	0 , $a - r_H c_H$	$\frac{a}{2}$, $\frac{a}{2}$

Table 3.5 Game in normal form in the situation of heterogeneous policies and $\theta_j = H$

3.5.4.2 Strategies and actions

From athlete j's perspective, her opponent (athlete i) could again follow four different strategies:

(a) **D** if $\theta_i = L$, **D** if $\theta_i = H$

(b) **D** if $\theta_i = L$, **N** if $\theta_i = H$

(c) **N** if $\theta_i = L$, **D** if $\theta_i = H$

(d) **N** if $\theta_i = L$, **N** if $\theta_i = H$

Conversely, athlete j can either choose to take the drug (D) or stay clean (N).

3.5.4.3 Case distinctions

The identical case distinctions as in 3.5.3 need to be considered:

(2.1) $\frac{a}{2} > r_H c_H > r_L c_L$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$

(2.3) $r_H c_H > r_L c_L > \frac{a}{2}$

3.5.4.4 Solving for Nash Equilibria

In a similar manner to section 3.5.3, determining all Nash Equilibria requires to start by eliminating strictly dominated strategies for athlete i. After, it is necessary to determine athlete j's best response to the remaining strategies, given her beliefs about which of the two games will be played. Applying these steps, the game has the following Nash Equilibira per case.

A detailed solution process can be found in Appendix B.

Nash Equilibria[4]**:**

(2.1) $\frac{a}{2} > r_H c_H > r_L c_L$ $[(\mathbf{D\ if\ \theta_i = L\ , D\ if\ \theta_i = H}), \mathbf{D}]$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$ $[(\mathbf{D\ if\ \theta_i = L\ , N\ if\ \theta_i = H}), \mathbf{N}]$

(2.3) $r_H c_H > r_L c_L > \frac{a}{2}$ $[(\mathbf{N\ if\ \theta_i = L\ , N\ if\ \theta_i = H}), \mathbf{N}]$

3.6 Results

In this section, I analyze how case distinctions in the different scenarios relate to each other and which conclusions can be drawn concerning the overall doping incentives of a generic athlete j.

3.6.1 Transition to homogeneous policies with increased sanctions

Analyzing the effect of increased sanctions in the form of medium costs c_M, it is easy to observe that the general structure of Nash Equilibria is equal before and after the increase. If the expected reward from using the drug exceeds the expected costs of getting caught, it is optimal to dope (D).

Nash Equilibria							
Homogeneous policies (c_L)				**Increased sanctions (c_M)**			
Case		$a_i^*(\theta_i = L)$	$a_j^*(\theta_j = L)$	**Case**		$a_i^*(\theta_i = L)$	$a_j^*(\theta_j = L)$
1.1	$\frac{a}{2} > r_L c_L$	D	D	**1.3**	$\frac{a}{2} > r_L c_M$	D	D
1.2	$r_L c_L \geq \frac{a}{2}$	N	N	**1.4**	$r_L c_M \geq \frac{a}{2}$	N	N

Table 3.6 Nash Equilibria of the game for homogeneous policies, before and after increased sanctions

However, as a is known by all athletes but unaffected by the change in policy, and $r_L c_M > r_L c_L$, the threshold above which doping becomes the dominant action is moved upward (Table 3.6). Hence, if a is such that $r_L c_M \geq \frac{a}{2} > r_L c_L$, an increase in sanctions would change the optimal action for all athletes from D to N. While this may not alter optimal actions, if $\frac{a}{2} > r_L c_M$ or $r_L c_L \geq \frac{a}{2}$, the relationship between a, $r_L c_L$ and $r_L c_M$ should be similar for athletes with equal levels of professionalism that are competing against each other in the same sports. Hence, if we consider athletes from disciplines for which the decision to dope is not clear cut (expected reward ~ expected cost $r_L c_L$), an increase in sanctions **equally** reduces incentives to take the drug for all such athletes.

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[4] Syntax of Nash Equilibria: $[(\ \boldsymbol{a_i^*}(\boldsymbol{\theta_i = L}),\ \boldsymbol{a_i^*}(\boldsymbol{\theta_i = H})\ ),\ \boldsymbol{a_j^*}(\boldsymbol{\theta_j = H})]$:

This "deterrence effect" of increased punishment, as inititally introduced by Becker (1968) and intensively studied by the field of deterrence theory, aims to detain individuals from engaging in certain actions, by increasing the action's potential negative consequences. These negative consequences, however, can be increased in two distinct ways: Either by increasing the detection probability or by increasing punishment. In the 2015 revision of the WADC, only sanctions were increased, while adopting anti-doping laws intensifies both parts of the equation.

3.6.2 Transition to heterogeneous policies

To sensibly analyze the effects of transitioning from homogeneous to heterogeneous policies, it is necessary to find a way of comparing optimal actions before and after the policy change. As a solution, it is possible to use the fact that the relationship of *those* parameters that determine the initial threshold in the situation of homogeneous policies (a and $r_L c_L$) remain unchanged under heterogeneous policies. By knowing that $r_H c_H > r_L c_L$, case distinctions 2.1 and 2.2 can therefore be considered merely as "refinements" of case 1.1, which specify, where $r_H c_H$ could fall into the existing spectrum. To illustrate, cases 2.1 and 2.2 are equal to 1.1 in terms of $\frac{a}{2}$ and $r_L c_L$, but in 2.1 it is assumed that $\frac{a}{2} > r_H c_H$, while in 2.2 $r_H c_H \geq \frac{a}{2}$. Hence, it is possible to compare athlete j's optimal actions before and after the policy change depending on the size of $r_H c_H$.

3.6.2.1 Transition to heterogeneous policies for type L

If athlete j remains of type L, the only thing that changes in the transition from homogenous to heterogeneous policies is her arising uncertainty about the type of her opponent. Cases in which the expected rewards of doping strictly exceed potential costs (2.1), or vice versa (2.3), are unaffected by the introduction of type H. In 2.1, doping would always be profitable, while in 2.3 doping would never occur. More interestingly, for case 2.2 athlete j's optimal action is also unchanged after some of her potential competitors are transformed to type H. The transition is illustrated in table 3.7.

<table>
<tr><th colspan="9">Nash Equilibria</th></tr>
<tr><th colspan="4">Homogeneous policies ($\theta_i = L$, $\theta_j = L$)</th><th colspan="5">Heterogeneous policies ($\theta_j = L$)</th></tr>
<tr><th colspan="2">Case</th><th>$a_i^*(\theta_i = L)$</th><th>$a_j^*(\theta_j = L)$</th><th colspan="2">Case</th><th>$a_i^*(\theta_i = L)$</th><th>$a_i^*(\theta_i = H)$</th><th>$a_j^*(\theta_j = L)$</th></tr>
<tr><td rowspan="2">1.1</td><td rowspan="2">$\frac{a}{2} > r_L c_L$</td><td rowspan="2">D</td><td rowspan="2">D</td><td>2.1</td><td>$\frac{a}{2} > r_H c_H > r_L c_L$</td><td>D</td><td>D</td><td>D</td></tr>
<tr><td>2.2</td><td>$r_H c_H \geq \frac{a}{2} > r_L c_L$</td><td>D</td><td>N</td><td>D</td></tr>
<tr><td>1.2</td><td>$r_L c_L \geq \frac{a}{2}$</td><td>N</td><td>N</td><td>2.3</td><td>$r_H c_H > r_L c_L \geq \frac{a}{2}$</td><td>N</td><td>N</td><td>N</td></tr>
</table>

Table 3.7 Comparison of Nash Equilibria under homogeneous and heterogeneous policies for $\theta_j = L$

If $r_H c_H \geq \frac{a}{2} > r_L c_L$, athlete j expects a potential opponent of type H not to use the drug, still, choosing the drug remains the optimal action for her. Even if she is almost certain to meet an athlete of type H in competition (m close to 0), it is optimal to dope and avoid a fair competition.

Hence, the resulting Nash Equilibria suggest that despite exposing some of their potential competitors to anti-doping laws, the incentives to use the performance-enhancing drug for athletes of type L remain equal to the situation of homogeneous policies.

3.6.2.2 Transition to heterogeneous policies for type H

Lastly, I analyze the transition to heterogeneous policies from the perspective of athlete j, assuming that the partial adoption of anti-doping laws changed her type from L to H. Compared to the state of homogeneous policies, athlete j now has to take into consideration not only the arising uncertainty concerning her opponent's type, but also the increase of her own expected costs of doping ($r_H c_H$).

As before, cases in which the expected costs of doping strictly exceed potential gains (or vice versa) are unaffected by the introduction of type H. In 2.1 doping would always be profitable, while in 2.3 doping would never occur. However, as shown in table 3.8, now that athlete j's type changes to H, staying clean (N) is her optimal action in case 2.2 (compared to D if she remained of type L).

Nash Equilibria								
Homogeneous policies ($\boldsymbol{\theta_i = L}$, $\boldsymbol{\theta_j = L}$)				**Heterogeneous policies ($\boldsymbol{\theta_j}$ = H)**				
Case		$\boldsymbol{a_i^*(\theta_i = L)}$	$\boldsymbol{a_j^*(\theta_j = L)}$	**Case**		$\boldsymbol{a_i^*(\theta_i = L)}$	$\boldsymbol{a_i^*(\theta_i = H)}$	$\boldsymbol{a_j^*(\theta_j = H)}$
1.1	$\frac{a}{2} > r_L c_L$	D	D	**2.1**	$\frac{a}{2} > r_H c_H > r_L c_L$	D	D	D
				2.2	$r_H c_H \geq \frac{a}{2} > r_L c_L$	D	N	N
1.2	$r_L c_L \geq \frac{a}{2}$	N	N	**2.3**	$r_H c_H > r_L c_L \geq \frac{a}{2}$	N	N	N

Table 3.8 Comparison of Nash Equilibria under homogeneous and heterogeneous policies for $\boldsymbol{\theta_j = H}$

If $r_H c_H \geq \frac{a}{2} > r_L c_L$, athlete j expects a potential opponent of type L to use the drug (D), still, choosing to stay clean (N) is the optimal action for her. Even if she is almost certain to meet an athlete of type L in competition (m close to 1), she would still decide to stay clean despite her knowledge that it would constitute a certain loss in the competition.

Therefore, as optimal actions in cases 2.1 and 2.3 remain equal to the situation of homogeneous policies, this transition in case 2.2 suggests that the policy change reduces the incentives to use the performance-enhancing drug for athletes of type H.

3.7 Interpretation of the results

Despite the simplifying assumptions of the game, it is reasonable to conclude that both policy changes have an impact on athletes' doping incentives.

Universally increased sanctions in the situation of homogeneous policies elevate the common threshold above which doping is unprofitable. Hence, they have the potential to deter athletes from doping without wronging particular groups of competitors.

Concerning the partial introduction of anti-doping laws, the optimal actions remain unchanged for athletes that stay of type L after the policy change. Thus, their overall tendency to use doping should also remain equal to the state of homogeneous policies. However, for athletes that are transformed to type H, staying clean is their best option despite knowing that competing against an athlete of type L would result in a certain loss in the competition.

As sanctions of the *World Anti-Doping Code* are primarily based on lengthy bans from competitions, there is a strong connection between levels of c_i (or c_j) and a. Conversely, the scope of judicial consequences as part of c_H are much less connected to rewards of winning the competition. For example, the potential negative consequences of a conviction on the post-career life of a soccer player are not exponentially larger than those of a cross-country skier or long-track speed skater. Hence, imagining different levels of a and reasonably considering $r_H c_H \gg r_L c_M$, the deterrence effect of anti-doping laws should change the decision-making process of affected athletes much more frequently and especially in sporting disciplines in which absolute levels of a are already relatively small.

As already described, in the particular cases where $r_H c_H \geq \frac{a}{2} > r_L c_L$, the optimal action for an athlete of type L is to dope, while for an athlete of type H it is optimal to stay clean. Hence, for these cases (upholding the assumed effectiveness of the drug), the heterogeneity of expected costs ultimately determines the winner of the competition. As a result, it is fair to conjecture that also in reality, situations arise in which athletes who are not exposed to anti-doping laws, are left with a significant competitive advantage over those competitors who are.

4 Empirical Analysis

This section aims to discover whether the insights I derived from extending the *Performance-Enhancing Drug Game* can explain some of the dynamics in real-world decision making. The goal is to analyze how athletes react to policy changes in the long-term and, specifically, identify the impact of universally increased sanctions and national anti-doping laws on the peak-performance of elite-athletes.

4.1 Deterrence effect of anti-doping laws

In the first part of the empirical analysis, I would like to detect the deterrence effect of anti-doping laws through econometric modelling of individual and socioeconomic parameters.

4.1.1 Background and intuition

To reiterate, the *World Anti-Doping Code* (WADC), since its inception in 2004, intends to harmonize anti-doping rules worldwide. Hence, assuming the WADC to be enforced by standardized regulations would represent the situation of homogeneous policies. Meanwhile, some countries decided to adopt anti-doping laws to adhere to the principles of the WADC. These laws allow the criminalization of disobedient athletes and enable the use of forensic intelligence to expose otherwise undetected perpetrators. Following the example of Italy (since 2000), governments in Austria (2007), France (2008), Australia (2013) and Germany (2015) have adopted similar legislation, creating a situation of heterogeneous anti-doping policies.

According to the yearly ADRVs-report (Anti-Doping Rule Violations) of the World Anti-Doping Agency, only about 1-2% of all doping tests per year yield positive results. On the other hand, Ulrich (2017) explains that only a very minimal fraction of athletes that use banned substances are indeed exposed by standard testing mechanisms. To guarantee anonymity for participants, they conducted a randomized-response survey for 2167 athletes at the 2011 Athletics World Championships in Daegu, South Korea and the 2011 Pan-Arab Games in Doha, Qatar. At both events, more than 93% of athletes agreed to take the survey. As a result, even most conservative figures suggest that over 30% of athletes were using forbidden practices within the previous year, while some estimates reach up to 57%. Hence, to evaluate whether the presence of anti-doping laws influences athletes' behaviors, it might prove more useful to directly examine athletic performance for unusual variation rather than analyzing the incidents of positive doping-tests.

The extension of the *Performance-Enhancing Drug Game* suggests that in case 2.2, increased expected costs for athletes of type H deter them from doping regardless of the beliefs about the type or action of their opponent (→ deterrence effect anti-doping laws). Thus, according to to the auxiliary assumption that increased punishment and elevated detection probability effectively reduce athletes' incentives to use risky nutritional supplements[5] or forbidden practices (those difficult to detect using standard testing[6]), athletes from countries with anti-doping laws (type H) should, on average, achieve worse peak-performances than their opponents of type L.

After careful consideration, personal-best times of long-track speed skaters were selected to conduct the explained analysis. Due to its "one-on-one" nature of competitions, its perfect measurability of performance and consistent external environment (all professional events take place indoor), it serves as the optimal discipline to verify the developed conclusions.

4.1.2 Hypotheses

In the first part of the econometric analysis, I aim to test the following hypotheses:

H_0: The presence of an anti-doping law in an athlete's home country has **no effect** on an athlete's personal best time.

H_1: The presence of an anti-doping law in an athlete's home country has a **"negative" effect** on an athlete's personal best time. ("Negative" in the sense of a slower/higher personal best time represented by a positive regression coefficient)

4.1.3 Data:

The dataset consists of the top 500, all-time personal best times (PB) of male and female long-track speed skaters across the distances of 500, 1,000 and 1,500 meters. These are the only events over which both genders compete at the Olympic Games and other international championships. Firstly, to ensure that the dataset mainly consists of professional athletes[7], an athlete's best time is required be within the top 250 in at least one of the three distances. As an example, table 4.1 illustrates the distribution of all-time best times of females over the distance of 500 meters. One can see that approximately above the top 500, times are much denser, indicating that also many amateur (or at least not world-class) athletes are able to achieve such times. Secondly,

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[5] Supplements that may be contaminated or are in a grey-area of being forbidden or not
[6] For example, autologous blood doping
[7] Some anti-doping laws (e.g. Italy) only apply to professional athletes, but not amateurs

information about an athletes' height and weight must be available online. After applying these restrictions, the dataset consists of, on average, 265 (male) and 233 (female) athletes per event from 27 and 24 different countries, respectively, and personal best times were achieved between the years of 1998 and 2020.

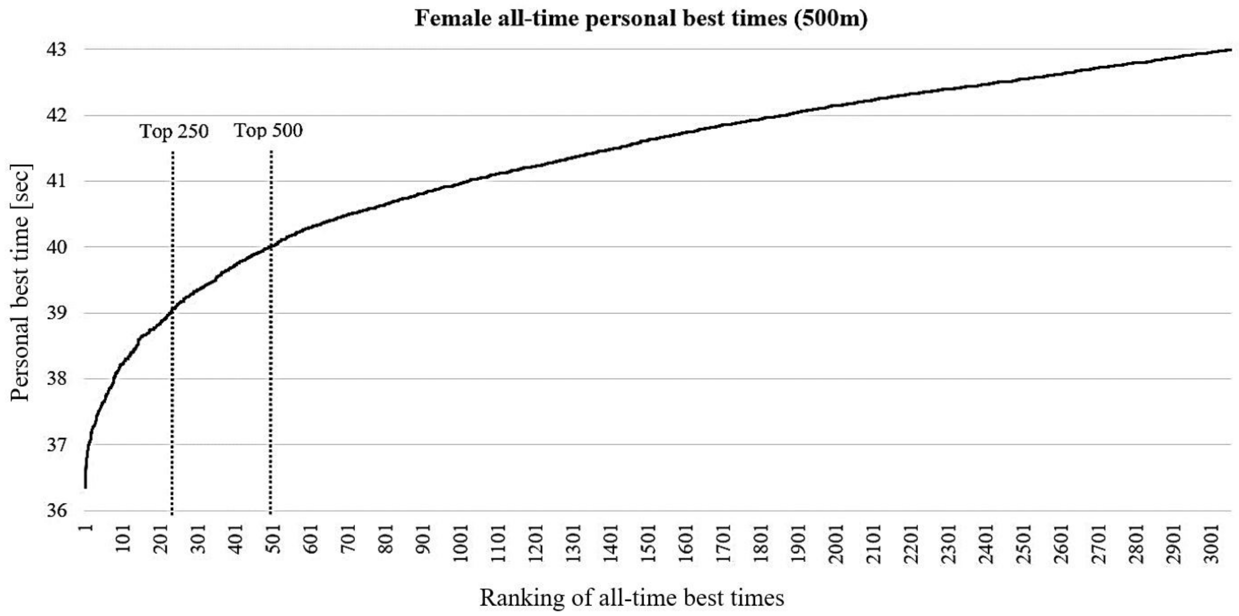

Figure 4.1 Distribution of female all-time personal best times across 500m

4.1.4 Econometric model

The idea of the econometric model is to predict an athlete's peak-performance using several uncorrelated independent variables, and assess whether the presence of an anti-doping law (during the year in which the athlete achieved this performance) had any impact on the respective time. As doping obviously improves athletic performance, I implicitly assume that, if an athletes were using performance-enhancing drugs during their career, they (also) used them at the time of achieving their personal best. Strictly speaking, the goal is to assess whether, on average, an athlete's individual peak in performance was substantially lower if the athlete was subject to an anti-doping law during the year of achieving the best performance.

During preliminary evaluation of the data, it surfaced that the place in which competitions are held has a considerable influence on the achieved times. More precisely, the geographical elevation of a skating rink seems to substantially contribute to the level of achieved performance. Hence, to control for any external effects of the location, I decided to conduct two different kinds of regression analyses, one in which only geographical elevation is used as regressor, and another in which all skating rinks in the data represent indicator variables. Since results do not differ significantly and rinks appear in very unequal proportion in the dataset, I decided to primarily consider the model using geographical elevation for further analysis. The respective tables of the regression using indicator variables can be found in Appendix C.

Dependent variable:

Personal best time over the respective distance (500, 1000, 1500 meters)

Independent variables:

abs_latitude: Average absolute latitude of an athlete's home country

avg_altitude: Average altitude of an athlete's home country in meters

Intuition: As, historically, most ice-skating rinks were outdoors, ***abs_latitude*** and ***avg_altitude*** (in combination) should be a proxy for the climatic conditions and, hence, the tradition of long-track speed skating in a certain country.

antidopinglaw: Indicator-variable (1, if anti-doping law was enforced in an athlete's home country while personal best time was achieved)

comp_age: Athlete's exact age in years when the personal best time was achieved (→ date of competition – date of birth)

comp_elevation: Elevation of skating rink (in meters) on which competition took place (alternatively, place of competition as indicator-variable → ***.data***)

comp_year: Year (yyyy) in which personal best time was achieved

Intuition: To control for overall improvement of all times due to, for example, advanced skating technique or better equipment

gdp_per_capita: GDP per capita (PPP - 2011 international $ thousand) of an athlete's home country in the year of achieving his/her personal best time[8]

Intuition: Bernard and Busse (2004) shows the connection between a country's GDP per capita and won medals at the Olympic games. The authors argue that initial talent is distributed relatively evenly among countries, but economic resources are necessary to develop it.

height: Height of the respective athlete in meters

owg_comp_year: Indicator-variable (1, if Olympic Games were held in the same year

[8] Country-specific data on GDP per capita from the world bank was only available until 2018. Hence, I extrapolated values for 2019 and 2020 according to the average growth rates between 2015 to 2018.

as personal best time was achieved)

Intuition: In the years of Olympic Games, national associations generally spend extra resources for training or equipment. Also, athletes from countries with less developed anti-doping programs increasingly compete abroad and are tested more frequently.

record_abroad: Indicator-variable (1, if personal best time was achieved outside of athlete's home country)

Intuition: Testing whether, on average, athletes achieve different levels of performance at competitions abroad or in their home country

weight: Weight of the respective athlete in kilograms

Methodology:

Ordinary Least Squares (OLS) regression

Tests for validity of model:

- **Studentized Breusch-Pagan test** for heteroscedasticity of residuals (negative)
- **Variance Inflation Factor (VIF) test** for multi-collinearity of regressors (negative)
- **Ramsey RESET-Test** for validity of regression equation (suggests that a non-linear combination of regressors could constitute a better fit of the model. However, as my main interest is the sign of ***antidopinglaw*** I consider the test result to be of less importance)

4.1.5 Results

Over 500 and 1,000 meters, personal best times of male type H – athletes (who were exposed to anti-doping laws) are significantly slower at the 95% confidence level compared to those of their type L - competitors. A similar effect seems to be present for female type H - athletes, however, regression coefficients do not turn out statistically significant. As a result, it is reasonable to reject H_0 (and accept H_1) with respect to male athletes over 500 and 1,000 meters, but not to reject H_0 for female athletes. Figures 4.2 and 4.3 represent the respective regression tables of the analysis.

FEMALE | Deterrence Effect of anti-doping laws			
	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.030***	-0.077***	-0.103***
	(0.009)	(0.016)	(0.027)
comp_age	-0.036***	-0.105***	-0.204***
	(0.013)	(0.023)	(0.039)
height	2.771*	-1.788	-10.059**
	(1.426)	(2.563)	(4.739)
weight	-0.040***	-0.038	0.010
	(0.014)	(0.026)	(0.047)
antidopinglaw	0.376	0.454	0.117
	(0.247)	(0.420)	(0.819)
abs_latitude	0.011*	0.013	-0.021
	(0.006)	(0.010)	(0.020)
avg_altitude	-0.00002	0.0002	0.0004
	(0.0003)	(0.0005)	(0.001)
record_abroad	-0.030	-0.158	-0.626
	(0.143)	(0.263)	(0.482)
owg_comp_year	0.279*	0.364	0.150
	(0.147)	(0.261)	(0.588)
gdp_per_capita	-0.001	-0.018**	-0.013
	(0.004)	(0.007)	(0.014)
comp_elevation	-0.001***	-0.002***	-0.002***
	(0.0002)	(0.0003)	(0.001)
Constant	98.215***	241.369***	350.036***
	(17.544)	(31.122)	(54.080)
Observations	231	245	221
R^2	0.252	0.332	0.296
Adjusted R^2	0.214	0.301	0.259
Residual Std. Error	0.735 (df = 219)	1.419 (df = 233)	2.412 (df = 209)
F Statistic	6.698*** (df = 11; 219)	10.537*** (df = 11; 233)	7.978*** (df = 11; 209)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 4.2 Regression of female personal best times to determine deterrence effect of anti-doping laws

MALE | Deterrence Effect of anti-doping laws

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.027***	-0.051***	-0.052***
	(0.005)	(0.010)	(0.019)
comp_age	-0.041***	-0.034**	-0.061**
	(0.009)	(0.017)	(0.027)
height	2.775***	1.288	-3.352
	(0.793)	(1.418)	(2.733)
weight	-0.026***	-0.035***	0.011
	(0.007)	(0.013)	(0.025)
antidopinglaw	0.274**	0.411**	0.592
	(0.118)	(0.205)	(0.360)
abs_latitude	0.005*	0.001	0.005
	(0.003)	(0.006)	(0.013)
avg_altitude	0.0001	-0.0001	0.001
	(0.0002)	(0.0003)	(0.001)
record_abroad	0.074	-0.035	0.359
	(0.084)	(0.160)	(0.303)
owg_comp_year	0.184**	0.231	0.646**
	(0.088)	(0.171)	(0.306)
gdp_per_capita	0.002	-0.007*	-0.013
	(0.002)	(0.004)	(0.008)
comp_elevation	-0.0004***	-0.001***	-0.004***
	(0.0001)	(0.0002)	(0.001)
Constant	87.869***	175.264***	219.580***
	(10.668)	(20.758)	(39.053)
Observations	256	291	247
R^2	0.272	0.256	0.258
Adjusted R^2	0.239	0.227	0.223
Residual Std. Error	0.456 (df = 244)	0.891 (df = 279)	1.547 (df = 235)
F Statistic	8.269*** (df = 11; 244)	8.730*** (df = 11; 279)	7.429*** (df = 11; 235)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 4.3 Regression of male personal best times to determine deterrence effect of anti-doping laws

4.2 Deterrence effect of increased sanctions

4.2.1 Background and intuition

On January 1st, 2015, a revision of the *World Anti-Doping Code* came into effect that significantly increased sanctions for doping-offenders compared its previous version (in force since 2009). It included, for example, an extended competition ban from two to four years for first-time offenders, as well as the possibility for financial claims of sponsors and organizations. Yet, the revision mainly consisted of an increase in sanctions, while only very minor changes were made to elevate detection probability (e.g. extending the list of banned substances).

According to the results of extending the *Performance-Enhancing Drug Game*, athletes' incentives to dope should be reduced after a universal increase in sanctions (→ deterrence effect of increased sanctions). Hence, the goal of the empirical analysis is to test, whether, on average, athletes' personal best times after January 1st, 2015, are substantially slower compared to those during the period of 2009 until 2015. As due to improved training methods or more sophisticated equipment, one would expect best times to improve over time. As these effects are controlled for in the model, whether the time was achieved before or after 2015 should have no effect on an athlete's personal best. Therefore, a negative regression coefficient could be an indicator that after the increase in sanctions, some athletes decide to abstain from the use of performance-enhancing practices. Analogous to the game theoretical model, only athletes without anti-doping laws in their home countries (type L) are considered for the analysis.

4.2.2 Hypotheses:

H_0: The increased sanctions of the 2015 revision of the WADC have **no effect** on an athlete's personal best time.

H_1: The increased sanctions of the 2015 revision of the WADC have a **"negative" effect** on an athlete's personal best time. ("Negative" in the sense of a slower/higher personal best time represented by a positive regression coefficient)

4.2.3 Data:

The dataset again consists of the top 500, all-time personal best times (PB) of male and female long-track speed skaters across 500, 1,000 and 1,500 meters. All other limitations described in 4.1.3 apply as well, yet, only data points **after** January 1st, 2009, excluding athletes with active anti-doping laws (type H) are considered for the regression. Thus, only athletes of type L are relevant for the analysis. This restriction should assist to better separate the effects of increased sanctions from those of adopting anti-doping laws (e.g. Germany's anti-doping law also came into effect in 2015). Eventually, the dataset consists of, on average, 184 (male) and 168 (female) athletes per event from 24 and 19 different countries, respectively.

4.2.4 Econometric model

The model is mostly identical to 4.1.4, I only exchange regressor ***antidopinglaw*** for ***wadc_2015:***

Dependent variable:

Personal best time over the respective distance (500, 1000, 1500 meters)

Independent variables:

abs_latitude: Average absolute latitude of an athlete's home country

avg_altitude: Average altitude of an athlete's home country in meters

Intuition: As, historically, most ice skating rinks were outdoors, ***abs_latitude*** and ***avg_altitude*** (in combination) should be a proxy for the climatic conditions and, hence, the tradition of long-track speed skating in the certain country.

antidopinglaw: Indicator-variable (1, if anti-doping law was enforced in an athlete's home country while personal best time was achieved)

comp_age: Athlete's exact age in years when the personal best time was achieved (→ date of competition – date of birth)

comp_elevation: Elevation of skating rink (in meters) on which competition took place (alternatively, place of competition as indicator-variable → ***.data***)

comp_year: Year (yyyy) in which personal best time was achieved

Intuition: To control for overall improvement of all times due to, for example, advanced skating technique or better equipment

gdp_per_capita: GDP per capita (PPP - 2011 international $ thousand) of an athlete's home country in the year of achieving his/her personal best time[9]

Intuition: Bernard and Busse (2004) shows the connection between a country's GDP per capita and won medals at the

[9] Country-specific data on GDP per capita from the world bank was only available until 2018. Hence, I extrapolated values for 2019 and 2020 according to the average growth rates between 2015 to 2018.

Olympic games. The authors argue that initial talent is distributed relatively evenly among countries, but economic resources are necessary to develop it.

height: Height of the respective athlete in meters

owg_comp_year: Indicator-variable (1, if Olympic Games were held in the same year as personal best time was achieved)

Intuition: In the years of Olympic Games, national associations generally spend extra resources for training or equipment. Also, athletes from countries with less developed anti-doping programs increasingly compete abroad and are tested more frequently.

record_abroad: Indicator-variable (1, if personal best time was achieved outside of athlete's home country)

Intuition: Testing whether, on average, athletes achieve different levels of performance at competitions abroad or in their home country

weight: Weight of the respective athlete in kilograms

wadc_2015: Indicator-variable (1, if the personal best time was achieved after the revision of the WADC on 1.1.2015)

Methodology

Ordinary Least Squares (OLS) regression

Tests for validity of model:

As in 4.1, the Ramsey RESET-test suggests, that a non-linear combination of regressors could constitute a better fit for the model. Since again the main interest of the analysis is in the sign of the regressor ***wadc_2015***, it is sensible to consider the test result to be of less importance.

4.2.5 Results:

Average personal best times after 2015 are significantly slower at the 95% confidence level for female type L - athletes across 500 and 1,000 meters (at 90% level for 1,500 meters). For male type L - athletes, the negative effect on personal best times is only statistically significant over 500 meters. Therefore, it is reasonable to reject H_0 (and accept H_1) with respect to female athletes across all distances, but to reject H_0 (and accept H_1) for male athletes only over the distance of 500 meters. Figures 4.4 and 4.5 represent the respective regression tables of the analysis.

FEMALE | Deterrence Effect of the 2015 World Anti-Doping Code Revision			
	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.125***	-0.294***	-0.324***
	(0.035)	(0.071)	(0.118)
comp_age	-0.029*	-0.089***	-0.268***
	(0.017)	(0.031)	(0.057)
height	1.678	-3.528	-11.154*
	(1.687)	(3.045)	(5.806)
weight	-0.035**	-0.026	0.027
	(0.017)	(0.030)	(0.059)
wadc_2015	0.602**	1.245**	1.715*
	(0.242)	(0.480)	(0.871)
abs_latitude	0.013*	0.018	-0.036
	(0.006)	(0.013)	(0.025)
avg_altitude	-0.0002	-0.0002	0.001
	(0.0003)	(0.001)	(0.001)
record_abroad	-0.077	-0.417	-0.803
	(0.178)	(0.330)	(0.608)
owg_comp_year	0.537**	1.120***	0.663
	(0.224)	(0.384)	(0.836)
gdp_per_capita	-0.003	-0.020**	-0.008
	(0.005)	(0.009)	(0.017)
comp_elevation	-0.001***	-0.001***	-0.002***
	(0.0002)	(0.0004)	(0.001)
Constant	290.579***	678.285***	796.420***
	(71.174)	(143.243)	(237.873)
Observations	157	160	144
R^2	0.313	0.368	0.334
Adjusted R^2	0.261	0.321	0.278
Residual Std. Error	0.742 (df = 145)	1.429 (df = 148)	2.489 (df = 132)
F Statistic	6.000*** (df = 11; 145)	7.829*** (df = 11; 148)	6.008*** (df = 11; 132)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 4.4 Regression of female personal best times to determine deterrence effect of increased sanctions

MALE | Deterrence Effect of the 2015 World Anti-Doping Code Revision

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.093***	-0.101***	-0.094
	(0.020)	(0.037)	(0.075)
comp_age	-0.048***	-0.039*	-0.075**
	(0.010)	(0.021)	(0.036)
height	3.655***	2.260	-3.143
	(0.972)	(1.825)	(3.654)
weight	-0.030***	-0.042**	0.002
	(0.009)	(0.017)	(0.035)
wadc_2015	0.458***	0.397	0.803
	(0.151)	(0.283)	(0.585)
abs_latitude	0.003	-0.001	0.007
	(0.004)	(0.007)	(0.016)
avg_altitude	0.0001	-0.0001	0.001*
	(0.0002)	(0.0004)	(0.001)
record_abroad	0.077	-0.023	0.489
	(0.097)	(0.191)	(0.385)
owg_comp_year	0.067	0.347	0.977*
	(0.115)	(0.261)	(0.523)
gdp_per_capita	0.002	-0.007	-0.010
	(0.003)	(0.005)	(0.010)
comp_elevation	-0.001***	-0.001***	-0.004***
	(0.0001)	(0.0002)	(0.001)
Constant	219.223***	273.890***	304.121**
	(40.990)	(75.416)	(150.541)
Observations	181	198	159
R^2	0.338	0.281	0.320
Adjusted R^2	0.295	0.239	0.269
Residual Std. Error	0.450 (df = 169)	0.900 (df = 186)	1.593 (df = 147)
F Statistic	7.849*** (df = 11; 169)	6.618*** (df = 11; 186)	6.287*** (df = 11; 147)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 4.5 Regression of male personal best times to determine deterrence effect of increased sanctions

4.3 Limitations of the empirical analysis:

4.3.1 Change of incentives for athletes of type L

Another result of extending the *Performance-Enhancing Drug Game* is that, by introducing uncertainty about the type of their opponent, the incentives to dope for athletes of type L do not change. A major problem in testing this hypothesis using an empirical model is that countries did not adopt anti-doping laws simultaneously. Hence, by analyzing the effect of the policy change of a single country it is difficult to distinguish, whether there is no measurable effect because the incentives did not change, or because the policy change of one single country has such a small effect on the decision-process of all other type L - athletes in the population. Thus, a sensible analysis would require distinct "winner takes it all" - scenarios in which athletes mainly compete against each other and their own action depends largely on the actions of their opponents (e.g. boxing, tennis, wrestling). Unfortunately, these disciplines often lack absolute measurements of performance such as time or distance. While measuring overall wins or points across a certain period could be a viable tool, deriving convincing results is much more elaborate and exceeds the scope of this thesis.

4.3.2 Uncertainty about independent variables height and weight:

Firstly, some figures concerning the athletes' height and weight stem from unofficial online databases, in which the validity of the values cannot be verified. However, by randomly comparing values from these resources with information from athletes' personal websites and information of their respective associations, it seems that, overall, errors concerning these parameters can be assumed modest.

Secondly, the independent variable weight only reflects one certain point in an athlete's career and could obviously changes within a given range of time. Especially as the analysis is not restricted to athletes who already ended their career, potentially outdated information about height and weight of younger athletes might also lead to slightly biased estimates. While errors of this kind may reduce the model's quality of predicting athletes' personal best times, they can be assumed to be evenly spread among both types of athletes. Hence, such errors should have a negligible impact on the analysis of whether effects of certain policies are negative or positive.

4.3.3 Low amount of type H - athletes in dataset

As anti-doping laws are only present in a small portion of countries, relatively few athletes are among the best in history and are, consequently, considered in the regression analysis. As this fact may underline the point that harsh laws are indeed a competitive disadvantage for affected athletes, there would also be another way of testing the described effects. One could carry out a similar analysis of individual performances but restrict the dataset to only athletes from one certain country (e.g. Germany or Austria), which are affected by the policy changes. However, this would require more comprehensive data concerning individual athletes' body composition (height/weight) as well as information about their career status (professional/amateur). When assembling the dataset for this thesis, I realized that facts were hardly available online for athletes beyond the top 500 of historic best times.

Since this analysis could yield much more specific insights concerning athletes' doping incentives concerning certain policy changes, it could also allow for analyzing policy differences among countries with existing anti-doping legislation. As a result, it would be possible to evaluate the effectiveness of much more subtle distinctions concerning different kinds of anti-doping laws. However, gathering this data and carrying out such in-depth analysis of legislative differences again exceeds the scope of this thesis.

5 Conclusion and Outlook

By introducing policy changes to the original *Performance-Enhancing Drug Game*, I extended the game to the situation of heterogeneous costs and incomplete information concerning the type of athletes‘ opponents. Introducing anti-doping laws that transfer some athletes to type H, I concluded that for those, who stay of type L after the policy change, incentives to use performance-enhancing drugs do not change compared to the situation of homogeneous policies. Conversely, athletes changing to type H indeed experience reduced incentives to use performance-enhancing drugs due to the deterrence effect of increased expected costs of doping. Compared to universally increased sanctions for all athletes, the adoption of anti-doping laws only reduces incentives for a distinct group of athletes. As a result, the game suggests that in the situation of heterogeneous policies, using performance-enhancing drugs is more attractive for athletes from countries without anti-doping laws criminalizing its use.

In the second part of the analysis, I combined these results with findings of Oswald (2017) and suspected that by adopting harsh anti-doping legislation, governments put their domestic athletes at a significant competitive disadvantage compared to countries with a more lenient attitude towards punishing offenders. I based this suspicion on the low percentage of positive doping-tests using standard testing schemes that vastly underestimate the real prevalence of doping in elite sports. I tested the hypothesis analyzing all-time personal best times of long-track speed skaters and discovered that, especially for male athletes, peak-performances under anti-doping laws are substantially lower at a statistically signifant level. While not being statistically significant, regression coefficients indicate a similar effect for female athletes. Conversely, universally increased sanctions reduce the performance of female athletes at a statistically significant level, while the impact on males is only significant over the distance of 500 meters. However, most importantly, this deterrence effect of universally increased sanctions carries the advantage of not systematically wronging distinct groups of participating athletes (type H).

With regards to the game theoretical model, the analysis could obviously be extended in multiple ways. For example, considering athletes’ individual success probabilities or levels of risk-aversion under the aspect of incomplete information may yield much more diverse opportunities for analysis. Furthermore, changing the setup of the game from a single event to repeated competitions would also constitute a substantial step towards realistic insights.

Pertaining to the empirical model, rendering the analysis to other athletic disciplines, and further refining the regression coefficients or composition of the dataset would yield countless opportunities of deriving more sophisiticated conclusions. However, the aim of this thesis was to illustrate the main forces heterogeneous anti-doping policies impose on the incentives of athletes and their real athletic performance. As elite sporting events like World Championships or Olympic Games constitute one of the most globalized microstructures of humans, it only seems natural that the global problem of anti-doping also requires homogeneous, global policy implementations.

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Appendix

Appendix A: Detailed Solution - Heterogeneous policies (type L)

As representative athletes i and j draw from the same population of athletes, and all athletes in the population have identical utility structures, it is sufficient to only solve the game from the perspective of one representative athlete, in our case athlete j.

We assume athlete j to be an athlete who remained of type L after the second kind of policy change. Athlete j knows that she is of type L, but she does not know whether her opponent in the competition will be an athlete of type L or H. With probability m, athlete j believes to compete against an athlete of type L, and with probability $1 - m$ to meet an athlete of type H. In other words, with probability m she beliefs the left, and with $1 - m$ the right game to manifest:

$\boldsymbol{m}$	
Type spaces :	$\Theta_i \in \{ L \}$
	$\Theta_j \in \{ L \}$
Action spaces :	$A_i \in \{ D, N \}$
	$A_j \in \{ D, N \}$
Strategies :	$s_i : \{ L \} \rightarrow \{ D, N \}$
	$s_j : \{ L \} \rightarrow \{ D, N \}$

$\boldsymbol{1 - m}$	
Type spaces :	$\Theta_i \in \{ H \}$
	$\Theta_j \in \{ L \}$
Action spaces :	$A_i \in \{ D, N \}$
	$A_j \in \{ D, N \}$
Strategies :	$s_i : \{ H \} \rightarrow \{ D, N \}$
	$s_j : \{ L \} \rightarrow \{ D, N \}$

Game in normal form

Hence, from athlete j's perspective, the possible games in normal form materialize as follows:

$\boldsymbol{m}$

Athlete j $(\theta_j = L)$

Athlete i $(\theta_i = L)$		**D**	**N**
	D	$\frac{a}{2} - r_L c_L$, $\frac{a}{2} - r_L c_L$	$a - r_L c_L$, 0
	N	0 , $a - r_L c_L$	$\frac{a}{2}$, $\frac{a}{2}$

$\mathbf{1-m}$		Athlete j ($\theta_j = L$)			
		D		**N**	
Athlete i ($\theta_i = H$)	**D**	$\frac{a}{2} - r_H c_H$,	$\frac{a}{2} - r_L c_L$	$a - r_H c_H$,	0
	N	0 ,	$a - r_L c_L$	$\frac{a}{2}$,	$\frac{a}{2}$

Games in normal form in the situation of heterogeneous policies and $\boldsymbol{\theta_j = L}$

Strategies and actions

From athlete j's perspective, her opponent (athlete i) could follow four different strategies:

(a) **D** if $\theta_i = L$, **D** if $\theta_i = H$

(b) **D** if $\theta_i = L$, **N** if $\theta_i = H$

(c) **N** if $\theta_i = L$, **D** if $\theta_i = H$

(d) **N** if $\theta_i = L$, **N** if $\theta_i = H$

Conversely, athlete j can either choose D or N.

Expected payoffs

Considering strategies (a) – (d), athlete i's expected payoffs $\pi_{i_a}(a_j = D)$ through $\pi_{i_d}(a_j = N)$ and athlete j's expected payoffs $\pi_{j_a}(a_j = D)$ through $\pi_{j_d}(a_j = N)$ materialize as follows:

Athlete i	Athlete j ($\theta_j = L$): **D**		**N**	
(a): **D** if $\theta_i = L$, **D** if $\theta_i = H$	$\pi_{i_a}(a_j = D)$,	$\pi_{j_a}(a_j = D)$	$\pi_{i_a}(a_j = N)$,	$\pi_{j_a}(a_j = N)$
(b): **D** if $\theta_i = L$, **N** if $\theta_i = H$	$\pi_{i_b}(a_j = D)$,	$\pi_{j_b}(a_j = D)$	$\pi_{i_b}(a_j = N)$,	$\pi_{j_b}(a_j = N)$
(c): **N** if $\theta_i = L$, **D** if $\theta_i = H$	$\pi_{i_c}(a_j = D)$,	$\pi_{j_c}(a_j = D)$	$\pi_{i_c}(a_j = N)$,	$\pi_{j_c}(a_j = N)$
(d): **N** if $\theta_i = L$, **N** if $\theta_i = H$	$\pi_{i_d}(a_j = D)$,	$\pi_{j_d}(a_j = D)$	$\pi_{i_d}(a_j = N)$,	$\pi_{j_d}(a_j = N)$

Expected payoffs for both athletes in the situation of heterogeneous policies and $\boldsymbol{\theta_j = L}$

Athlete *i*'s expected payoffs:

$$\pi_{i_a}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{i_b}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)(0)$$

$$\pi_{i_c}(a_j = D) = m(0) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{i_d}(a_j = D) = m(0) + (1-m)(0)$$

$$\pi_{i_a}(a_j = N) = m(a - r_L c_L) + (1-m)(a - r_H c_H)$$

$$\pi_{i_b}(a_j = N) = m(a - r_L c_L) + (1-m)\frac{a}{2}$$

$$\pi_{i_c}(a_j = N) = m\frac{a}{2} + (1-m)(a - r_H c_H)$$

$$\pi_{i_d}(a_j = N) = m\frac{a}{2} + (1-m)\frac{a}{2}$$

Athlete *j*'s expected payoffs:

$$\pi_{j_a}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_L c_L\right)$$

$$\pi_{j_a}(a_j = N) = m(0) + (1-m)(0)$$

$$\pi_{j_b}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)(a - r_L c_L)$$

$$\pi_{j_b}(a_j = N) = m(0) + (1-m)\frac{a}{2}$$

$$\pi_{j_c}(a_j = D) = m(a - r_L c_L) + (1-m)\left(\frac{a}{2} - r_L c_L\right)$$

$$\pi_{j_c}(a_j = N) = m\frac{a}{2} + (1-m)(0)$$

$$\pi_{j_d}(a_j = D) = m(a - r_L c_L) + (1-m)(a - r_L c_L)$$

$$\pi_{j_d}(a_j = N) = m\frac{a}{2} + (1-m)\frac{a}{2}$$

Case distinctions

In solving the game, it is necessary to consider the following case distinctions:

(2.1) $r_H c_H > r_L c_L > \frac{a}{2}$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$

(2.3) $\frac{a}{2} > r_H c_H > r_L c_L$

Solving for Nash Equilibria

To determine all Nash Equilibria of the game, it is best to start by eliminating strictly dominated strategies for athlete i. After, I determine athlete j's optimal response to the remaining strategies, given her beliefs m about which game will be played. Though the setup looks like a Bayesian Game, it lacks the initial random draw of nature determining athlete i's type. Athlete i reprents two (possibly) different athletes of the population, each with a distinct type instead of one athlete for which nature determines her type. Yet, I still use similar steps in the solution process as I would in a Baysian Game as it is possible to immediately write down doping probabilities for j depending on her belief m without any additional steps.

(2.1)

Athlete i:

Strategy (a) strictly dominates all other strategies, regardless of athlete j's action:

$$\pi_{i_a}(a_j = D) > \pi_i'(a_j = D)$$

Athlete j:

Since $\frac{a}{2} > r_L c_L$, athlete j's best response to strategy (a) is to choose D:

$$\pi_{j_a}(a_j = D) > \pi_{j_a}(a_j = N)$$

$$\frac{a}{2} - r_L c_L > 0$$

$$\Leftrightarrow \quad \frac{a}{2} > r_L c_L$$

$$\Leftrightarrow$$

Hence, **[(D if $\boldsymbol{\theta_i = L}$, D if $\boldsymbol{\theta_i = H}$) , D]** is a unique **pure strategy Nash Equilibrium**.

(2.2)

Athlete i:

If athlete j chooses D, strategy (b) strictly dominates strategies (c) and (d), since $m \in (0,1)$ and $r_H c_H \geq \frac{a}{2} > r_L c_L$:

$$\pi_{i_b}(a_j = D) > \pi_{i_d}(a_j = D) > \pi_{i_c}(a_j = D)$$

$$\Leftrightarrow \quad m\left(\frac{a}{2} - r_L c_L\right) > \quad 0 \quad > (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

As $r_H c_H \geq \frac{a}{2}$, strategy (b) also strictly dominates strategy (a):

$$\pi_{i_b}(a_j = D) \geq \pi_{i_a}(a_j = D)$$

$$m\left(\frac{a}{2} - r_L c_L\right) \geq m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\Leftrightarrow \quad 0 \geq (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\Leftrightarrow$$

$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

If athlete j chooses N, strategy (b) strictly dominates strategy (a), since $m \in (0,1)$ and $r_H c_H \geq \frac{a}{2} > r_L c_L$. Consequently, all other strategies are dominated as well.

$$\pi_{i_b}(a_j = N) \geq \pi_{i_a}(a_j = N)$$
$$m(a - r_L c_L) + (1-m)\frac{a}{2} \geq m(a - r_L c_L) + (1-m)(a - r_H c_H)$$
$$\Leftrightarrow \quad (1-m)\frac{a}{2} \geq (1-m)(a - r_H c_H)$$
$$\Leftrightarrow$$
$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

Athlete j:

Since $\frac{a}{2} > r_L c_L$, athlete j's best response to strategy (b) is to choose D:

$$\pi_{j_b}(a_j = D) > \pi_{j_b}(a_j = N)$$
$$m\left(\frac{a}{2} - r_L c_L\right) + (1-m)(a - r_L c_L) > m(0) + (1-m)\frac{a}{2}$$
$$\Leftrightarrow \quad m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_L c_L\right) > 0$$
$$\Leftrightarrow \quad 1 > 0$$

Hence, **[(D if $\boldsymbol{\theta_i = L}$, N if $\boldsymbol{\theta_i = H}$), D]** is a unique **pure strategy Nash Equilibrium**.

(2.3)

Athlete i:

If athlete j chooses D, strategy (d) strictly dominates all other strategies, as $r_H c_H \geq r_L c_L > \frac{a}{2}$ and $m \in (0,1)$:

$$\pi_{i_d}(a_j = D) > \pi'_i(a_j = D)$$

If athlete j chooses N, strategy (d) also strictly dominates all other strategies, as $r_H c_H \geq r_L c_L > \frac{a}{2}$ and $m \in (0,1)$:

$$\pi_{i_d}(a_j = N) > \pi'_i(a_j = N)$$

Athlete j:

Since $r_L c_L > \frac{a}{2}$, athlete j's best response to strategy (d) is to choose N:

$$\pi_{j_d}(a_j = N) \geq \pi_{j_d}(a_j = D)$$
$$\frac{a}{2} \geq a - r_L c_L$$
$$\Leftrightarrow$$
$$\Leftrightarrow \quad r_L c_L \geq \frac{a}{2}$$

Hence, **[(N if $\boldsymbol{\theta_i = L}$, N if $\boldsymbol{\theta_i = H}$), N]** is a unique **pure strategy Nash Equilibrium**.

Appendix B: Detailed Solution - Heterogeneous policies (type H)

Now, I consider athlete j to represent an athlete who transitioned to be of type H after the second kind of policy change. Again, with probability m, athlete j believes to compete against an athlete of type L, and with probability $1-m$ to meet an athlete of type H in competition. In other words, with probability m she beliefs the left, and with $1-m$ the right game to manifest:

$\boldsymbol{m}$			$\boldsymbol{1-m}$	
Type spaces :	$\Theta_i \in \{L\}$		**Type spaces :**	$\Theta_i \in \{H\}$
	$\Theta_j \in \{H\}$			$\Theta_j \in \{H\}$
Action spaces :	$A_i \in \{D, N\}$		**Action spaces :**	$A_i \in \{D, N\}$
	$A_j \in \{D, N\}$			$A_j \in \{D, N\}$
Strategies :	$s_i : \{L\} \rightarrow \{D, N\}$		**Strategies :**	$s_i : \{H\} \rightarrow \{D, N\}$
	$s_j : \{H\} \rightarrow \{D, N\}$			$s_j : \{H\} \rightarrow \{D, N\}$

Game in normal form

From athlete j's perspective, the possible games in normal form materialize as follows:

$\boldsymbol{m}$

		Athlete j $(\theta_j = H)$: D	*Athlete j* $(\theta_j = H)$: N
Athlete i $(\theta_i = L)$	**D**	$\frac{a}{2} - r_L c_L$, $\frac{a}{2} - r_H c_H$	$a - r_L c_L$, 0
	N	0 , $a - r_H c_H$	$\frac{a}{2}$, $\frac{a}{2}$

$\boldsymbol{1-m}$

		Athlete j $(\theta_j = H)$: D	*Athlete j* $(\theta_j = H)$: N
Athlete i $(\theta_i = H)$	**D**	$\frac{a}{2} - r_H c_H$, $\frac{a}{2} - r_H c_H$	$a - r_H c_H$, 0
	N	0 , $a - r_H c_H$	$\frac{a}{2}$, $\frac{a}{2}$

Game in normal form in the situation of heterogeneous policies and $\boldsymbol{\theta_j = H}$

Strategies and actions

From athlete j's perspective, her opponent (athlete i) could again follow four different strategies:

(a) **D** if $\theta_i = L$, **D** if $\theta_i = H$

(b) **D** if $\theta_i = L$, **N** if $\theta_i = H$

(c) **N** if $\theta_i = L$, **D** if $\theta_i = H$

(d) **N** if $\theta_i = L$, **N** if $\theta_i = H$

Conversely, athlete j can either choose to take the drug (D) or stay clean (N).

Case distinctions

In solving the game, it is necessary to consider the following case distinctions:

(2.1) $\frac{a}{2} > r_H c_H > r_L c_L$

(2.2) $r_H c_H \geq \frac{a}{2} > r_L c_L$

(2.3) $r_H c_H > r_L c_L > \frac{a}{2}$

Expected payoffs

Considering strategies (a) – (d), athlete i's expected payoffs $\pi_{i_a}(a_j = D)$ through $\pi_{i_d}(a_j = N)$ and athlete j's expected payoffs $\pi_{j_a}(a_j = D)$ through $\pi_{j_d}(a_j = N)$ materialize as follows:

	Athlete j $(\theta_j = L)$	
Athlete i $(\theta_i = \{L, H\})$	**D**	**N**
(a): **D** if $\theta_i = L$, **D** if $\theta_i = H$	$\pi_{i_a}(a_j = D)$, $\pi_{j_a}(a_j = D)$	$\pi_{i_a}(a_j = N)$, $\pi_{j_a}(a_j = N)$
(b): **D** if $\theta_i = L$, **N** if $\theta_i = H$	$\pi_{i_b}(a_j = D)$, $\pi_{j_b}(a_j = D)$	$\pi_{i_b}(a_j = N)$, $\pi_{j_b}(a_j = N)$
(c): **N** if $\theta_i = L$, **D** if $\theta_i = H$	$\pi_{i_c}(a_j = D)$, $\pi_{j_c}(a_j = D)$	$\pi_{i_c}(a_j = N)$, $\pi_{j_c}(a_j = N)$
(d): **N** if $\theta_i = L$, **N** if $\theta_i = H$	$\pi_{i_d}(a_j = D)$, $\pi_{j_d}(a_j = D)$	$\pi_{i_d}(a_j = N)$, $\pi_{j_d}(a_j = N)$

Expected payoffs in the situation of heterogeneous policies and $\theta_j = H$

Athlete *i*'s expected payoffs:

$$\pi_{i_a}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{i_b}(a_j = D) = m\left(\frac{a}{2} - r_L c_L\right) + (1-m)(0)$$

$$\pi_{i_c}(a_j = D) = m(0) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{i_d}(a_j = D) = m(0) + (1-m)(0)$$

$$\pi_{i_a}(a_j = N) = m(a - r_L c_L) + (1-m)(a - r_H c_H)$$

$$\pi_{i_b}(a_j = N) = m(a - r_L c_L) + (1-m)\frac{a}{2}$$

$$\pi_{i_c}(a_j = N) = m\frac{a}{2} + (1-m)(a - r_H c_H)$$

$$\pi_{i_d}(a_j = N) = m\frac{a}{2} + (1-m)\frac{a}{2}$$

Athlete *j*'s expected payoffs:

$$\pi_{j_a}(a_j = D) = m\left(\frac{a}{2} - r_H c_H\right) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{j_a}(a_j = N) = m(0) + (1-m)(0)$$

$$\pi_{j_b}(a_j = D) = m\left(\frac{a}{2} - r_H c_H\right) + (1-m)(a - r_H c_H)$$

$$\pi_{j_b}(a_j = N) = m(0) + (1-m)\frac{a}{2}$$

$$\pi_{j_c}(a_j = D) = m(a - r_H c_H) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\pi_{j_c}(a_j = N) = m\frac{a}{2} + (1-m)(0)$$

$$\pi_{j_d}(a_j = D) = m(a - r_H c_H) + (1-m)(a - r_H c_H)$$

$$\pi_{j_d}(a_j = N) = m\frac{a}{2} + (1-m)\frac{a}{2}$$

Solving for Nash Equilibria

With regards to the same case distinctions as in section 3.5.3 (or Appendix A), determining all Nash Equilibria requires to start by eliminating strictly dominated strategies for athlete i. After, it is necessary to determine athlete j's best response to the remaining strategies, given her beliefs about which of the two games will be played.

(2.1)

Athlete i:

Strategy (a) strictly dominates all other strategies, regardless of athlete j's action:

$$\pi_{i_a}(a_j = D) > \pi_i'(a_j = D)$$

$$\pi_{i_a}(a_j = N) > \pi_i'(a_j = N)$$

Athlete j:

Since $\frac{a}{2} > r_H c_H$, athlete j's best response to strategy (a) is to choose D:

$$\pi_{j_a}(a_j = D) > \pi_{j_a}(a_j = N)$$

$$\Leftrightarrow \quad \frac{a}{2} - r_H c_H > 0$$

Hence, **[(D if $\boldsymbol{\theta_i = L}$, D if $\boldsymbol{\theta_i = H}$) , D]** is a unique **pure strategy Nash Equilibrium**.

(2.2)

Athlete i:

If athlete j chooses D, strategy (b) strictly dominates strategies (c) and (d), since $m \in (0,1)$ and $r_H c_H \geq \frac{a}{2} > r_L c_L$:

$$\pi_{i_b}(a_j = D) > \pi_{i_d}(a_j = D) > \pi_{i_c}(a_j = D)$$

$$\Leftrightarrow \quad m\left(\frac{a}{2} - r_L c_L\right) > \quad 0 \quad > (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

As $r_H c_H \geq \frac{a}{2}$, strategy (b) also strictly dominates strategy (a):

$$\pi_{i_b}(a_j = D) \geq \pi_{i_a}(a_j = D)$$

$$\Leftrightarrow \quad m\left(\frac{a}{2} - r_L c_L\right) \geq m\left(\frac{a}{2} - r_L c_L\right) + (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\Leftrightarrow \quad 0 \geq (1-m)\left(\frac{a}{2} - r_H c_H\right)$$

$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

If athlete j chooses N, strategy (b) strictly dominates strategy (a), since $m \in (0,1)$ and $r_H c_H \geq \frac{a}{2} > r_L c_L$. Consequently, all other strategies are dominated as well.

$$\pi_{i_b}(a_j = N) \geq \pi_{i_a}(a_j = N)$$

$$m(a - r_L c_L) + (1-m)\frac{a}{2} \geq m(a - r_L c_L) + (1-m)(a - r_H c_H)$$

$$\Leftrightarrow \quad (1-m)\frac{a}{2} \geq (1-m)(a - r_H c_H)$$

$$\Leftrightarrow$$

$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

Athlete j:

Since $r_H c_H \geq \frac{a}{2}$ and $m \in (0,1)$, athlete j's best response to (b) is to choose N:

$$\pi_{j_b}(a_j = N) \geq \pi_{j_b}(a_j = D)$$

$$(1-m)\frac{a}{2} \geq m\left(\frac{a}{2} - r_H c_H\right) + (1-m)(a - r_H c_H)$$

$$(1-m)\frac{a}{2} - (1-m)(a - r_H c_H) \geq m\left(\frac{a}{2} - r_H c_H\right)$$

$$\frac{a}{2} \geq a - r_H c_H$$

$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

Hence, **[(D if $\boldsymbol{\theta_i = L}$, N if $\boldsymbol{\theta_i = H}$), N]** is a unique **pure strategy Nash Equilibrium**.

(2.3)

Athlete i:

Strategy (d) strictly dominates all other strategies, regardless of athlete j's action:

$$\pi_{i_d}(a_j = D) > \pi_i'(a_j = D)$$

$$\pi_{i_d}(a_j = N) > \pi_i'(a_j = N)$$

Athlete j:

Since $r_H c_H \geq \frac{a}{2}$, athlete j's best response to strategy (d) is to choose N:

$$\pi_{j_d}(a_j = N) \geq \pi_{j_d}(a_j = D)$$

$$\frac{a}{2} \geq a - r_H c_H$$

$$\Leftrightarrow$$

$$\Leftrightarrow \quad r_H c_H \geq \frac{a}{2}$$

Hence, **[(N if $\boldsymbol{\theta_i = L}$, N if $\boldsymbol{\theta_i = H}$), N]** is a unique **pure strategy Nash Equilibrium**.

Appendix C: Empirical analysis – Location as indicator variable

The following regression models are identical in structure to those analyzed in section 4, only the parameter ***comp_elevation*** is represented by indicator variables of the respective place of the competition. Figures C.1 and C.2 illustrate the deterrence effect of anti-doping laws for male and female athletes, while figures C.3 and C.4 show the effect of increased sanctions with regards to the 2015 revision of the World Anti-Doping Code.

FEMALE | Deterrence Effect of anti-doping laws (INDIC)

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.029***	-0.076***	-0.094***
	(0.009)	(0.016)	(0.027)
comp_age	-0.043***	-0.098***	-0.184***
	(0.013)	(0.024)	(0.039)
height	2.066	-1.849	-6.857
	(1.432)	(2.609)	(4.723)
weight	-0.032**	-0.038	0.010
	(0.014)	(0.026)	(0.047)
antidopinglaw	0.243	0.276	0.253
	(0.256)	(0.433)	(0.808)
abs_latitude	0.010*	0.010	-0.040**
	(0.006)	(0.011)	(0.020)
avg_altitude	0.0001	0.0002	0.0005
	(0.0003)	(0.001)	(0.001)
record_abroad	0.013	-0.171	-0.661
	(0.159)	(0.289)	(0.512)
owg_comp_year	0.359**	0.476*	0.667
	(0.149)	(0.275)	(0.611)
gdp_per_capita	0.0005	-0.018**	-0.009
	(0.004)	(0.008)	(0.014)
.dataCollalbo	0.380		
	(0.776)		
.dataCalgary		-1.128	-3.029
		(1.468)	(2.443)
.dataChangchun		0.512	
		(2.080)	

.dataHamar	1.100**	1.398	-2.911
	(0.526)	(2.082)	(3.002)
.dataHeerenveen	0.203	0.204	-1.990
	(0.277)	(1.563)	(2.582)
.dataInzell	0.085	0.124	-3.267
	(0.518)	(1.554)	(2.762)
.dataKolomna	0.145	0.122	-3.053
	(0.437)	(1.728)	(3.465)
.dataMinsk	0.965		
	(0.766)		
.dataMoskva	-0.113		-0.458
	(0.749)		(3.470)
.dataMilwaukee		-1.131	
		(2.049)	
.dataNagano	0.144	-0.795	-2.696
	(0.446)	(1.792)	(2.921)
.dataObihiro	0.719		
	(0.537)		
.dataShenyang	0.955		
	(0.752)		
.dataSLC	-0.580***	-1.878	-4.889**
	(0.104)	(1.462)	(2.447)
.dataStavanger	0.114		
	(0.727)		
.dataSotsji			-6.394*
			(3.361)
.dataTsjeljabinsk			1.450
			(3.470)
.dataUrumqi	0.423	-0.617	-4.293
	(0.469)	(1.727)	(3.039)
Constant	96.941***	238.183***	328.040***
	(17.475)	(32.108)	(54.401)
Observations	231	245	221
R^2	0.327	0.355	0.365
Adjusted R^2	0.253	0.298	0.298
Residual Std. Error	0.717 (df = 207)	1.422 (df = 224)	2.348 (df = 199)
F Statistic	4.378*** (df = 23; 207)	6.176*** (df = 20; 224)	5.442*** (df = 21; 199)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure C.1 Regression of female personal best times to determine deterrence effect of anti-doping laws

MALE | Deterrence Effect of anti-doping laws (INDIC)

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.028^{***}	-0.055^{***}	-0.051^{***}
	(0.005)	(0.010)	(0.019)
comp_age	-0.038^{***}	-0.033^{**}	-0.062^{**}
	(0.009)	(0.016)	(0.027)
height	2.752^{***}	1.626	-2.780
	(0.800)	(1.394)	(2.751)
weight	-0.025^{***}	-0.034^{**}	0.008
	(0.008)	(0.013)	(0.025)
antidopinglaw	0.257^{**}	0.457^{**}	0.567
	(0.119)	(0.207)	(0.358)
abs_latitude	0.006^{*}	-0.00004	0.006
	(0.003)	(0.006)	(0.013)
avg_altitude	0.0002	0.0002	0.001
	(0.0002)	(0.0003)	(0.001)
record_abroad	0.100	0.139	0.267
	(0.092)	(0.169)	(0.317)
owg_comp_year	0.207^{**}	0.344^{**}	0.816^{**}
	(0.091)	(0.172)	(0.316)
gdp_per_capita	0.002	-0.007	-0.014^{*}
	(0.003)	(0.004)	(0.009)
.dataCalgary	-0.404		-2.561
	(0.465)		(1.555)
.dataHamar	-0.201	0.069	0.114
	(0.525)	(0.629)	(2.225)
.dataHeerenveen	0.039	0.554	-1.244
	(0.502)	(0.373)	(1.943)
.dataInzell	-0.170	0.437	-0.391
	(0.565)	(0.414)	(1.738)
.dataKolomna	-0.546	1.487^{***}	-1.533
	(0.518)	(0.538)	(2.229)
.dataNagano	-0.311	1.325^{**}	0.274
	(0.541)	(0.533)	(1.904)
.dataObihiro	-0.010	0.352	
	(0.665)	(0.903)	
.dataSLC	-0.614	-0.768^{***}	-3.819^{**}
	(0.466)	(0.113)	(1.556)

.dataStavanger	0.290	1.857**	
	(0.569)	(0.890)	
.dataUrumqi	-0.032	0.767	-2.920
	(0.536)	(0.549)	(1.964)
Constant	89.294***	181.055***	215.714***
	(11.121)	(20.291)	(39.184)
Observations	256	291	247
R^2	0.304	0.318	0.295
Adjusted R^2	0.245	0.270	0.240
Residual Std. Error	0.454 (df = 235)	0.866 (df = 271)	1.530 (df = 228)
F Statistic	5.135*** (df = 20; 235)	6.648*** (df = 19; 271)	5.306*** (df = 18; 228)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure C.2 Regression of male personal best times to determine deterrence effect of anti-doping laws

FEMALE | Deterrence Effect of the 2015 World Anti-Doping Code Revision (INDIC)

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.107***	-0.285***	-0.257**
	(0.036)	(0.072)	(0.122)
comp_age	-0.035**	-0.088***	-0.234***
	(0.017)	(0.032)	(0.057)
height	1.618	-3.697	-5.775
	(1.670)	(3.100)	(5.812)
weight	-0.035**	-0.028	0.016
	(0.016)	(0.030)	(0.059)
wadc_2015	0.351	1.131**	0.717
	(0.249)	(0.498)	(0.920)
abs_latitude	0.013**	0.015	-0.054**
	(0.007)	(0.013)	(0.025)
avg_altitude	-0.0002	-0.0003	0.0005
	(0.0003)	(0.001)	(0.001)
record_abroad	-0.205	-0.695*	-0.924
	(0.206)	(0.377)	(0.666)
owg_comp_year	0.835***	1.277***	1.251
	(0.247)	(0.411)	(0.892)
gdp_per_capita	-0.004	-0.024**	-0.007
	(0.005)	(0.010)	(0.018)

.dataCalgary			-1.659
			(2.636)
.dataHamar	1.246**		-1.981
	(0.538)		(3.643)
.dataHeerenveen	-0.217	0.971*	-0.878
	(0.374)	(0.579)	(2.770)
.dataInzell	0.015	1.559**	-1.365
	(0.517)	(0.629)	(3.045)
.dataKolomna	-0.673	0.695	-1.792
	(0.583)	(0.935)	(3.737)
.dataMinsk	0.216		
	(0.818)		
.dataMoskva	-0.207		
	(0.758)		
.dataMilwaukee		0.719	
		(1.473)	
.dataNagano	0.403	-0.646	0.412
	(0.544)	(1.157)	(3.662)
.dataObihiro	0.232		
	(0.557)		
.dataShenyang	0.296		
	(0.778)		
.dataSLC	-0.647***	-0.544**	-3.689
	(0.131)	(0.269)	(2.636)
.dataStavanger	0.073		
	(0.729)		
.dataSotsji			-5.708
			(3.521)
.dataTsjeljabinsk			2.948
			(3.754)
.dataUrumqi	-0.152	-0.364	-3.513
	(0.506)	(0.982)	(3.284)
Constant	252.997***	660.252***	654.907***
	(72.940)	(145.619)	(244.223)
Observations	157	160	144
R^2	0.419	0.396	0.416
Adjusted R^2	0.323	0.324	0.321
Residual Std. Error	0.710 (df = 134)	1.425 (df = 142)	2.414 (df = 123)
F Statistic	4.385*** (df = 22; 134)	5.480*** (df = 17; 142)	4.380*** (df = 20; 123)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure C.3 Regression of male personal best times to determine deterrence effect of increased sanctions

MALE | Deterrence Effect of the 2015 World Anti-Doping Code Revision (INDIC)

	Dependent variable:		
	time_500	time_1000	time_1500
	(1)	(2)	(3)
comp_year	-0.089***	-0.089**	-0.086
	(0.021)	(0.037)	(0.074)
comp_age	-0.043***	-0.042**	-0.075**
	(0.011)	(0.021)	(0.035)
height	3.706***	2.738	-1.801
	(1.000)	(1.812)	(3.627)
weight	-0.029***	-0.040**	-0.001
	(0.009)	(0.017)	(0.035)
wadc_2015	0.434***	0.243	0.748
	(0.154)	(0.282)	(0.579)
abs_latitude	0.002	-0.003	0.006
	(0.004)	(0.007)	(0.016)
avg_altitude	0.0002	0.0001	0.001
	(0.0002)	(0.0004)	(0.001)
record_abroad	0.088	0.121	0.249
	(0.109)	(0.210)	(0.404)
owg_comp_year	0.112	0.505*	1.196**
	(0.121)	(0.268)	(0.539)
gdp_per_capita	0.003	-0.006	-0.012
	(0.003)	(0.006)	(0.010)
.dataCalgary	-0.530		-2.293
	(0.468)		(1.580)
.dataHamar		0.142	0.322
		(0.646)	(2.277)
.dataHeerenveen	-0.104	0.504	-1.093
	(0.514)	(0.466)	(2.004)
.dataInzell	-0.271	0.664	-0.207
	(0.568)	(0.644)	(1.814)
.dataKolomna	-0.500	1.537***	-1.603
	(0.573)	(0.559)	(2.298)
.dataNagano	-0.435	1.275**	0.256
	(0.546)	(0.558)	(1.937)
.dataObihiro	-0.109	0.130	
	(0.675)	(0.944)	
.dataSLC	-0.781*	-0.752***	-3.901**
	(0.470)	(0.140)	(1.583)

.dataStavanger	-0.028	1.910^{**}	
	(0.575)	(0.913)	
.dataUrumqi	-0.299	0.589	-3.282
	(0.546)	(0.586)	(2.034)
Constant	210.441^{***}	246.921^{***}	285.330^{*}
	(42.202)	(74.426)	(148.195)
Observations	181	198	159
R^2	0.361	0.348	0.392
Adjusted R^2	0.285	0.278	0.313
Residual Std. Error	0.453 (df = 161)	0.877 (df = 178)	1.543 (df = 140)
F Statistic	4.780^{***} (df = 19; 161)	4.995^{***} (df = 19; 178)	5.007^{***} (df = 18; 140)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure C.4 Regression of male personal best times to determine deterrence effect of increased sanctions