ESTIMATING TRANSFER VALUES IN PROFESSIONAL SOCCER

A SCISPORTS WHITEPAPER

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Introduction

As one of the more tangible metrics in professional soccer, transfer fees are among the most important key performance indicators (KPI's) when it comes to for example squad management, player and coach evaluation, or performance prediction. Being able to accurately predict transfers fees not only provides valuable insights to decision makers, analysts and commentators, but can also lead to a competitive edge that potentially results in performance gains and profits that exceed millions of euros. And while popular belief can sometimes induce the feeling that transfer fees are volatile, random, subject to public sentiment and biased by recent events or the time pressure of deadline-day narratives, research has shown the soccer transfer market mostly behaves predictably and structured, and transfer fees can be modelled and estimated using data driven approaches.

With this whitepaper, we aim to provide a deeper insight in the economics and characteristics of the transfer market in professional soccer, while elaborating on how we have developed a state-of-the-art artificial intelligence (AI) driven approach to model and predict Estimated Transfer Values for over 100.000 professional soccer players. As a secondary objective, we aim to provide several use-case examples that illustrate how our SciSports Estimated Transfer Value (ETV) model can be applied for various use-cases such as squad management, compliance & governance, or player scouting and recruitment.

This whitepaper is structured as follows. First, we will do a deep dive on the soccer transfer market and the mechanisms determining its behavior, answering questions like: how has the market evolved over the past decades, what are the most important determinants of transfer fees paid on the market, and how do leagues differ in their internal and external transfer market characteristics? Next, we will discuss the development and validation of our ETV model. Providing background on how it has been developed, its accuracy in terms of predicting transfer fees and comparing its usage to industry standards like the *transfermarkt.com Market Value*[7] and the *CIES Statistical Model to assess transfer value*[1,2]. Finally, we will present an in-depth discussion of multiple use-cases, that illustrate the various applications of the SciSports ETV model, and provides a starting point for technical directors,

scouts and analysts exploring the potential applications of data & AI driven models like the SciSports ETV.

The soccer transfer market

The soccer transfer market as we came to know it finds its origins in the *1995 Bosman Arrest*[5] that ruled a player is free to move clubs without compensation for their former club after their contract terminates. As of then, players could move clubs with much more ease, the number of transfers increased, as did the number of foreign players per team, and clubs became more willing to sell their players for a transfer fee before the end of their contract. Whereas in 1996 just 263 paid transfers were recorded for a total amount of €472M, by 2006 over 1400 paid transfers were recorded for a total amount of ±€2.1B. Anno 2025, an average of 1500 – 2500 paid transfers are recorded every year, and the total market size ranges from €6B-€9B in paid transfer fees (Figure 1).

The numbers seem astronomical, especially when you consider the fees paid for the most talented players on market. If one considers the media coverage or fan sentiment in relation to so-called transfer busts one could even be inclined to consider the market to be volatile and random. In reality though, the soccer transfer market behaves like any economic market, and its behavior is fairly predictable. In the following paragraphs we will dive into the development of the soccer transfer market, the determinants of individual transfer values, and the characteristics of specific leagues when it comes to their role on the international soccer transfer market.

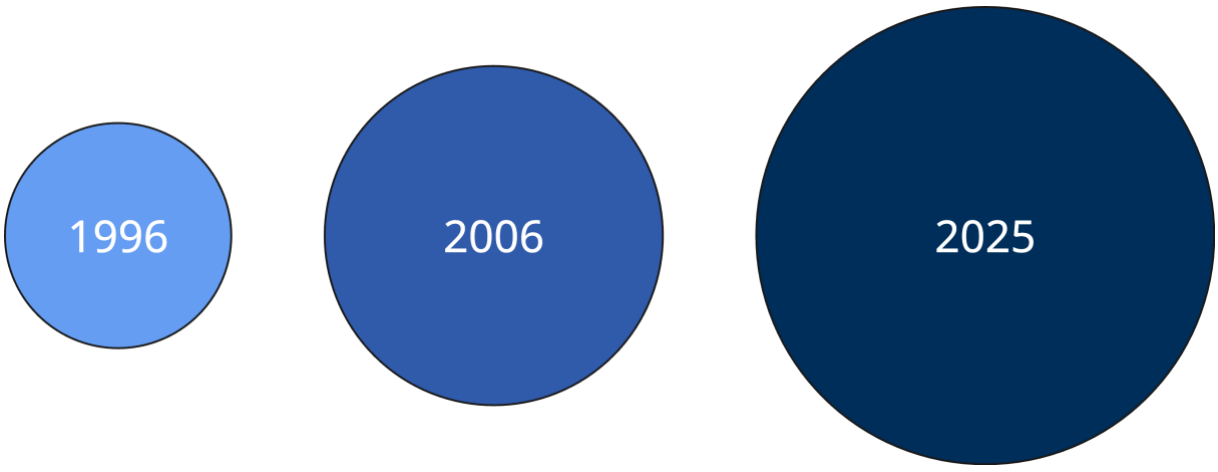


Figure 1: Size of the annual global soccer transfer market over time in terms of billions (€) spend.

Development of the soccer transfer market

Despite the 20x-30x increase in the economic size of the soccer transfer market over the last decades, most of the transfers are free transfers, where a player moves clubs after a contract has been terminated or expired, and no transfer fee is involved. To date, over 800.000 transfers have been recorded since January 1st, 1996, of which only ±5% (±42.500) concerned paid transfers. Many of those free transfers concern academy players or players in the lower regions of professional soccer, where money plays a vastly different role compared to the big leagues. It is the top level where most paid transfers happen, and especially that market has developed significantly over the last 30 years.

From a maximum transfer fee of €18M paid by Newcastle United to buy Alan Shearer from Blackburn Rovers in 1996 to €220M paid by Paris Saint Germain to buy Neymar from FC Barcelona in 2017, transfer fees paid on the soccer transfer market have significantly developed over time (Figure 2). And while some of those record-breaking transfer fees seemingly lack any rationale for the sum that is being paid, the average fees paid on the market have followed global economic developments, thus indicating the soccer transfer market is not unlike many other economic markets. One can for example spot a slight dip in the market during the global financial crisis of 2007-2011, after which transfer fees again consistently increased in accordance with economic growth, before dropping in 2019-2021 due to the global COVID pandemic, and then steeply growing again in 2022-2024 in par with global economic inflation. And although it is still too soon to tell with certainty, prices have recently seemed to normalize again after the post-pandemic surge.

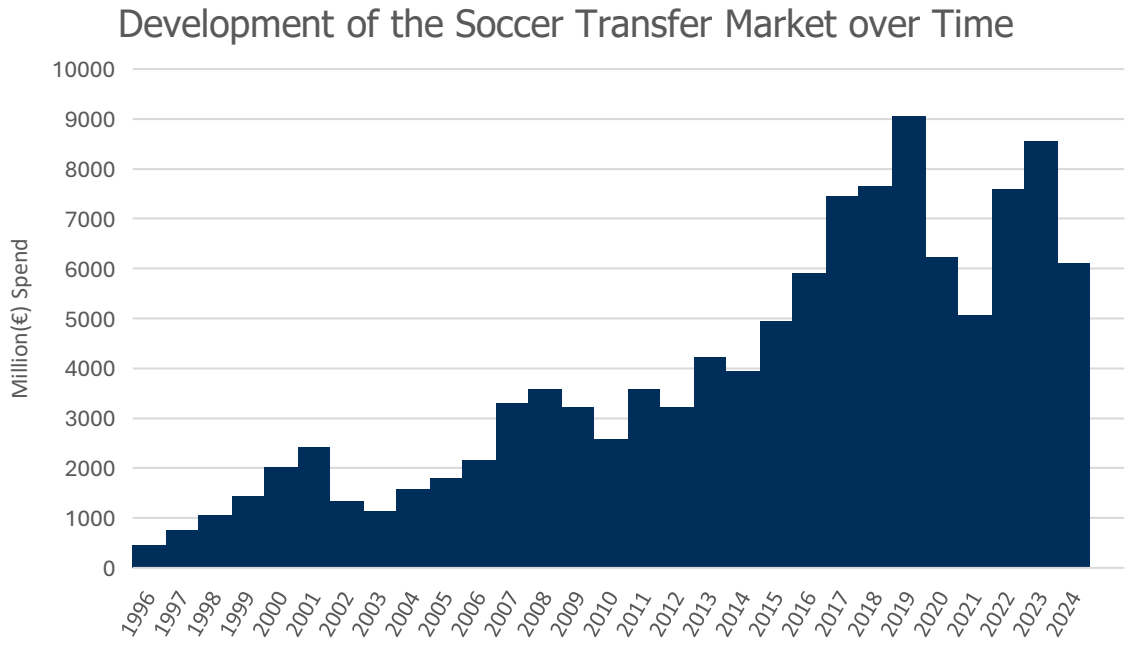


Figure 2: Market size of the global soccer transfer market over time since 1996.

Based on the developments outlined above, we can draw three conclusions that are of significance to professionals in the soccer industry. First, despite some individual edge cases, the soccer transfer market follows global economic developments, and grows and shrinks accordingly. Second, when modelling transfer fees or projecting financial revenue & budgets, one needs to account for the economic outlook, as the age-old adagio "results of the past are no guarantee for the future" holds in case of the soccer transfer market. And finally, while the impression might sometimes be that the ceiling is raised year-in year-out, breaking record after record, this is not the case, and fees paid on the market right now are moving back to a level lower than that in 2017-2018.

The Determinants of Transfer Value

Now that we have established the soccer transfer market behaves as a global economic market, and closely follows global economic developments, let us dive into the determinants of individual transfer values. In other words, why is a given player bought for a given price?

In a systematic review published in 2024, Franceschi, Brocard, Follert & Gouguet[4] have studied precisely this question. They found that according to research, an individual transfer fee as it is paid on the soccer transfer market is determined by six distinctively different groups of variables:

1. Performance: simply said, how good is the player relative to their peers, and what have they contributed to their team.
2. Player Characteristics: this concerns non-performance related characteristics like experience, position, nationality and height, but also age and potential.
3. Popularity: this relates to the popularity of a player amongst fans, which can increase or decrease the pressure on a team to buy/sell a given individual.
4. Club Characteristics: this considers both the buying and selling club and refers to for example the financial power of a club, its status and other club specific attributes.
5. Labor: this especially concerns a player's contract and remaining contract duration, as well as previous fees paid for the player or specific contract clauses.
6. Time: this mainly concerns economic developments as previously described, but also for example relates to the summer vs. winter window.

With these research findings in mind, we exploratively studied the data of ±10.000 paid transfers recorded in the past decade, further enriched with additional data like playing minutes, career stats, contract duration and *Transfermarkt.com* Market Value, as well as SciSports features like *SciSkill* & *Potential*. The result is a framework for the determinants of Estimated Transfer Value (ETV), as can be seen in Figure 3.

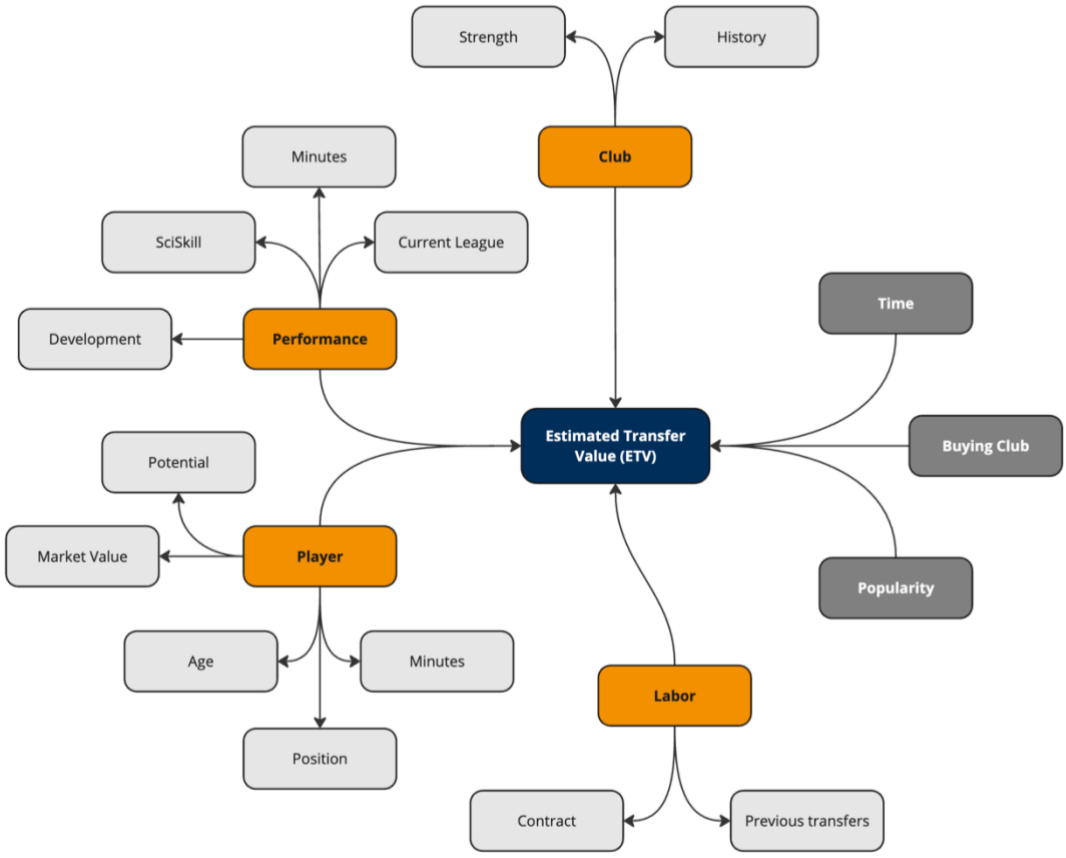


Figure 3: Framework for the determinants of ETV, based in part on the research of Francheschi et al (2024). Main intrinsic determinants are shown in orange, extrinsic determinants are shown in dark gray.

The framework work clearly differentiates between so-called intrinsic and extrinsic determinants of ETV. Intrinsic determinants have to do with the player itself and the team they are part of. They are constant, regardless of what club is buying the player, if it is summer or winter, or if strikers are in high demand on the market. They can also – to some extent – be controlled by the selling club and/or player. The contract can be extended, a player can get more playing time, a player can be developed over time, etc. Extrinsic factors on the other hand are volatile and conditional, as they depend on the moment and specific circumstances. As such, they are harder to control and more difficult to model and anticipate.

This differentiation between intrinsic and extrinsic determinants is critical, as we will see in the section comparing various industry standards. Models capturing the intrinsic determinants only will be more stable and have a stronger connection to the player's performance and characteristics, but the estimates can be further from the actual fees paid as not all information is accounted for. Models accounting for intrinsic *and* extrinsic determinants

on the other hand will be closer to the truth, but they cannot be used to make comparisons across players and clubs, as their output is specific to a certain club buying a certain player at a certain time.

League-Specific Market Characteristics

Knowing how the soccer transfer market behaves, and what factors determine the transfer values that are ultimately paid on the market, how do individual leagues behave in comparison to the market as a whole? To answer that question, we analyzed national transfer markets as one would analyze any national economic market: by analyzing their internal market, and their import vs. their export balance. The results are shown in Table 1.

	Internal Market Size	Import Size	Export Size	Export Surplus
England	€742M	€1.1B	€380M	-€720M
Italy	€382M	€408M	€350M	-€58M
Germany	€194M	€340M	€360M	+€20M
Spain	€178M	€434M	€409M	-€26M
France	€163M	€360M	€442M	+€82M
China	€53M	€123M	€19M	-€104M
Mexico	€51M	€68M	€39M	-€29M
Brazil	€40M	€73M	€187M	+€114M
Argentina	€31M	€33M	€122M	+€89M
Russia	€30M	€100M	€67M	-€33M
Portugal	€28M	€104M	€282M	+€178M
Turkey	€23M	€67M	€72M	+€5M
Netherlands	€22M	€68M	€199M	+€131M
Belgium	€20M	€77M	€151M	+€74M
Saudi Arabia	€12M	€156M	€11M	-€145M

Table 1: Annualized market size per country. Based on all paid transfers recorded from 2014 – 2025, showing the top 15 markets based on internal market size. Note that all (professional) leagues within a country are included.

What immediately stands out from Table 1 is the differentiation between the Big 5 Leagues and the rest of the competition. England, Italy, Germany, Spain & France have considerable internal markets, which indicates players remain within the country for prolonged durations. They also spend significant amounts on import (typically because they buy the best players at or before their prime for premium fees). Interestingly though, the English market stands out as a very clear net import market, while the other 4 have a much more balanced market. Especially the French market is interesting in this regard, as the comparatively small internal market, sizeable import size and the substantial export surplus seems to indicate France is importing a lot of talent and can resell that talent at a premium relatively quickly.

Further down the Top 15 markets we can also differentiate between net import and net export markets. Countries like China, Mexico, Russia and Saudia Arabia have large import vs. export deficits, as they spend sizable amounts on attracting players without making a lot of money with selling players. Countries like Brazil, Portugal, Argentina and the Netherlands on the other hand are obvious talent pools. They have a large export surplus, and in comparison, small internal markets, indicating most talent is leaving the country for premium fees.

Estimating Transfer Values

Knowing how the global soccer transfer market functions and using the framework for determinants of Estimated Transfer Value as a foundation, we have developed a state-of-the-art AI-driven ETV model to predict Estimated Transfer Values for over 100.000 professional soccer players in the world. We deliberately choose to model only the intrinsic determinants of ETV as referred to in the framework. Although including extrinsic determinants in our model could theoretically increase model accuracy, it would also be detrimental to the functionality of our model, as it makes the model less suitable for comparisons across players, teams and leagues and for applications like squad management, scouting & recruitment. In the following section, we provide a detailed description of how the model has been developed and validated, how it compares to other industry standards, and how we maintain model quality using our MLOps framework.

Developing a state-of-the-art ETV Model

SciSports AI models are developed based on the following key principles: simplicity, domain expertise, trustworthiness and practical relevance. We develop our applications in close collaboration with domain experts and always strive towards models that are not needlessly complicated, that have outcomes that are accurate, robust, reliable and unbiased, and that provide practical relevance and significance to users within the professional soccer industry. Our ETV model is no different, as we have developed it using extensive feedback of various domain experts, and striving towards a model that closely aligns with the objectives and vision of our users.

The SciSports ETV model aims to estimate the transfer fee of a player, if that player were to be sold right now, regardless of the buying club or any other extrinsic variables. To achieve this aim, we had to create a dataset of historic transfers, including features that represent the various intrinsic determinants from the ETV framework. We could then use this dataset to *train* an AI model so that the model can *learn patterns from the data* allowing it to apply those patterns to other players while using the same logic. In other words, using transfers from the past, enriched with data-driven features from our database, we create a model that applies the learned patterns to all players in our database, at any point in time.

To train the model, a dataset of ±10.000 paid transfers from the last decade was collected and enriched with features like the remaining contract duration, age, SciSkill[7], Potential[7], (potential) development, playing minutes at various levels, strength of the current team and league and the player's main position. Finally, to allow for a fair evaluation of how well our model performs, we split the dataset into two groups: 80% of the data is being used to train the model, while 20% of the data is being set aside to use for evaluation, so that the model's accuracy can be evaluated on data the model has never seen before.

As we learned from domain experts, features like contract duration and potential have very different levels of importance for "cheaper" players (in the range of €0M-€5M). Therefore, instead of training a single model, we developed a multistage ETV model, consisting of a suite of AI models that together estimate a players ETV (Figure 4).

1. First, we use a so-called *classifier* model to predict if a player is going to fall in the €0M-€5M range or not.

2. Next, we have different *regressor* models for different price ranges, and depending on the ballpark estimate from step 1, we use specific models to provide exact estimates of a player's ETV.



Figure 4: Multistage SciSports ETV model, that uses one or multiple regressors depending on the predicted probability a player is part of one class or the other.

The result is a multi-stage ETV model that can classify in what price range a player is likely to be sold with 93.6% accuracy, to subsequently estimate the exact transfer value with a median absolute error of €355K - €2.7M (see Table 2 for all model evaluation metrics). As such, the model is 5-20% closer to the actual transfer fee in comparison to a player's Transfermarkt.com Market Value at the time of a transfer and can predict the actual transfer fee within a 10% error margin of the paid fee for most of the players.

ETV Range Classification Accuracy	93,7%
ETV Range Classification Log Loss	0,173
ETV Explained Variance (R^2)	51,7 - 74,7%*
ETV Mean Absolute Percentage Error (MAPE)	0,3 - 3,1%*
ETV Root Mean Squared Error (RMSE)	€780K - €7,3M*
ETV Median Absolute Error (MedAE)	€355K - €2,7M*

*Table 2: SciSports ETV evaluation metrics. *Note that the range in these metrics is the result of having different models for different ETV range groups.*

Industry Standards

Given the size of the global soccer transfer market and the possibility to model transfer fee estimates with good accuracy, using such models could provide a competitive advantage to decision makers in professional soccer, allowing one to find value for money on the market and make informed decisions when it comes to for example buying and selling players or extending contracts. It should therefore come as no surprise that the SciSports ETV model is not the only available solution. Two of the most notable alternatives are the *Transfermarkt.com* Market Value[7] and *CIES Statistical Model to assess transfer value*[1,2]. Rather than competing models, the models could be seen as somewhat complementary or at least directed towards different use-cases (Table 3).

The Market Value on Transfermarkt.com is not data-driven but community driven, as it is based on the input of its many volunteers. As such, it is hard to judge what factors are included in a valuation, it is not explainable, but it does represent a solid indication of the popularity of a player on the market. It allows direct comparison over lots of players and can serve as a tool in scouting and recruitment. The value can lack responsiveness though, especially in smaller competitions or for lesser-known players where moderators do not quickly pick up on changes in their situation.

The CIES model on the other hand is a data-driven model. It is trained on a highly curated dataset that excluded possible outliers and includes add-ons like sell-on clauses and bonuses, and as such it is harder to maintain and retrain automatically. Unlike the SciSports ETV it is based on a statistical model and not an AI model. But more importantly, the CIES model includes extrinsic determinants, as it accounts for the buying club. As such, the model is potentially more accurate in predicting the exact transfer fee paid on the market, but less suitable for comparison across players, as the extrinsic determinants can differ from player to player and from time to time, independent of player performance or other intrinsic determinants. It is also less suitable for squad management and scouting use-cases, as it comes from a more academic background and is not integrated with a scouting or squad management tool like the SciSports ETV is.

	SciSports ETV	CIES	Transfermarkt.com
Intrinsic Factors	✓	✓	—
Extrinsic Factors	✗	✓	—
Explainability	✓	✓	✗
Data-Driven	✓	✓	✗
Uses AI	✓	✗	✗
Responsiveness	✓	✓	✗
Player Comparison	✓	✗	✓
Squad Management	✓	✗	✗
Scouting Integration	✓	✗	✓

Table 3: Comparison across industry standards for modelling Estimated Transfer Values.

Maintaining State-of-the-art using our MLOps Framework

The introduction already illustrated how the global soccer transfer market reacts to global economic developments, which means that today's models can be outdated tomorrow. If one would train an ETV model once, over time this would result in model drift. Model drift happens when the market develops (for example due to inflation), and the output of the model becomes less accurate over time (as it is trained on the pre-inflation data). To prevent this from happening we automatically retrain our SciSports ETV model after every transfer window, to always include the newest information and follow any trends on the market. We use an open source MLOps framework called MLFlow, that automatically picks the best model and uses that for our predictions. Additionally, we have implemented automated tests that automatically flag players for review if their ETV rises of falls suddenly, or if it exceeds certain safety thresholds, creating a human-on-the-loop evaluation system.

SciSports' dedication to safe and trustworthy AI applications

With the "AI For Europe" strategy, followed by the AI Act and Digital Services act, and preceded by the GDPR, Europe is a global leader when it comes to the regulation of AI & data-driven products and services. More specifically, the EU aims to promote safe and trustworthy AI applications that are understandable and accessible for its citizens. Being on the forefront of the development of AI applications for recruitment and performance analysis, SciSports is committed to ensuring the safety and trustworthiness of our AI. As such, we are part of an EU Horizon funded research program that investigates the trustworthiness of AI for planning purposes (in our case squad management), in which we collaborate with 5 top European universities and 2 other industry partners. For more info:

SciSports ETV Use-Case & Examples

Knowing the mechanisms that drive the global soccer transfer market, its characteristics and the specifics of the SciSports ETV model as well as the framework determining a player's ETV, we can investigate various examples of real-world use-case applications. In the following section we will discuss the use of the SciSports ETV model for finding the most valuable players on the market, for scouting undervalued players that could be acquired for a cost-effective price and for using the SciSports ETV as a tool for compliance & governance in the boardroom. In doing so, we will highlight how decision makers within professional soccer can utilize the SciSports ETV model, and how and why certain players are valued highly – or the other way around – by the model.

Use-Case 1: Finding the most valuable players on the market

We start by identifying the most valuable players on the market. Although this is obviously a snapshot analysis (conducted in January 2025), it does provide a decent face validation and allows us to discuss common factors we see in the most valuable players, allowing us to discuss the patterns that underly this group of players (Table 4).

	Position	Club	Age	ETV
Erling Haaland	CF	Manchester City	24,5	€189M
Lamine Yamal	RW	FC Barcelona	17,5	€165M
Kylian Mbappé	CF	Real Madrid	26,1	€133M
Bukayo Saka	RW	Arsenal FC	23,4	€130M
Martin Ødegaard	AM	Arsenal FC	26,1	€127M
Florian Wirtz	AM	Bayer 04 Leverkusen	21,7	€123M
Pau Cubarsí	CB	FC Barcelona	18,0	€121M
Declan Rice	DM	Arsenal FC	26,0	€118M
Cole Palmer	AM	Chelsea FC	22,7	€117M
Federico Valverde	CM	Real Madrid	26,5	€115M

Table 4: Top 10 most valuable players ranked by SciSports ETV.

Inspection of the most valuable players immediately provides insight in what types of players generate the most value on the market. First and foremost, talent is the key driver of value. As is also shown in various studies, young talented players are the most likely to be transferred for large sums of money, while older players are less likely to be sold for premium fees. As a result, we do not see any players who are at or past their peak age at the top of the ranking. Buying players at or past their peak age (27-29 years) will result in diminishing returns on the investment over time, and thus clubs often spend lower fees on these players, which is reflected in the model. Not surprisingly, we further see the top of the ranking is populated by players from the top leagues (see Table 1), and making (consistent) minutes in these leagues is another driver behind high ETV. Finally, we see the most valuable players are predominantly offensive players. Although offensive players are not necessarily more valuable compared to their defensive counterparts, they are transferred more often, and often for more money, as the market tends to be goal-oriented, and attributes value to goal-scorers and assist-kings.

Use-Case 2: Scouting for under-valued players

Although interesting, finding the most valuable players is not what most decision makers within professional soccer clubs will use ETV models for. Most teams cannot afford to spend €100M on a single transfer and are rather looking for players that one day might be developing into a €100M player. Those hidden gems are the players scouts & clubs are in the market for,

as they can potentially return a lot of value for money if they are acquired while still under the radar.

To find such players, we compare the SciSports ETV to the *Transfermarkt.com* Market Value. As previously discussed in the section on "Industry Standards", the Market Value is a community driven value. It is indicative of popularity and often a fair reflection of prices paid on the market, but as it is depending on the community to pick up on the talent, it can lack responsiveness. As the SciSports ETV can more quickly detect hidden gems based on data, it could provide a competitive edge to its users by highlighting players the market has not picked up on just yet.

We could for example search for all players under 23 years old, with a SciSports ETV <€10M, that is at least twice as high as their *Transfermarkt.com* Market Value. The result is a list of players that one could consider to be under the radar. As an example, we picked 5 young players with potential (Figure 5), that have a market value of €2M-€4M but are estimated at €7.5-€10M by the SciSports ETV model, and that are showing promising performances in their respective competitions. Obviously, their age and limited number of minutes does warrant some uncertainty when it comes to their future, but at the very least they are interesting targets to pay close attention to.

Alvaro Rodriguez: 20-year-old striker from the academy of Real Madrid, currently playing for Getafe CF. Amongst top contributes in LaLiga in 24/25.

Lukas Ullrich: 20-yeard-old left-back from the Hertha BSC academy, currently playing for Borussia Mönchengladbach. Rapid development over last 6 months.

Kodai Sano: 21-year-old midfielder from Japan, currently playing for NEC Nijmegen in the Dutch Eredivisie. Promising dribbler & passer.

Jonas Adjetey: 21-year-old Centre Back from Ghana, currently playing for FC Basel 1893. Significant development over past 6 months.

Matheus Gonçalves: 19-year-old winger from Brazil, currently playing for CR Flamengo. High performer in Brazil and rapid development.

Figure 5: Sample of promising young potential that have a SciSports ETV that is significantly higher than their Transfermarkt.com Market Value.

Use-Case 3: Boardroom compliance & governance.

As a final use-case, we used the SciSports ETV not for scouting individual players but for governance and compliance purposes on the level of teams and leagues. As we have seen throughout this article, large amounts of money are involved in transferring players on the soccer transfer market, and clubs & leagues typically have a board of directors overseeing those transfers. As it concerns millions of euros, and large parts of a club's budget, having the right tools to quickly assess if transfer fees offered fall within the boundaries of logic and comply with market standards is paramount for executives.

One could think of a system that monitors transfers and runs the SciSports ETV model for any paid transfer, comparing the fee paid for a player to the estimated value. As we have shown, the SciSports ETV makes predictions that are close to the actual fee paid on the market, and actual fees typically fall within a 10% error margin of the predicted ETV. Therefore, if fees fall outside of that 10% margin, we could flag them as potential anomalies. If they fall outside of a 25% margin, we could even flag them as certain anomalies. Table 5 shows some of the biggest anomalies that would have been detected by such a system in recent years, as the fee paid was much higher than the SciSports ETV for that transfer suggested.

	Date	From	To	Fee	ETV
Dembélé	Aug '17	Borussia Dortmund	FC Barcelona	€140M	€76M
Arrizabalaga	Aug '18	Athletic	Chelsea	€80M	€25M
Antony	Aug '22	Ajax	Manchester United	€95M	€42M
Neymar	Aug '23	PSG	Al-Hilal SFC	€90M	€45M
Malcom	June '23	Zenit St. Petersburg	Al-Hilal SFC	€60M	€29M
Martial	Sept. '15	AS Monaco	Manchester United	€60M	€16M

Table 5: Biggest Transfer Anomalies in the past decade.

One should note that an anomaly in and by itself is not necessarily a reason for concern. Transfer fees are not always reliably reported in public media, there could be add-ons like sell-on clauses, bonus or buy-back options, and there could be other commercial arguments for paying a certain price. Therefore, we would like to stress that an anomaly is not necessarily an error but might warrant further review by the board before approval.

Conclusion

With this whitepaper we have dived into the inner workings and characteristics of the global soccer transfer market, showing that it behaves as an economic market that allows for accurate modelling of transfer fees that are being paid. With the SciSports ETV model we have developed a state-of-the-art model for predicting Estimated Transfer Value, that can be used by executives and decisions makers in professional soccer for various use-cases. The SciSports ETV model illustrates the promising potential of using AI & data-driven solutions in sports analytics. By lifting the hood of our model, we wanted to showcase its construction, reliability and application, as well as share our research with the industry to help advance the field of sports analytics.

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