Measuring Individual Competitiveness and its Impact on Sporting Success

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1. Introduction

Few concepts receive as much attention in sports as *competitiveness*.

Competitiveness may be intuitively defined as an individual trait that captures an athlete's attitudes towards competition, as a *taste* for competition or simply as a *propensity* to prefer a competitive environment or a competitive option. It is broadly recognized as an intangible skill that acts as a key determinant of success, training, motivation and decision-making.

Indeed, competitiveness drives athletes to make choices that influence their training, performance and long-term success. As such, coaches, talent scouts and sports administrators consider the role it has in athletes' behavior and often try to tailor their decisions accordingly. Thus, understanding this trait seems essential for optimizing talent development, fostering a competitive yet equitable sports environment, and promoting the success of athletes at all levels. As the world of sports continues to evolve, few would disagree with the idea that the study of these interconnections is becoming increasingly important for athletes, coaches and organizations striving for excellence and inclusivity.

And yet, as intuitive and general as these ideas may seem, how can *competitiveness* be *measured*? Is it actually measured at all in sports? What type of data on this variable do the different sports collect? Do we know when is competitiveness formed? How malleable is it? What is the optimal level (if any) to be reached? Do we know how important competitiveness is for predicting sporting success after standard performance and talent variables are accounted for?

We don't know of any scientific evidence where these questions are answered.

Competitiveness seems more like an elusive, intangible "behavioral concept" whose precise measurement is absent in the scientific literature in sports. Interestingly, a recent scientific literature in behavioral economics *does* measure competitiveness. Unfortunately, though, this literature is concerned with various important aspects of the labor market in general and, to the best of our knowledge, is entirely unrelated to sports.

We fill this void. In an attempt to provide a first answer to the above questions, we bring the measurement of competitiveness from the behavioral economics literature into sports.

To put the analysis in an even broader perspective, there is one additional question worth addressing: What do we know about the "production function" of an athlete's skills over *his life before* he reaches (if he does) the top level of his sport or becomes professional? Specifically, how are his skills formed during this critical period?

Clearly, the study of the determinants of performance and success remain ubiquitous among sports scientists and social scientists alike. A large part of the literature in sports, however, is concerned with talent already developed, or mostly developed, and studies athletes that already "made it." However, missing out on athletes who did not make it creates selection effects and empirical biases that limit our understanding of lifecycle skill formation processes. Moreover, it is probably fair to say that not only for intangible skills but even for "easily measurable" tangible skills, empirical evidence is quite rare and very recent. An example at the vanguard of sports:

Luka Doncic started traveling halfway across the world to study his biomechanics *long before* he came to the NBA. He is not just one of the league's biggest stars, but also the face of the NBA's data generation. Ben Cohen starts his *Wall Street Journal* article only four years ago (March 15, 2019) "The Big Data Behind the NBA's Next Big Thing" as follows (italics ours):

> SANTA BARBARA, Calif.—Marcus Elliott is an unlikely source of wisdom for an industry that pours millions of dollars into scouting talent. A physician who founded a sports-science company here, Elliott freely admits to not watching much sports. But in the weeks before last year's NBA draft, Elliott knew something the league's 30 teams didn't. He was sitting on a trove of *secret* information about the best young basketball player in the world.
>
> Luka Doncic […] began flying in 2015 [at the age of 16] halfway across the world to spend his summers at Peak Performance Project (P3). He came here because Elliott's gym is at the vanguard of *collecting biomechanical measurements that detail in precise terms the way that professional athletes do their jobs*. And his time at P3 produced so much useful information that one team with a lottery pick in last year's draft suggested it would pay for Elliott's highly valuable intelligence.
>
> […] Doncic is now the face of basketball's next generation in part because of *what happened long before* his dazzling rookie season with the Dallas Mavericks. He's part of a wave of precocious talents flooding the league with *a deeper understanding of the economic assets that make them valuable: their own bodies.*
>
> […] that's why they visit P3: *to make the intangibles more tangible.*

We have highlighted in italics the words that we think best contribute to provide a broad perspective from which to interpret this paper: "long before," "measurements that detail the way professional athletes do their jobs," "to make the intangibles more tangible," and "industry that pours millions of dollars into scouting talent."

This paper is concerned with measurement, intangibles, long before, understanding of assets (mind instead of body) and the "production function" of talent.

It is neither concerned with a specific sport (although we use a specific setting of professional soccer, what we study is applicable to any sport) nor with biomechanics (which we view not as intangible but as tangible variables that are hard to gauge). Instead:

1. We introduce the measurement of what is likely, as just noted, a key intangible determinant of success, training, motivation and decision-making in sports: attitudes towards competition, a *propensity* to prefer a competitive environment or simply *competitiveness*.

We bring this variable from the behavioral economics literature (which we briefly review below). In recent years, economists have developed novel ways of measuring individual attitudes towards competition, and these efforts have proven successful in explaining several outcomes of interest in labor markets. This important research has not reached the sports literature yet, and we fill this gap.

2. Competitiveness resides not in the body of an athlete but in his mind. It is obviously quite different from biomechanics and similar physical variables. As we will see, we study a pool of prospects from the age of 10 until 23. Viewed from this perspective, if Donkic's biomechanical measurements were collected since the age of 16, we study measures of competitiveness collected from the age of 10. Thus, if Donkic's P3 measures were at the vanguard for tangible skills, this may be interpreted as at the vanguard of intangible skills.

In terms of specifics, what can we learn?

The answer, of course, depends on the open questions in the literature. Here, we note that although competitiveness plays a key role in a sports industry that pours millions of dollars into understanding talent, we do not know: how to measure individuals' attitudes towards competition, when these attitudes are formed, how they vary both within individuals over time and across individuals and, perhaps more importantly, how much competitiveness matters for sporting success once other determinants are accounted for.

In this paper, we study a longitudinal dataset of individuals repeatedly observed for over a decade (2011-2023) that combines demographic and performance evidence with experimental measures of competitiveness validated in the behavioral and labor economics literatures. The dataset encompasses ≈550 players aged 10-23, from an elite soccer academy in one the world's best leagues (Spain's *La Liga*). It also includes data on ≈50 coaches. In terms of empirical methodology, we implement a dynamic discrete-choice panel data analysis that accounts for unobserved heterogeneity and lagged endogenous variables. This allows us to obtain unbiased, efficient estimates of the relationships of interest. As discussed below, we also obtain causal estimates of the effects of competitiveness on different measures of successful outcomes.

This unique dataset allows us to study all the questions posed above. Specifically, and as anticipation of some of the main results, this paper contributes to the sports analytics literature in several ways:

• First, as just noted, this represents the first time that this specific behavioral trait (competitiveness) is introduced in the empirical scientific literature in sports analytics.

• Second, we measure how this intangible trait is formed both over time and across individuals. And we study not just one player but hundreds of top prospects, which we quantify for years before some turn elite professionals.

• Third, we establish the importance of competitiveness for predicting sporting success after standard variables are accounted for. Indeed, as we shall see, *differences in competitiveness* do help account for *differences in performance and success*, at strongly significance levels.

• Fourth, we find that players' preferences for competition are malleable, but only up to a certain age.

In terms of causality, the last two results are established not only in the raw data (accounting for endogeneity and unobserved heterogeneity effects) but also in a *causal* manner by exploiting the fact that certain coaches with varying degrees of competitiveness are allocated, from year to year, to teams for exogenous reasons. As such, players may receive training from coaches that are characterized by different degrees of competitiveness themselves, and this variation is exogenous.

• Fifth, establishing the relevance of competitiveness to predict sporting outcomes naturally leads to wider sports management implications for coaches, teams, clubs, and institutions, which we briefly discuss throughout the paper.

• Sixth, these ideas have full applicability to all other sports, as both the concept of measuring competitiveness and the measures we use can be applied to any sports.

• Finally, to put the contribution in perhaps a more vivid and direct perspective for sport practitioners, towards the end of his *Wall Street Journal* article Ben Cohen concludes (italics ours):

> Utah Jazz guard Kyle Korver and Doncic bonded despite their generational divide: Korver went to P3 to extend his NBA career, and Doncic went to P3 before he even had an NBA career.
>
> "Man, if I'd known this when I was 16 years old," said Korver, who turns 38 next week. "I can't even imagine what my data would look like."
>
> Doncic doesn't have to use his imagination. *He'll be able to trace his development through his data. He's among the first of many players whose lives in basketball will be quantified*.

Here, we quantify *competitiveness* during the *lives* of many prospects, which we follow up to their adult age and professional levels.

The rest of the paper is structured as follows. Section 2 briefly reviews the relevant behavioral economics and sports literatures. Section 3 goes over the methodologies: In subsection 3.1 we describe the econometric methodology (both the discrete choice dynamic panel data with unobserved heterogeneity and lagged endogenous variables, and the measurement of marginal effects), and in subsection 3.2 the experimental methodology. Section 4 describes the data, Section 5 the results and Section 6 concludes.

2. Related Literature

The concept of "intangible skills" in the social sciences refers to abilities that are not easily quantifiable in traditional terms. These skills are often contrasted with "tangible skills," which are more concrete and can be directly observed or assessed. We would include, for example, biomechanics and physical abilities among tangible skills.

Intangible skills encompass a wide range of human capabilities, including "soft skills" (leadership, teamwork and adaptability), emotional intelligence, creativity, cultural competence (ability to interact effectively with people from diverse cultural backgrounds), persuasion and others. Many of these skills are challenging to measure.

But challenging does not mean impossible.

Indeed, one of the most compelling developments in contemporary empirical social sciences lies in the empirical measurement of *non-cognitive* traits and in the study of their role in shaping human behavior. For instance, research by Nobel laureate James J. Heckman and coauthors formulates and estimates multistage production functions for cognitive and non-cognitive skills, revealing several key insights: (a) both types of skills emerge *early in life*; (b) both are determined in part by family and social environments at different stages of childhood, and (c) both predict success at an adult age on many dimensions. Interestingly, non-cognitive skills are often as influential, if not more so, than cognitive abilities in determining educational choices, wages, health outcomes, occupations and a wide array of risk-related behaviors. In terms of magnitudes, a change in non-cognitive skills from the lowest to the highest levels typically has an effect on behavior that is comparable or greater than a corresponding change in cognitive skills.

The influential articles that started this literature include Heckman, Stixrud and Urzua (2006) and Cunha, Heckman and Schennach (2010). For reviews of research showing how to foster and measure skills, and improve cognitive and non-cognitive skills (including soft skills) to promote lifetime success, see for example: Kautz, Heckman, Diris, ter Weel and Borghans (2014), Heckman and Kautz (2012, 2014), Heckman, Jagelka and Kautz (2019) and Kautz and Zanoni (2023).

A related strand of research comes from the behavioral economics literature. Specifically, research has found that *attitudes towards competition (competitiveness)* act as an important intangible skill for success in many contexts. Competitiveness is more about an individual's mindset, his approach to challenges, and his *willingness* to engage in competitive situations. As such, it is not strictly an interpersonal skill. This body of work originates in the influential work of Niederle and Vesterlund (2007), a study that was mainly concerned with differences across genders. The result is that, over the past few years, social scientists have become increasingly interested in investigating whether differences in a willingness to compete may contribute to explaining why labor market and other differences between men and women persist.[1]

Overall, competitiveness has been found to be an important determinant of many choices and outcomes of interests (e.g., choices in post-compulsory education, job entry decisions, wage expectations, health) and in many settings, including academic and professional fields, and business and entrepreneurship.[2] Buser and Oosterbeek (2023), Lozano and Reuben (2023) and Lüthi and Wolter (2023) provide excellent recent reviews of the anatomy and measurement of competitiveness, gender and labor market success.

Intuitively, there is no reason why we could not expect competitiveness to be as important, if not more so, in sports. Athletes who are highly competitive are more likely to train rigorously, set and pursue ambitious goals and perform well in competitive environments. And the extent to which competitiveness complements or balances other intangible skills like teamwork, cooperation, and emotional intelligence often appears to be crucial for long-term success, especially in collaborative

[1] A number of prominent studies show that, in fact, men appear to opt to compete more often than women, even controlling for performance, risk attitudes, beliefs, feedback and other aspects. See, for example, Buser, Niederle and Oosterbeek (2014), Niederle and Vesterlund (2011), Niederle (2017) and many references therein.
[2] In academic settings, competitiveness can drive students to excel, strive for top grades and seek academic achievements. In professional fields, it can encourage individuals to stand out, seek promotions and take on leadership roles. In the business world, competitive entrepreneurs often strive to outperform their competitors, identify market opportunities and drive innovation.

environments such as team sports. But, needless to say, more is not always better: an excessive degree of competitiveness may also have negative consequences in certain settings or periods of life.[3]

Unfortunately, as mentioned in the introduction, we are not aware of any empirical study in the scientific sports literature that measures and studies competitiveness. For example, leading academic handbooks on expertise and expert performance, such Ericsson et al (2018), and on embodied cognition and sport psychology, such as Cappuccio (2019), collect dozens of influential collaborations between sports scientists and cognitive scientists with hundreds of references. It is remarkable that while they consider the mind–body relationship in aspects of skill formation and sports practice, there is not a single reference to measuring and studying "competitiveness."

We view this aspect as a main contribution of the present study for the sports scientific literature.

3. Methodology

Our dynamic panel dataset involves measures of endogenous variables such as competitiveness and performance, in addition to exogenous individual and state variables. In subsection 3.1 we describe the econometric methodology that we implement to obtain unbiased estimates of the parameters of interest. In subsection 3.2 we describe how competitiveness is measured, in addition to risk aversion and beliefs on performance.

3.1 Econometric Methodology: Discrete-Choice Dynamic Panel Data

Our semi-parametric, random effects, discrete choice model with predetermined variables is based on Arellano and Carrasco (2003) and controls for the effects of unobservable heterogeneity and for state dependence. As is well known, in the presence of lagged endogenous variables in linear models with additive effects, the standard procedure in the econometrics literature is to consider instrumental-variables estimates that exploit the lack of correlation between lagged values of the variables and future errors in first differences. In non-linear settings such as ours, however, few results are available and care needs to be exercised.[4]

The basic idea of the Arellano-Carrasco model is to define conditional probabilities for every possible sequence of realizations of the state variables. Then, the estimator computes the probability of a given outcome along every possible path of past realizations of the endogenous regressors. This means that our panel data structure allows the identification of the effects of *individual unobserved heterogeneity* since outcomes can be different even when individuals share the same history of realizations of the state variables.

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[3] For instance, fostering a cutthroat or win-at-all-costs attitude may hinder performance, lead to unethical behavior and even harm relationships. Children and young players may be discouraged, especially in team sports, if teammates or coaches create negative externalities.

[4] We are grateful to Eugenio Miravete for his valuable teaching and advice. For fixed effects the few available methods are case-specific (logit and Poisson) and, in practice, lead to estimators that do not converge at the usual $\sqrt{n}$-rate. In the case of random effects, the main difficulty is the so-called initial conditions problem: if one begins to observe subjects after the "process" in question is already in progress, it is necessary to isolate the effect of the first lagged dependent variable from the individual-specific effect and the distribution of the explanatory variables prior to the sample.

Formally, consider two discrete outcomes denote as $y_{it} = \{1,0\}$. These could be discrete measures of, for example, performance, success (e.g., reaching professionalism) or competitiveness. The probability of an outcome depends on the specific sequence of past outcomes and the "state process" of the individual. Since outcomes can be different, different experiences change the information set and the expected realizations of future outcomes. To be specific, the probability of a given outcome may depend on the characteristics of the individual, as well as on his expectation on future realizations:

$$y_{it} \;=\; \mathbf{1}\{\gamma + \beta\, z_{it} + E(\eta_i \mid w_i^t) \;+\; \varepsilon_{it} \;\geq 0\}, \quad \text{with } \varepsilon_{it} \mid w_t^i \sim N(0, \sigma_t^2).$$

In this model, the constant γ captures the effect of all time-invariant determinants of the individuals (e.g., demographics, environment, etc).[5] The set of predetermined variables z_{it} includes the past realization of other endogenous variables x_{it} and previous outcomes $y_{i(t-1)}$, so that together they define the particular realization of the "state" for each individual *i*, that is $w_{it} = \{x_{it}, y_{i(t-1)}\}$. Thus, the estimates of β identify the effect of state dependence separately from time-invariant aspects since z_{it} includes time-varying regressors that are only predetermined, that is not directly correlated with the current or future values of the error ε_{it} (although lagged values of errors ε_{it} might be correlated with z_{it}). The third ingredient is the following. As time elapses, individuals may make different decisions and become increasingly different. These decisions are summarized by $w_t^i = \{w_{i1}, w_{i2}, \ldots, w_{it}\}$, which is the history of past $w_{it} = \{x_{it}, y_{i(t-1)}\}$. The last element of the model is η_i, an individual effect whose forecast is revised each period t as new information and experiences summarized by the history w_t^i accumulates. This value is not known to individuals and, hence, only its expectation enters the decision rule. In other words, y_{it} is not only affected by time-invariant aspects (γ) and state dependence (β), but also by the learning effect $E(\eta_i \mid w_t^i)$ after controlling for individual heterogeneity.

Summing up, the model defines conditional probabilities for every possible sequence of realizations of state variables in order to deal with regressors that are endogenously predetermined. Then the panel data structure allows us to identify the effect of individual unobserved heterogeneity since at each time individuals may have different outcomes even if they have shared the same history of realizations of state variables.

Finally, the conditional distribution of the sequence of expectations $E(\eta_i \mid w_t^i)$ is left unrestricted, and so the process of updating expectations as information accumulates is not explicitly modeled. This is the only aspect that makes the model semi-parametric. While the assumption of normality of the distribution of errors is not essential, the assumption that the errors ε_{it} are not correlated over time is necessary for the estimation. Since errors are assumed to be normally distributed, conditional on the history of past decisions, the probability of a given outcome at time t for any given history w_t^i can be written as:

$$Prob\,(y_{it} = 1 \mid w_t^i) = \Phi\left[\frac{\gamma + \beta\, z_{it} + E(\eta_i \mid w_t^i)}{\sigma_t}\right].$$

[5] The specification of Arellano and Carrasco (2003) is more general in that it includes a time-varying component common to all individuals γ_t .

In terms of econometric implementation, the support of our regressors is a lattice with J points. The vector w_{it} has a support defined by $2J$ nodes $\{\phi_1, \dots, \phi_{2J}\}$. The t×1-vector of regressors $z_t^i = \{z_{i1}, \dots, z_{it}\}$ has a multinomial distribution and may take up to J^t different values. Similarly, the vector w_t^i is defined on $(2J)^t$ values, for $j = 1,\dots, (2J)^t$. Given that the model has discrete support, any individual history can be summarized by a cluster of nodes representing the sequences for each individual in the sample. Thus, the conditional probability can be rewritten as:

$$p_{jt} = Prob\,(y_{it} = 1 \mid w_i^t = \phi_j^t) \equiv h(w_i^t = \phi_j^t) \qquad j=1,\dots,(2J)^t$$

In order to account for unobserved individual effects we compute the proportion of individuals with identical history up to time t that have outcome M at each time t. We then repeat this procedure for every available history in the data. For each history, we compute the percentage of individuals as this proportion provides a simple estimate of the unrestricted probability $\hat{p}_{jt}$ for each history present in the sample. Then, by taking first differences of the inverse of the above equation we get:

$$\sigma_t\, \Phi^{-1}\left[h_t\left(w_i^t\right)\right] - \sigma_{t-1}\, \Phi^{-1}\left[h_t\left(w_i^{t-1}\right)\right] - \beta\left(z_{it} - z_{i(t-1)}\right) = \xi_{it}$$

and, by the law of iterated expectations, we have:

$$E(\xi_{it} \mid w_i^{t-1}) = E\left[E(\eta_i \mid w_i^t) - E(\eta_i \mid w_i^{t-1}) \mid w_i^{t-1})\right] = 0$$

This moment condition serves as the basis of the General Method of Moments (GMM) estimation of parameters β after normalizing $\sigma_1 = 1$. To identify the effect of time-invariant determinants we use:

$$E(\eta_i \mid w_i^{t-1}) = E\left[\Phi^{-1}\left[h_t\left(w_i^{t-1}\right)\right] - \gamma - \beta\, z_{it}\right] = 0$$

Arellano and Carrasco (2003) show that there is no efficiency loss in estimating these parameters by a two-step GMM method where in the first step the conditional probabilities p_{jt} are replaced by unrestricted estimates $\hat{p}_{jt}$. Then:

$$\hat{h}_t\left(w_i^t\right) = \sum_{j=1}^{(2J)^t} \mathbf{1}\{\, w_i^t = \phi_j^t\} \cdot \hat{p}_{jt},$$

which is used to define the sample orthogonality conditions of the GMM estimator:[6]

$$\frac{1}{N}\sum_{i=1}^{N}\{\sigma_t\left[\Phi^{-1}\left[\widehat{h_t}\left(w_i^{t-1}\right)\right] - \gamma - \beta\, z_{it}\right]\} = 0, \qquad t = 2, \dots, T.$$

and

[6] We use the orthogonal deviations suggested in the classic Arellano and Bover (1995) rather than first differences among past values of the state variables.

$$\frac{1}{N}\sum_{i=1}^{N} d_{it}\{\sigma_t \Phi^{-1}[\widehat{h_t}(w_i^t)] - \sigma_{t-1}\Phi^{-1}[\widehat{h_{t-1}}(w_i^{t-1})] - \beta\,(x_{it} - x_{i(t-1)})\} = 0, \qquad t = 3, \dots, T.$$

and where d_{it} is a vector containing the indicators $\mathbf{1}\{\,w_i^t = \phi_j^t\}$ for j=1,..., $(2J)^{t-1}$.

With respect to the magnitude of the effects, the marginal effects associated with the "transition among different states" can be computed as follows. Arellano and Carrasco (2003) show that the probability of a given outcome when we compare two states $z_{it} = z^0$ and $z_{it} = z^1$ changes by the proportion:

$$\hat{\Delta}_t = \frac{1}{N}\sum_{i=1}^{N}\{\Phi\,(\hat{\sigma}_t^{-1}\hat{\beta}\,(z^1 - z_{it)}) + \Phi^{-1}[\widehat{h_t}(w_i^t)]) - \Phi\,(\hat{\sigma}_t^{-1}\hat{\beta}\,(z^0 - z_{it)}) + \Phi^{-1}[\widehat{h_t}(w_i^t)])\} = 0.$$

Since the evaluation depends on the history of past choices w_i^t, these marginal effects are different for each "partial change" in the sample and for each individual. This also means that, while we will report evidence for "representative" players, this feature of the econometric model would be useful for sports practitioners to obtain specific insights about specific players.

Finally, as in other settings where this method has been implemented, a reason why the Arellano-Carrasco is preferred in our setting is that alternative fixed-effect approaches such as Honoré and Lewbel (2002) and Honoré and Kyriazidou (2000) require the exogenous regressors to vary over time, something that does not occur in our setting. The alternative in Honoré and Kyriazidou (2000) includes one lagged dependent variable but requires that the remaining explanatory variables should be strictly exogenous, thus excluding the possibility of a lagged dependent regressor (e.g., past successes, past productivities or past competitive choices in our setting). Further, their estimator does not converge at the usual $\sqrt{n}$-rate. Honoré and Lewbel (2002) allow for additional predetermined variables but at the cost of requiring a continuous, strictly exogenous, explanatory variable that is independent of the individual effects. Fernandez-Val (2009) offers a useful characterization of the source of biases of fixed-effect estimators in non-linear panel data models.

3.2 Experimental Methodology

Competitiveness Measures. The goal in the behavioral economics literature is to measure *competitive inclinations* when observations are not bundled with stereotypes on tasks and other aspects. Here, we implement two different experimental designs (one for players and the other for coaches) that have been developed and validated in the literature that meet this requirement. Both designs have a simple and clean structure.

Measure #1: Players. This experimental task has been used in influential studies (see, e.g., Gneezy et al. 2009). Subjects have to throw a tennis ball into a bucket that is placed 3 meters away. They are informed that they have 10 chances and that they will be paid according to their performance. A successful shot means that the tennis ball enters the bucket and stays there. The task is simple and easy to implement for players of any age (unlike the measure implemented for coaches, where age would likely matter for young players). Throwing an object a short distance is a simple yet novel task, and no significant correlation between abilities and observable demographics (certainly within age cohorts) is expected, something that will be confirmed in the data.

Each player is told that he is randomly matched with another participant who is performing exactly the same task at the same time in another room in the same building in the academy. Subjects are informed that their identities will remain anonymous. The only decision they are asked to make concerns the way they would like to be paid for their performance, which they have to decide *before performing the task*. The two options they are asked to choose between are: (A) 1€ per successful shot, regardless of the performance of the other player, or (B) 3€ per successful shot if they outperformed the other player (if they tie they receive 1€ per successful shot).

The measure of competitiveness is 1 if the subject *chooses to compete* (option B) and 0 if he *chooses not to compete* (option A). After choosing the incentive scheme, participants complete the task and receive the corresponding earnings depending on their choice of payment scheme (after being told how the other player performs if they chose (b)). We also control for beliefs by asking players about their expected ranking in the team before performing the task.

Measure #2. Coaches. This experimental task is more suitable for adults than for younger players, and as such it is used with coaches. It comes directly from the classic Niederle and Vesterlund (2007) and has proven quite influential and robust in the literature as a series of subsequent papers have introduced only minor modifications to the original design and found similar results (see, e.g., Niederle (2017) for a review). We briefly go over the design next, and urge the reader to read the original study for a careful discussion of its advantages and specific details.

Essentially, the experiment examines choices between a *competitive* vs a *non-competitive* compensation scheme while controlling for performance and for beliefs about relative performance. Subjects are asked to add up sets of five two-digit numbers for five minutes under different compensation schemes. Each of these five-minute trials is a "task" and the "performance" is the number of correctly solved problems on the task. They are seated in a classroom with four subject per row, and are told that they form a group of four. Subjects are asked to complete four tasks and told that one of these tasks would be randomly chosen for payment at the end of the experiment. They know the nature of each task only immediately before performing it, and this is the only thing they know. So while they may have a sense of their own absolute performance on a task ex post (i.e., how many problems they solved correctly), they are not informed about how others perform until the end of the experiment. The order of tasks is as follows:

Task 1—Piece Rate: Subjects are given a five-minute addition task. If this Task 1 is randomly selected for payment, they receive 50 cents (€) per correct answer.

Task 2—Tournament: Subjects are given a five-minute addition task. If this Task 2 is randomly selected for payment, the subject who solves the largest number of correct problems *in the group* receives 2€ per correct answer, while the other subjects receive no payment.

Task 3—Choice of Compensation Scheme: <u>Before</u> performing a new five-minute addition task, subjects must select whether they want to be paid according to a piece rate (50 cents for each correct answer) or a tournament (2€ per correct answer if his score in Task 3 exceeds that of the other group members in the Task-2 tournament they just completed; otherwise he receives no payment).

The choice in this Task 3 is a measure of competitiveness: 1 if tournament, 0 if piece rate.

Note that subjects only know about their own absolute performance but that their choice in Task 3 may reflect their *beliefs about relative performance*. This means that it is important to account for *differences in overconfidence* or similar beliefs as potential drivers of their choices. To this end, one last task is implemented:

Task 4- Subjects do not have to perform in this task. They are asked to rank their performance on the initial tournament (Task 1) relative to that of the other group members. Correct guess are rewarded by 1€.[7]

Risk Attitudes. Choosing the tournament payment schemes in the previous competitiveness experiments is clearly *not only more competitive* but *also more risky* than choosing the piece rate schemes. This is important because *risk aversion* is a different dimension from a *taste for competition*. Researchers in the behavioral economics literature are aware of this aspect and know that, even though the literature send a moderate message about the potential relevance of differences in risk attitudes, it is important to account for such differences across individual subjects. We do this following standard practice, in particular using a standard risk game where subjects make a decision between two incentive schemes *without* actual competition taking place.

Specifically, the risk experiment has subjects play a one-shot game in which they are endowed with 100 units (worth 2 €uros). The subject must decide *what portion* of this pot [0, 100] he desires to bet in a lottery that returns three times the bet with 50 percent probability and nothing with 50 percent probability. Subjects are made aware that the lottery will be played directly after choices are made. Therefore, they know that they could earn anywhere between 0 and 300 units from this task. They are also informed that monies earned would be paid in private at the end of the experiment.

4. Data

The data comes from a top professional soccer club in Spain: Athletic Bilbao. The academy of this club typically ranks, and currently ranks, as the number #1 in Europe in terms of the number of homegrown club-trained players that it produces for the top 5 European leagues and the minutes players have played so far in the 2023/24 season. To put this ranking in perspective, second place is Olympique Lyonnais in France, and Real Madrid and FC Barcelona sit in fourth and ninth places, respectively. See the recent report by CIES Football Observatory (2023).

The academy of this club is known worldwide and has been praised in general interest articles by leading global media as the best youth system in Europe (see, e.g., *New York Times* articles by Sam Borden (2015) and Rory Smith (2022a)).

[7] Note that not taking draws into account, at most 30% of players should guess that they are the best in their group of four (see Niederle and Vesterlund (2007)). However, about 75% of players hold that belief in our sample: they are overconfident. This is similar to their results. Interestingly, there is not a great deal of variation in overconfidence (neither cross-sectional nor over time). The important aspect, however, is whether subjects' confidence is related to tournament entry. We find that we cannot reject the hypothesis that the correlation is zero at standard statistical confidence levels. As such, we take tournament entry (Task 3) as a suitable measure of competitiveness.

The experiments were conducted during the period 2011-18 at yearly frequencies, and the data on performance and demographic variables covers the period 2011-23. As in other countries, league soccer competition in Spain is hierarchical and runs from September of a given year to June of the next one. It has four professional divisions typically known as Primera División (*La Liga*), Segunda División A and B (both referred to as *La Liga2* here) and Tercera División (*La Liga3*) which is semi-professional. Athletic Bilbao has three senior professional male teams: one in *La Liga*, another in *La Liga2* and the third one in *La Liga3*.

In terms of youth leagues, competition in Spain is typically grouped into 8 different age categories, from Under11 to Under18. We obtain the standard demographic variables for each player, and we also know when they join the academy and leave. Players can be cut or released at any given season after they join the club. All the players are male. The earliest they can join the academy is 10 and at age 18 at the latest they either move to the squad of one of the senior teams (getting their first professional contract) or are loaned or released. Most players join the academy at age 10 (around 25-35 players per season), but other players also join at other ages (about 4-5 per age year each season).

All the leagues in Spain (professional, semiprofessional and youth) adhere to the same structure and calendar schedule, and are governed by the same rules of the world-governing body of soccer FIFA-*Fédération Internationale de Football Association* (FIFA, 2022).

Finally, in terms of performance, we know for each player several dichotomous variables: whether he continues in the academy or is cut, the team he plays in, whether he is selected to play for the national Spain team at any underage level, whether he is offered his first professional contract at or before the age of 18 (typically to play for a *LaLiga3* team), and whether he makes it to the second or first professional level in Spain's *La Liga2* and *La Liga*. We also have evidence on injuries, coaches they have, teams they play in and games played.

As discussed earlier, coaches complete competitive experiments (measure #2). In addition, we have evidence an index of their "competitiveness personality" from 1 (not competitive at all) to 10 (very competitive) from the Head of the Academy during 2011-18. This index captures his expert subjective assessment. As expected, it turns out that it is strongly correlated (but not perfectly) with the coaches' behavior in the experiments.

We split coaches into three types: Type A are those who *always* choose the competitive scheme in the experiments *plus* they have a high subjective valuation index from 9 to 10. Type B are those who *never* choose the competitive scheme *plus* they have a low index from 1 to 2. Type C are the rest.

Each team in the academy has two coaches. The typical coach is the first coach of a given team (say, U16 team) and the second coach of another team (say, U12 team). This is randomly chosen by the Head of the Academy in the sense that he follows the rule that every coach should be exposed to player of all ages, at least as a second team coach. More precisely, we consider that a player is "treated" by a *highly competitive coaching* staff if *both* coaches in his team are of Type A, and by a *low competitiveness coaching* staff if both coaches are of Type B. We choose these stringent classifications because we are interested in the best possible proxies of *treatments or shocks* that players may receive from the competitiveness perspective during their development.

5. Results

We first present some descriptive evidence in order to get a flavor for the data, before implementing the dynamic panel data analysis.

5.1 Descriptive Evidence

Table 1 summarizes the raw data

Table 1 – Descriptive Statistics

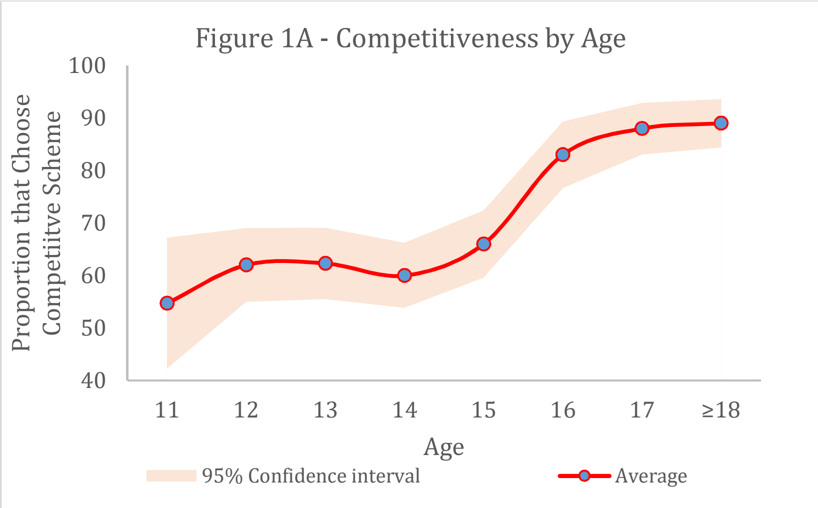
PLAYERS	*N*	Mean	St.Dev	Min	Max	Q3	Q1
Birth Year	551	2001.05	4.02	1994	2008	1998	2004
Age Entry	551	12.6	2.63	10	18	10	15
Competitiveness	551	0.66	0.18	0	1	0.33	1
Risk Aversion	551	63.7	19.6	0	100	30	100
Coach Treatment: High	551	0.25	0.43	0	1	0	1
Coach Treatment: Low	551	0.15	0.35	0	1	0	0
Released before age 18	551	0.22	0.42	0	1	0	0
Years in academy	551	5.20	2.16	1	8	4	8
Spain International	551	0.19	0.39	0	1	0	0
Pro Contract at 18	551	0.28	0.45	0	1	0	1
La Liga 2	551	0.10	0.30	0	1	0	0
La Liga	551	0.04	0.20	0	1	0	0
COACHES							
Birth Year	52	1976	14.03	1950	1985	1998	2004
Age Entry	52	33.1	8.2	25	52	26	42
Competitiveness (Experiments)	52	0.73	0.18	0	1	0.47	0.93
Competitiveness (Index 1-10)	52	5.70	2.21	1	10	3	7
Risk Aversion	52	72.3	17.9	0	100	25	100

Notes: Q1 and Q3 denote the first and third quartiles. *Spain International* is one if a player plays at least one game for Spain in underage levels below the age of 23. *Pro Contract at 18* is one if the player gets a professional contract at age 18. *La Liga2* and *La Liga* are one if the player has played at least one game at this level (as of November 30, 2023).

In term of competitiveness, about two thirds of the year-subjects choose the competitive scheme. As for risk attitudes, players risk about 63 percent of their endowment in the risk games. Twenty five percent of year-subjects are coached by a "highly competitive coaching" staff, and fifteen percent by a low competitiveness coaching staff. On average, players spend 5.2 years in the academy. Twenty two percent are released or cut before the age of 18. Almost one in five play for Spain at least once in at least on the underage levels. Twenty eight, ten and four percent of players make it to La Liga3, La Liga2 and La Liga as professionals, respectively.

Figure 1A provides a first overview of the raw results from the competitive experiments. It simply reports the proportion of players per age year that choose the competitive scheme. As may be observed, this proportion starts at around 55 percent at age 10, and steadily rises over time up to

92 percent at age 18. Interesting, we observe a rather steep change at ages 14-15 while it tends to be somewhat flatter before and after these age years.



For comparison purposes, Figure 1B includes evidence from non-players from Spain and Germany.[8] The proportion starts at around 43-45 percent at age 10 in both countries, which suggests that there is a *selection effect* at this early age of about 10% point difference between sports talents and others. Interestingly, this difference tends to increase with age: from age 12 (a 20% points difference) to age 16 (a 30% points difference), to remain at about 23-29% point difference at ages 17-18.

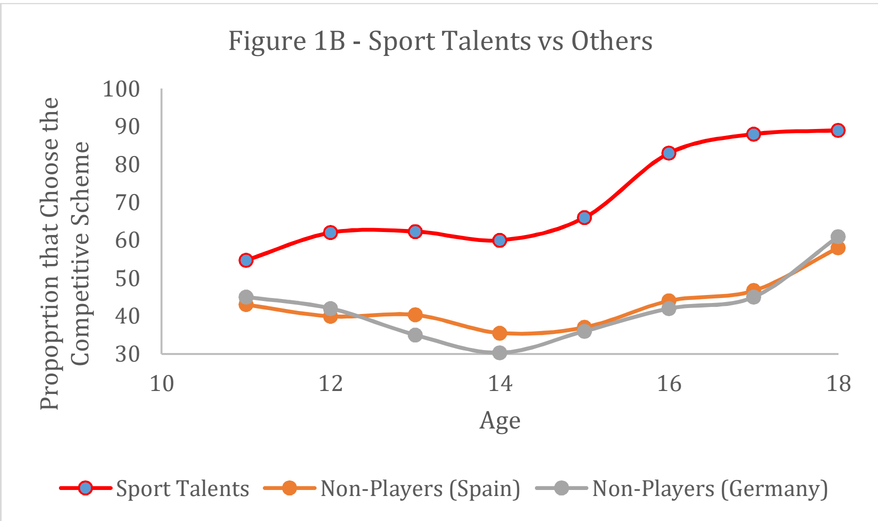
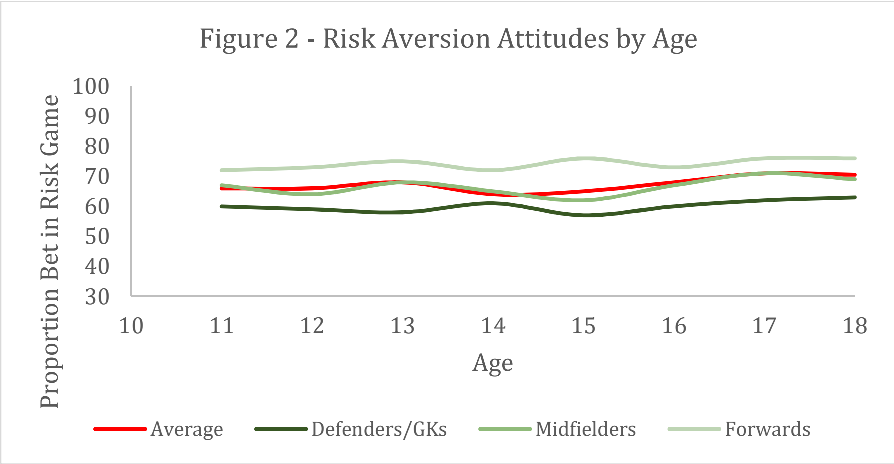


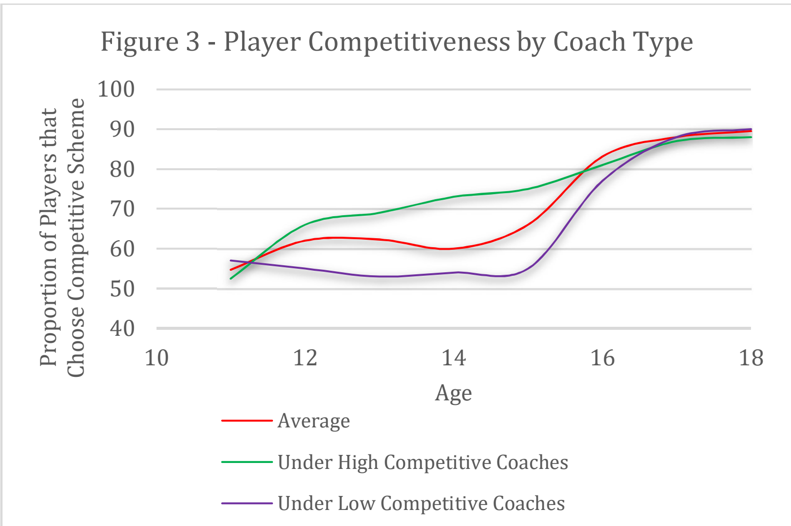
Figure 2 reports the results of the risk experiments for players. As can be observed, there is not much variation by age in the sample, on average, hovering around 60-70 percent across ages.

[8] See Satter and Glätztle-Rüztler (2015) for Germany, which is replicated with Spain's students.



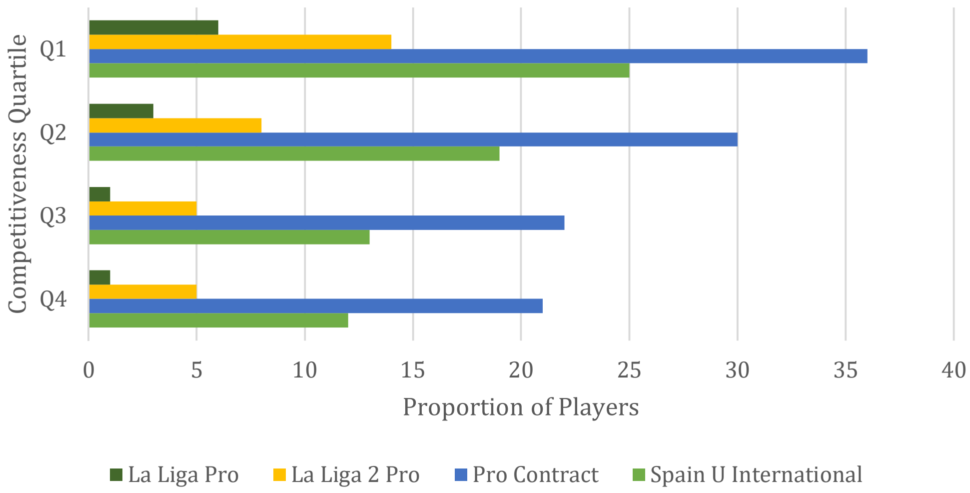
Interestingly, we observe some differences across positions: goalkeepers and defenders appear to be more risk averse than midfielders, and midfielders more risk averse than forwards. We will have players' fixed effects in our econometric work, which means that since players tend not to change positions much and since there is no significant correlation between risk attitudes and competitiveness, it is likely that position has no significant impact on the results (this is confirmed in the different econometric specifications we have implemented).

Figure 3 reports some preliminary evidence on the extent to which competitiveness might be malleable by coaches. Although these are simply the raw data where players are sorted by those who get highly competitive coaches and those who get low competitiveness coaches, the data already suggest interesting effects. As expected, high competitiveness coaching would appear to increase a player's competitiveness, and low competitiveness coaching to decrease it. However, highly competitive coaches tend to have *no effect at early ages* (and may even have a *negative* impact), and the impact of both types of coaches tends to be meaningless after age 16. Although merely descriptive, these raw data appears to suggest that "interventions" in a player's competitiveness could be most productive around ages 13-15.



Finally, Figure 4 reports some initial evidence correlating competitiveness with measures of success. Players are sorted by competitiveness quartile (Q1 top quartile to Q4 bottom quartile) depending on the proportion of times that they choose the competitive scheme in the experiments. And as measures of success we consider: (1) Spain International in underage levels, (2) whether the player is offered a professional contract at age 18, (3) plays in *La Liga2*, and (4) in the top professional division *La Liga.* As may be seen, the raw data strongly suggests that the higher the competitiveness quartile the greater the likelihood that players will be successful. Indeed Q1 players show a clear difference relative to players in other quartiles, while Q3 and Q4 are similarly low in every measure of successful outcomes.

Figure 4-Correlates of Competitiveness Quartiles with Success Outcomes



Summing up, the raw data does suggests a number of interesting and potentially important relationships between our variables of interest. We turn next to the empirical work.

5.2 Econometric Results

We study the determinants of competitiveness in subsection 5.2.1 and then the determinants of successful outcomes in subsection 5.2.2. These are our two endogenous variables having an effect upon each other over the life cycle of a player. Formally, they are denoted as $y_{it} = \{1,0\}$. They both depend on the specific sequence of past choices and outcomes, and the "state process" of the individual. As described earlier, the probability of a given outcome can be written as:

$$y_{it} = \mathbf{1}\{\gamma + \beta\, z_{it} + E(\eta_i \mid w_i^t) + \varepsilon_{it} \geq 0\}, \quad \text{with } \varepsilon_{it} \mid w_t^i \sim N(0, \sigma_t^2).$$

where γ captures the impact of time-invariant characteristics, β the impact of dynamic state dependence effects z_{it} that include past realizations of other endogenous variables x_{it} and previous outcomes $y_{i(t-1)}$ (both define the "state" for each individual i, that is $w_{it} = \{x_{it}, y_{i(t-1)}\}$), and

$E(\eta_i \mid w_t^i)$ the learning effects after controlling for individual heterogeneity. As described earlier as well, the marginal effects when comparing two states $z_{it} = z^0$ and $z_{it} = z^1$ are:

$$\hat{\Delta}_t = \frac{1}{N}\sum_{i=1}^{N}\{\Phi\left(\hat{\sigma}_t^{-1}\hat{\beta}\left(z^1 - z_{it)}\right) + \Phi^{-1}\left[\widehat{h_t}\left(w_i^t\right)\right]\right) - \Phi\left(\hat{\sigma}_t^{-1}\hat{\beta}\left(z^0 - z_{it)}\right) + \Phi^{-1}\left[\widehat{h_t}\left(w_i^t\right)\right]\right)\} = 0.$$

Since the evaluation depends on the history of past w_i^t, these marginal effects are different for each "partial change" in the sample.

5.2.1 Competitiveness

Is competitiveness malleable? How exactly is competitiveness formed during ages 10-18? It is affected by the initial competitiveness level when a player is selected to join the academy? What is the effect of a "coach treatment" on players' competitiveness? Is this effect modulated by the number of years of treatment? Is it modulated by the sign of the treatment? Is it affected by the age at which the treatment takes place? These are some of the questions that can be addressed in our setting.

Before implementing the panel data analysis, we begin by trying to get a sense beyond what the raw data suggest. Table 2 implements various probit specifications in four panels, *all of which include controls* for birth and entry years, age, team, coach, risk aversion and beliefs using standard Maximum Likelihood.

Panel A reports the effect of age with no interactions. After the age of 13, the magnitude of the estimates steadily increases and they are all strongly significant. Consistent with the early intuition from the raw data, ages 13-15 seem where we observe the greatest changes.

In the rest of panels, we interact the coach treatment with age and report the coefficients. In Panel B, we study the impact on a player's competitiveness of "highly competitive" coaches. The impact is positive and strongly significant for ages 12-14, and insignificant after age 16. Also interesting is the fact that for the early age of 10 the impact is *negative* and almost significant at the ten percent level. This suggests that, if the goal was to increase competitiveness (to be studied in the next subsection), it may be *detrimental* to expose players to highly competitive coaches at younger ages.

In the dataset, some players were treated twice by highly competitive coaching during their years in the academy. Panel C shows that in these cases the effect is not significant, except for age 14, at standard confidence levels. Interestingly too, the sign of all the coefficients is negative in this case. This suggests that there are *decreasing returns* to being treated by a very competitive coach, and that the effect may be even *detrimental* if the goal is to induce more competitiveness in players.

Finally, in Panel D we consider the effect on a player's competitiveness level of coaches that have low competitiveness by our measure. This treatment does not seem to have much of an effect in a player's competitiveness. Further, the sign of the coefficients tends to be negative. Except for the case age 15 the effect is not significant at conventional statistical confidence levels.

Table 2 – Probit Coefficients for Impact of Age and Coach Treatment on Competitiveness

	Age								
	10	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Panel A: All									
		0.03	0.28***	0.16	0.40***	0.66***	0.74***	0.92***	1.18***
		(0.15)	(0.15)	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.21)
Panel B: Coach Treatment *Highly Competitive*									
	-0.39	-	0.71***	1.15***	1.04***	-	0.15	-	0.12
	(0.24)	-	(0.27)	(0.30)	(0.26)	-	(0.26)	-	(0.27)
Panel C: Coach Treatment *Highly CompetitiveX2*									
	-	-	-	-0.18	-0.85***	-0.63**	-	-	-
	-	-	-	(0.44)	(0.34)	(0.39)	-	-	-
Panel D: Coach Treatment *Low Competitiveness*									
	-0.01	0.36	-	-	-	-0.67***	-0.19	-0.53	-
	(0.15)	(0.31)	-	-	-	(0.31)	(0.27)	(0.36)	-

Notes: ***, ** and * in red denote significant at 1, 5 and 10 percent levels, respectively. Std. errors in parentheses. Panels B, C and D report the coefficients for the interaction terms between Age and Coach Treatments. All the specifications control for birth and entry years, age, team, coach, position, risk aversion and beliefs.

We next move to Arellano-Carrasco analysis. In what follows, we simply report the *coefficient estimates* of Age in Figure 5, and then the *marginal effects* of the two main Coach treatments by age in Figures 6 and 7. The specifications include all of our observables, and are implemented the two-step GMM described earlier

As may be seen, the results are quite consistent with the above analysis. Competitiveness is malleable and changes with the number of years in the academy. The impact is small at ages 10-11 and could be zero. It is also somewhat flat during ages 12-14 and after 17. As for the marginal effects, highly competitive coaches can increase a players' competitiveness, but basically only during ages 12-16. Before the age of 12-13 they have little or no impact, and may even be negative. After the age of 16 the impact is again statistically zero. In Figure 7 we see that coaches that have low competitiveness have no marginal impact on players' competitive attitudes.

Finally, as a prelude to the analysis in the next section, note that the previous exercises use the coach treatment as an exogenous regressor, not as an instrument for competitiveness. But if the treatment has no other influence on the outcomes except through its effect on competitiveness (e.g., all coaches have the same quality; it is not that the more competitive coaches in the academy are better or worse as "teachers" than the others), it could serve as a way to identify the causal impact of competitiveness on success. If that is the case, then the results suggest a positive causal effect of competitivenesss. We turn next to this question.

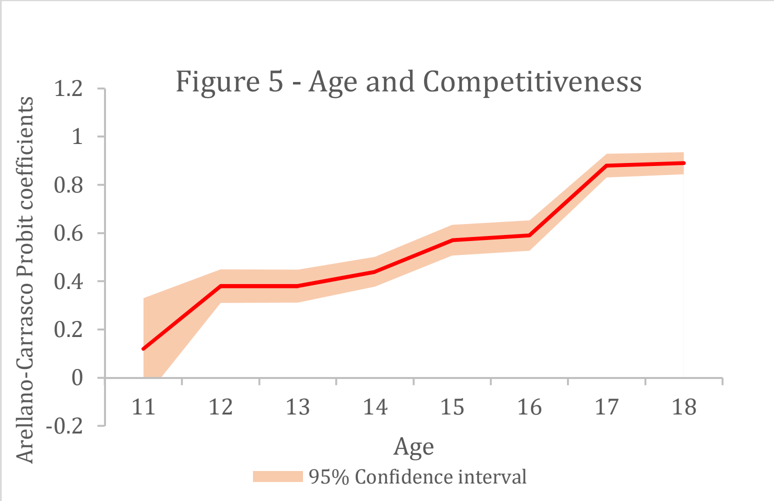


Figure 5 - Age and Competitiveness
Arellano-Carrasco Probit coefficients
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
11
12
13
14
15
16
17
18
Age
95% Confidence interval

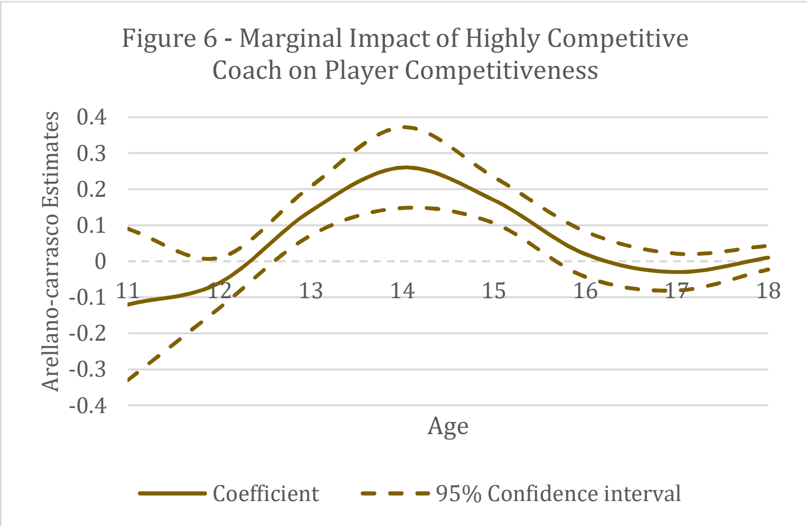


Figure 6 - Marginal Impact of Highly Competitive Coach on Player Competitiveness
Arellano-carrasco Estimates
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
11
12
13
14
15
16
17
18
Age
Coefficient
95% Confidence interval

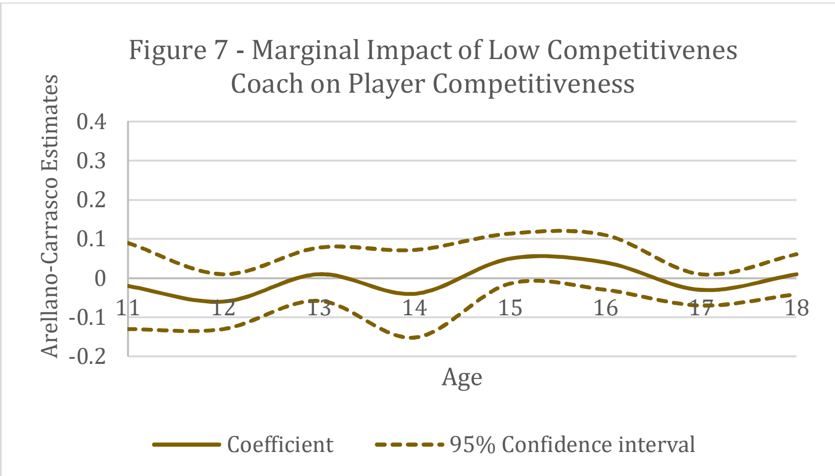


Figure 7 - Marginal Impact of Low Competitivenes Coach on Player Competitiveness
Arellano-Carrasco Estimates
0.4
0.3
0.2
0.1
0
-0.1
-0.2
11
12
13
14
15
16
17
18
Age
Coefficient
95% Confidence interval

5.2.2 Success Outcomes

What is the relationship between competitiveness and successful outcomes? Does the initial level of competitiveness at selection matter? Can the probability of successful outcomes be increased through changes in competitiveness? If so, when could we expect a greater positive impact? At what age? Do coaches matter? Can the probability of success be *decreased* by too much competitiveness? How do the answers to these question vary by age?

Here we used the five measures of success mentioned earlier: (1) number of years in the academy (relative to the maximum number that each player could be since he joined), (2) whether the player is offered a professional contract at age 18, (3) whether he plays for Spain at least one game at any underage level (from under Under12 to Under23), (4) whether he makes it as a professional to LaLiga2 (in Athletic Bilbao or in other club), and (5) whether he makes it as a professional to the top La Liga (in Athletic Bilbao or in other club).

Table 3 studies the relationship between competitiveness and these measures. All the specifications control for the initial level of competitiveness when they join they academy ("initial competitiveness"). As in the previous subsection, we include all of our observables.

Panel A reports the initial analysis without coach treatments. As we can see, competitiveness is strongly significant in every specification for each of our successful outcome variables. Interestingly, both the magnitude and significance of the effects increase when including fixed effects for birth year, entry year and age at entry. It is also interesting to observe that the initial level of competitiveness is much smaller in magnitude, and never significantly different from zero except in one case (becoming Spain international in underage levels). It also tends to have a negative sign. This suggests that the initial selection effect that we observed relative to non-talents in the raw data at age 10 may matter for selection, but will not matter conditional on selection

Panel B adds the coach treatments. The basic pattern of results is maintained (although for *competitiveness* the magnitudes are smaller) and the coefficients are strongly significant at beyond <0.001 significance levels in all cases. *Initial competitiveness* is never significant. In terms of our "coach treatments," highly competitive coaches do increase the probability of success in almost every case, while low competitiveness coaches have no statistically significant effects except, interestingly, for years in the academy without being released (it could, perhaps, be conjectured that this type of treatment contributes to producing team players that are valued in a squad).

Next, as in the previous subsection, we first report the Arellano-Carrasco coefficients (Figure 8), and then the marginal effects of our transitions and treatments of interest (Table 4). Recall that the probability of a successful outcome y_{it} is computed as:

$$y_{it} \ = \ \mathbf{1}\{\gamma + \ \beta \, z_{it} + E(\eta_i \mid w_i^t) \ + \ \varepsilon_{it} \ \geq 0\}, \quad \text{with } \ \varepsilon_{it} \mid w_t^i \sim N(0, \sigma_t^2).$$

where γ and z_{it} include all of our observables. In our case, our lagged endogenous variables always include (for every measure of success) years in the academy as an indication of successful continuation. Needless to say, although rare, a player may be released or leave voluntarily and still play at professional levels.

Table 3 – Impact of Competitiveness on Long-Term Success Outcomes

	Years in Academy		*Spain Underage International*		*Pro Contract at Age 18*		*La Liga 2 Pro*		*La Liga Pro*	
Panel A:										
Competitiveness	**1.32**	**2.28**	**1.73**	**2.27**	**1.75**	**2.17**	**1.04**	**1.30**	**1.46**	**1.74**
	(0.41)	(0.34)	(0.33)	(0.39)	(0.31)	(0.36)	(0.40)	(0.48)	(0.61)	(0.72)
Initial Level	-0.17	-0.29	**-0.43**	**-0.50**	-0.19	-0.29	0.11	-0.10	-0.18	-0.23
	(0.33)	(0.26)	(0.23)	(0.24)	(0.22)	(0.24)	(0.29)	(0.36)	(0.39)	(0.44)
Fixed effects										
Birth Year	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Entry Year	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Age of Entry	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	551	551	551	551	551	551	551	551	551	551
Adj/Pseudo R2	0.03	0.37	0.08	0.18	0.11	0.16	0.70	0.20	0.07	0.14
Panel B:										
Competitiveness	**1.02**	**1.75**	**1.60**	**1.96**	**1.70**	**1.98**	**0.91**	**1.13**	**1.33**	**1.32**
	(0.40)	(0.34)	(0.35)	(0.40)	(0.32)	(0.38)	(0.41)	(0.51)	(0.64)	(0.77)
Initial Level	-0.07	-0.14	-0.29	-0.31	-0.16	-0.23	0.21	0.04	-0.02	0.07
	(0.23)	(0.26)	(0.23)	(0.25)	(0.22)	(0.24)	(0.30)	(0.39)	(0.39)	(0.48)
Coach Treatment										
High Compet.		**1.21**	**0.72**	**0.67**	**0.30**	**0.42**	**0.33**	**0.19**	**0.60**	**0.80**
		(0.20)	(0.14)	(0.19)	(0.14)	(0.18)	(0.17)	(0.24)	(0.22)	(0.36)
Low Compet.		**0.61**	-0.01	-0.32	0.13	0.07	-0.23	-0.29	-0.08	-0.37
		(0.25)	(0.18)	(0.24)	(0.17)	(0.22)	(0.23)	(0.32)	(0.28)	(0.39)
Fixed effects										
Birth Year	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Entry Year	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Age of Entry	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	551	551	551	551	551	551	551	551	551	551
Adj/Pseudo R2	0.04	0.42	0.13	0.21	0.13	0.17	0.08	0.21	0.11	0.18

Notes: Coefficients in **red bold** are significant at 1% level. Std. errors in parenthesis. All the specifications control for birth and entry years, age, team, coach, position, risk aversion and beliefs.

The results in Figure 8 show that competitiveness matters as a determinant of all the successful outcomes we study. The impact of this intangible is highly significant in all cases, while the magnitude is greater for outcomes that would seem less demanding. This is intuitive. That is, it matters to make it to the top professional levels (La Liga2 and La Liga), but in relative terms it matters less than to make it to La Liga3, be Spanish international or continue in the academy.

Table 4 collects the *average* marginal effects from different transitions on the success outcomes. For competitiveness, we study transitions from 0 to 1 and from 1 to 0, and for coaches we study transitions where coaches' competitiveness is increased or decreased. Consistent with intuition and the previous results, transitions that increase competitiveness have a positive effect (recall these are averages over ages) while transitions that decrease competitiveness have a negative effect (which is smaller in absolute terms). In terms of magnitudes, the table reports the average *percentage change in* probabilities. Increasing a players' competiveness from 0 to 1 level increases his probability of becoming Spanish underage international by 12.7 percent, his probability of getting a professional contract by 10.1 percent, and his probability of playing in LaLiga2 and La Liga by 9.3 and 8.7 percent respectively. Similar interpretations for the rest of transitions.

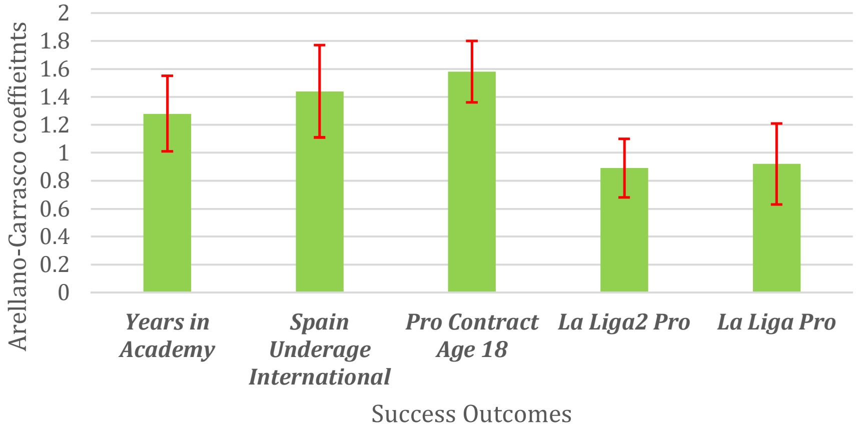


Figure 8 - Dynamic Impact of Competitiveness on Success Outcomes

Table 4- Average Arellano-Carrasco Marginal effects for Success Outcomes

Transition	*Years in Academy*	*Spain Underage Intn'l*	*Pro Contract at Age 18*	*La Liga2 Pro*	*La Liga Pro*
Competitiveness					
From 0 to 1	10.5	12.7	10.1	9.3	8.7
From 1 to 0	2.3	-0.3	-1.4	-1.7	-2.3
Coaches					
From Normal					
to High	4.3	5.5	3.7	3.3	1.9
to Low	0.2	-0.3	-0.7	-1.8	-2.3
From Low					
to Normal	3.3	3.8	4.1	4.2	4.8
to High	6.7	10.1	8.3	6.3	5.7
From High					
to Normal	0.8	0.4	-0.3	-0.7	-0.9
to Low	-0.3	-0.3	-0.2	-2.1	-2.2

Note: Average percentage changes in probability of successful outcomes.

6. Conclusions

The pursuit of expertise and success is as old as humankind, and we all have views about the two processes. Rory Smith (2020b) in the *NY Times* notes:

> "Too often, as fans and as observers, we write off players when they fail to meet some indistinct performance standard. We determine that they are not good enough for this team or that level. We demand that they are dropped or sold or upgraded. We decide that they will never make it."

While we all have views, true knowledge is scarce, even among expert professionals. In his piece in *The Guardian*, Sean Ingle (2015) quotes James Bunce, the Head of Sport Science at the English Premier League:

> "as an industry, soccer still doesn't know a lot about what it takes to become a top player."

We reckon that it is probably the same across other sports, perhaps most sports (or even all sports?). The pertinent conclusion then is that there is a huge deal of room to add fundamental knowledge, definitely to this industry and perhaps to others too, in terms of a deeper understanding of the assets that make a player valuable. Ingle continues:

> "Of course the industry doesn't. Bringing through young players remains a bit like pin the tail on the donkey: clubs know what they are searching for, but success remains dizzying and often elusive."

In this paper we have brought the behavioral concept of "competitiveness" and its measurement over the life-cycle of top prospects to bear on the determinants of success in a professional sport. Using a unique dataset constructed over a decade in a top academy in European soccer (by some standard metrics, *the* top academy), we obtain a number of insights. We have learned how this intangible trait is formed over time and across individuals. We have found that *differences in competitiveness* do help account for *differences in performance and successful outcomes*, that players' preferences for competition are malleable, but only up to a certain age (more precisely, within a certain age), and that coaches may have a *causal* impact on this intangible (typically positive, but not always). These and other findings naturally lead to wider sports management implications for coaches, teams, clubs and institutions. The econometric methodology is such that individual specific recommendations are readily possible since "marginal effects" can be computed for each pattern of experiences in the dataset, which is typically different across subject characteristics.

Finally, we believe that these ideas have full applicability to all other sports, as both the concept of measuring competitiveness and the measures we bring from the behavioral economics literature can be applied to any sports. More broadly, our results, together with several findings in the labor economics literature, show that measuring intangibles in general (and competitiveness in particular) has a great deal of promise to help us better identify, nurture and develop sports talent over the life cycle.

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