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Players Market Value at Risk: A Model and Some Evidence for the German Bundesliga

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Summary
The market value of players forms a major asset of any modern professional football club. As with any asset, the expected benefits from having the right to use a player within a team, are also offset by risks that must be managed adequately by the club. To this end we, describe a simple risk-management tool that managers of football clubs can use to model and monitor a player's market value at risk. Our model consists of three elements. First, we use a quantile-regression approach to study how performance parameters of football players affect their market values. To this end, we study data for 327 players of the German Bundesliga for the season 2015/2016. Our estimation results show that the time played significantly affects the lower part of the conditional distribution of players market value, while the number of goals and passes (assists) affect the upper (middle) part of the conditional distribution. Second, we fit a flexible continuous probability density function to the estimated quantiles of the conditional distribution of players market value. Third, we analyze how performance parameters affect the market value at risk and the expected shortfall of market value. We use an out-of-sample analysis to validate our empirical model.

Keywords
Market value; Football Bundesliga; quantile-regression; risk management, value at risk

1 Introduction

Sports economists have explored in much significant earlier research the determinants of the market value of football players (see Carmichael, Forrest, and Simmons 1999; Bryson, Frick, and Simmons 2013; Müller, Simons, and Weinmann 2017; Prockl and Frick 2018; Frenger et al. 2019; Kirschstein and Liebscher 2019; Richau et al. 2019; Coates and Parshakov 2021; Poli, Besson, and Ravenel 2022, among others; for a survey, see Frick 2007). On the one hand, the interest of sports economists in modeling the market value of football players stems from the fact that the availability of detailed data on market value, transfer fees, and players performance parameters makes the labor market of professional football players a leading candidate to test rival economic models of the labor market. On the other hand, it is obvious that the market value of players forms a major component of any professional football club's assets and buying or selling a player often constitutes a major human-capital investment for football clubs (see Leifheit and Follert 2021). Companies in other industries manage the market price risks of their assets using certain risk measures. In particular, the value at risk[i] and, alternatively, the expected shortfall[ii] are well-founded approaches to risk measurement. While the transfer market value is not a price that is the result of supply and demand in an active market, on the one hand it serves as an indicator for clubs and can also be used for negotiation purposes (Ackermann and Follert 2018). Given the outstanding economic importance of the market value of players for football clubs, we go beyond earlier research in that we not only study how various performance parameters like the number of goals scored and the time played determine the market value of football players, but rather study how a football club can use this information to set up in a straightforward way an easy-to-implement risk-management tool that helps to assess risks and opportunities that arise due to probabilistic fluctuations of the market value of players. An approach that allows clubs to measure and monitor the risks arising from their most important asset positions – the player licenses – appears important, particularly from a practical perspective. But also, from a scientific point of view, our approach further develops the existing set of tools.

To set up such a risk-management tool, we use, in a first step, a quantile-regression approach to study how performance parameters of football players affect their market value. Lehmann and Schulze (2008) argue that a quantile-regression approach is particularly suited to model a superstar effect that most likely is a characteristic feature of the top end of the income distribution of football players. A quantile-regression approach has the advantage that performance parameters can have a differential effect on different parts of the conditional distribution of players market value. In our empirical analysis of data for the German Bundesliga, we in fact find such differential effects. We find that the time played significantly affects the lower part of the conditional distribution of players market value, while the number of goals and passes (assists) affect the upper (middle) part of the conditional distribution of players market value.

In a second step, we build on recent research by Adrian, Bayarchenko, and Giannone (2019) and fit the flexible skew t-distribution studied by Azzalini and Capitano (2003) to the estimated quantiles of the conditional distribution of players market value. The skew t-distribution is a continuous probability density function that has, for the purpose of our analysis, three interesting features. First, only four parameters characterize this distribution, and so four estimated quantiles of the conditional distribution of players market value suffice to estimate these parameters by means of an exactly identified nonlinear optimization problem. Second, and economically more important, the skew t-distribution can capture in a natural way the presence of a superstar effect in the data, which manifests itself in a low probability that a few players have a very large market value. Finally, the skew t-distribution is straightforward to use this continuous probability density function to calculate numerically standard risk-management

statistics like market value at risk and expected shortfall of players market value. The skew t-distribution, however, also has limitations in the context of our empirical analysis. For this reason, we present the results of a mixture of log-normals model as an alternative model of player market value.
To establish a link between market value, its determinants and the risk that can arise from a falling market value, we assume the following relationship: If the independent variables that determine the market value in its amount are known, then the market value is nothing more than an aggregation of certain sporting factors into a monetary point value. If a player's performance deteriorates over a longer period, if injuries increase over time, if a midfielder's passes or a defender's duels won decrease, this is reflected systematically in a declining market value.
Managers of professional football clubs can easily use the market value at risk and expected shortfall of players market value as risk-management tools to quantify potential dangers that their club may confront in case of a large decline in the market value of football players. At the same time, we also illustrate that the value-at-risk concept can be easily transformed into a value-at-hope statistic that quantifies chances that arise in case the market value of a player substantially increases. Finally, we illustrate how these concepts differ across different player types. For example, we analyze how the value at risk and the expected shortfall of players market value are affected when a player scores above average goals or spends above average time playing on the pitch.
We organize the further ideas of our research approach as follows. In Section 2, we describe our data. In Section 3, we report our empirical results. In Section 4, we offer some concluding remarks.

2 The data

We use in our empirical analysis data on the average market value (in Euros) that players of the German Bundesliga scored in the 2015/16 season. The data are taken from the popular internet platform Transfermarkt (transfermarkt.de). Our data contain, in addition to player market value, information on the age of a player, the number of matches played, and the position played.
Transfermarkt is operated by the company Transfermarkt GmbH & Co. KG (Transfermarkt 2018). According to the IVW (German Audit Bureau of Circulation), the internet platform is one of the most frequently visited sports websites in Germany, the platform has nearly 400,000 registered members, and market-value analysis is the centerpiece of its business model (for a discussion and further references, see Ackermann and Follert 2018). Sports economists have studied data on market value published by Transfermarkt in several recent empirical studies (see, e.g., Herm, Callsen-Bracker and Kreis 2014; Müller, Simmons and Weinmann 2017; Peeters 2018; Richau et al. 2019; Coates and Parshakov 2021; Majewski 2021).
In addition to reports by sports journalists and updates of statistical data on individual players, teams, and leagues, Transfermarkt operates a discussion forum, where private users can discuss and propose the market values of individual soccer players. Market values are part of the individual profile pages for players. Profile pages contain personal data and statistics on some basic player performance such as the number of goals scored, yellow/red cards[1] and in a certain time frame, past club changes, and injury history. The profiles of players also list rumors concerning transfers.
Transfermarkt values that users propose must be substantiated and are based, for example, on current age, contract terms, performance data, and a player’s injury history (Müller et al. 2017). Transfermarkt users are explicitly advised to focus on comparable players (Transfermarkt 2013). A reason for a proposed change in value must be provided. So-called sponsors aggregate the

proposed values and establish a single value which is agreed upon with management (Herm et al. 2014). Peeters (2018) shows that forecasts of international soccer results derived from Transfermarkt values are more accurate than forecasts derived from other popular predictors like the FIFA ranking.

We combine the data from the Transfermarkt portal with data on player performance hand-collected from the internet site https://fussball.hermesworld.com/games.[iii] For every player, we have available data on the playing time, the running distance, the number of tackles, the number of passes, and the number of goals and assists during the season. In addition, we include player's age and position played in our list of predictors of player market value.

To be able to trace out how individual player performance rather than the transfer of a player to, for example, a top club affects market value, we only consider players who played for the same club on all 34 match days of the 2015/16 season.[iv] In addition, we exclude goalkeepers and players who have not had a representative role during the season due to the lack of consistent data. Finally, we use the score published by the Kicker magazine to limit the sample to those players who had at least one significant bet in the season[v], that is, a non-negligible match time. The final dataset contains a sample of 327 players.

Figure 1 depicts a histogram of the data on player market value.[vi] The histogram reveals that most players have an average market value of less than € 10 million. The players with the highest market values have a market value of approximately € 65 million (mean = € 5.8 million, median = € 2.9 million, SD = € 8.6 million). Table 1 shows descriptive statistics of the player performance parameters that we use in our empirical analysis to model player market value.

Figure 1: Frequency distribution of average market value

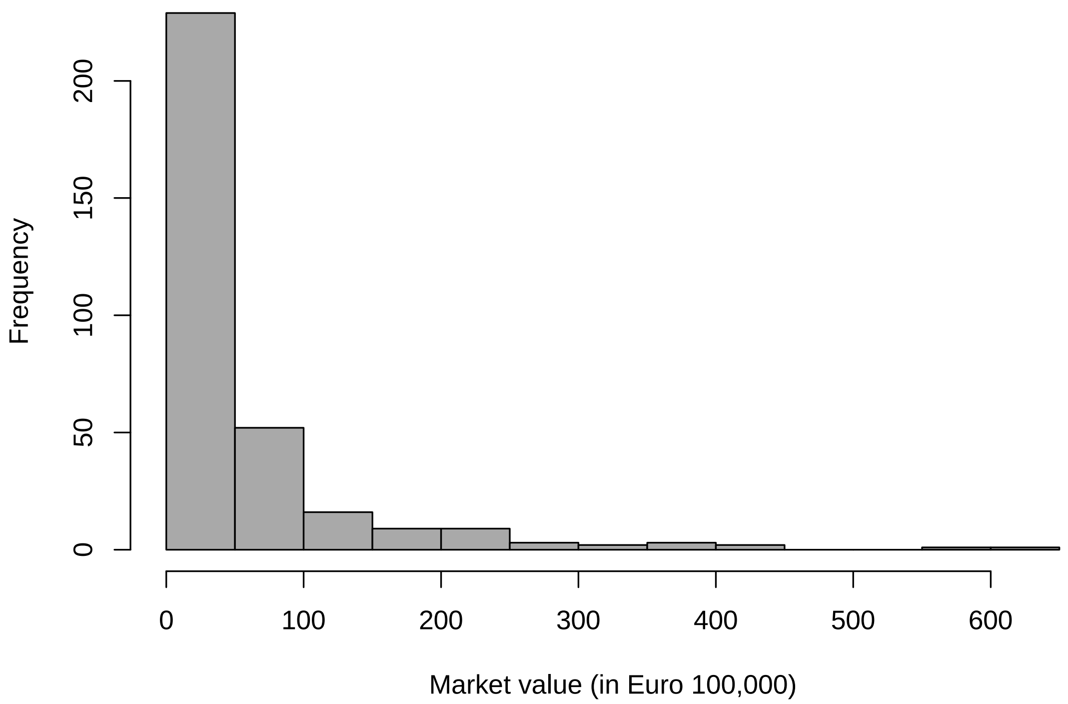


Table 1: Descriptive statistics of the player performance parameters (N=327)

Variable	Description	Mean (SD)	Median
Time (min)	Playing time during the season	1563.00 (885.15)	1607
Goals	Number of goals	2.23 (3.72)	1
Passes	Pass rate (ratio of arrived passes to played passes)	0.74 (0.10)	0.75
Tackles	Tackle quote (won duels to led duels)	0.50 (0.08)	0.50
Distance (km)	Running distance per 90min (total distance relative to working time)	10.47 (1.01)	10.49
Assists	Assists	1.65 (2.09)	1.00
Age	Age (at beginning of season)	24.93 (3.77)	25.00

3 Empirical analysis

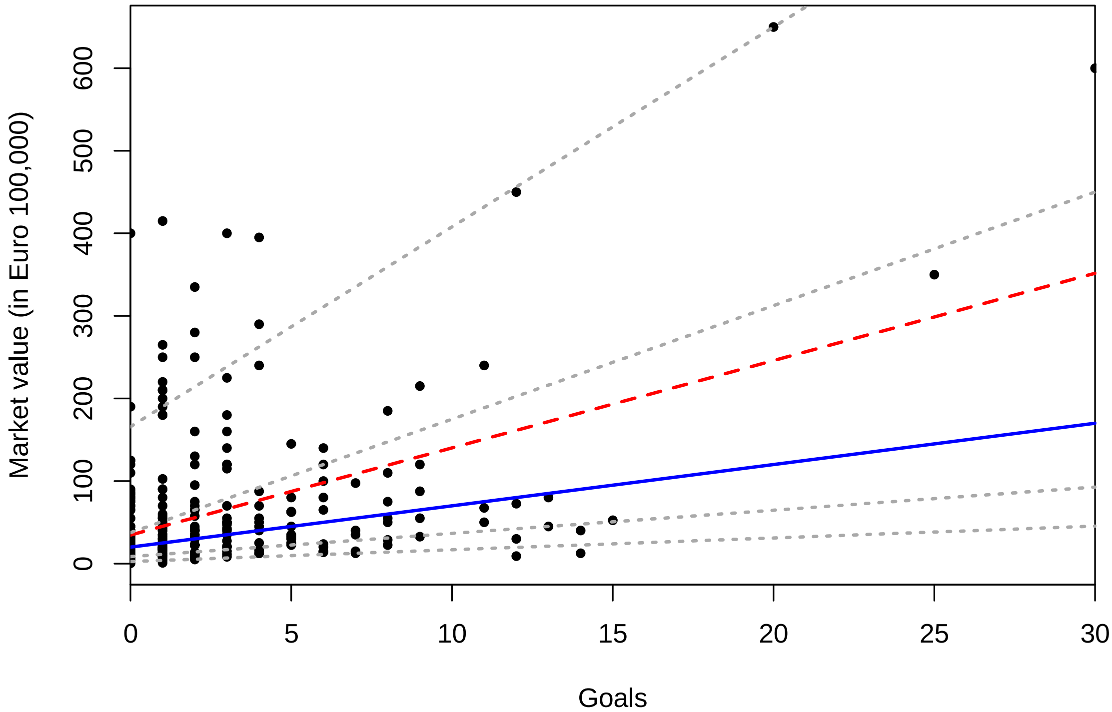
Table 2 summarizes estimation results for our quantile-regression models. [vii] We present estimation results for two models. The first model is our core model. The core model features our core performance parameters: time, goals, passes, and assists. The second model is an extended model. The extended model features, in addition to the performance parameters already included in the core model, the further explanatory variables, tackles, age, distance, and the position played. For estimation of our empirical model, we standardize the variables by their standard deviations.

Table 2: Quantile-regression estimates

	Model 1 (core model) Quantile					Model 2 (extended model) Quantile				
	0.05	0.25	0.5	0.75	0.95	0.05	0.25	0.5	0.75	0.95
Intercept	-0.25	-0.56	-0.99	-1.74	-3.14	-0.45	-0.71	-1.01	-1.47	-4.63
	(-1.68)	(-4.30)	(-4.97)	(-4.55)	(-4.53)	(-1.94)	(-3.09)	(-2.62)	(-1.46)	(-2.11)
Time	0.05	0.05	0.01	-0.04	-0.18	0.03	0.06	-0.01	-0.10	-0.37
	(2.90)	(4.64)	(0.49)	(-0.98)	(-1.21)	(1.38)	(3.69)	(-0.24)	(-1.90)	(-2.18)
Goals	0.01	0.05	0.13	0.49	0.88	0.01	0.05	0.14	0.56	1.04
	(0.27)	(2.41)	(2.75)	(2.36)	(3.70)	(0.30)	(1.88)	(1.80)	(2.52)	(4.33)
Passes	0.03	0.08	0.15	0.29	0.61	0.03	0.08	0.16	0.24	0.56
	(1.72)	(4.69)	(5.12)	(5.47)	(5.50)	(1.34)	(3.81)	(4.84)	(4.48)	(5.11)
Assists	0.04	0.10	0.16	0.13	0.47	0.05	0.08	0.18	0.14	0.54
	(1.63)	(5.50)	(3.69)	(1.89)	(1.79)	(1.96)	(4.03)	(3.64)	(1.93)	(1.82)
Tackles	-	-	-	-	-	0.02	0.02	0.04	0.11	0.33
						(1.20)	(1.00)	(1.67)	(1.60)	(1.54)
Age	-	-	-	-	-	0.01	-0.01	-0.01	-0.02	0.08
						(1.04)	(-0.76)	(-0.40)	(-0.27)	(0.61)
Distance	-	-	-	-	-	0.01	0.01	-0.02	-0.04	-0.03
						(0.74)	(0.41)	(-0.85)	(-0.77)	(-0.22)
Position	-	-	-	-	-	0.01	0.02	0.02	-0.03	-0.14
						(0.35)	(0.73)	(0.56)	(-0.35)	(-0.55)

Market value and all predictors (except for the position played) are scaled by their respective standard deviation before estimation (that is, variables are measured in units of standard deviation).
Additionally, to the estimated coefficients for the different quantiles, we report t-statistics computed using bootstrap simulations. The t-statistics show that the time played has a negative impact on quantiles above the median and a positive impact on quantiles of the conditional distribution of market value below the median. The impact of goals scored and passes on the conditional distribution of market value, in turn, tends to become larger when we look at the upper quantiles. The estimated coefficients of the performance parameter assists are significant at median and the neighboring quantiles. Finally, the additional performance parameters that we include in the extended model are largely insignificant. Hence, we focus on the core model in the remainder of our empirical analysis.

Figure 2: Impact of goals on market value



Note: OLS= dashed red line – Quantile-regression = blue line – Other quantiles = dashed gray lines

Figure 2 illustrates the impact of the number of goals scored on market value. The dots represent the combination of market value and the goals scored for every player in our sample. The dashed red line represents the effects of goals on market value estimated by means of an ordinary-least-squares (OLS) model that features goals as the only performance parameter. The solid blue line, in turn, represents the estimation result we obtain when we estimate a quantile-regression model for the median market value with goals as the only performance parameter. The dashed gray lines represent the estimation results we obtain for such a model for some other quantiles of the conditional distribution of market value. The figure illustrates that the effects estimated by means of a quantile-regression model differ from the estimate for the OLS model, and that, in line with the estimation results we report in Table 2, the effect of goals on market value tend to be larger at the larger than at the lower quantiles.

Figure 3 shows the results that we obtain when we fit a skew t-distribution to the estimated quantiles. We use the 5%, 25%, 75%, and 95% quantiles to estimate the four parameters of the skew t-distribution.[viii] Furthermore, we define five different types of players: A baseline type that can be described by the performance parameters evaluated at their respective mean values, and four other players for whom one of the performance parameters assumes a value two units above the respective mean. We then use the estimation results for our core quantile-regression model to predict the quantiles of the conditional distribution of market value for these five player-types, and fit a skew t-distribution to the predicted quantiles to obtain a smooth probability density curve.

Figure 3: Estimated probability density functions

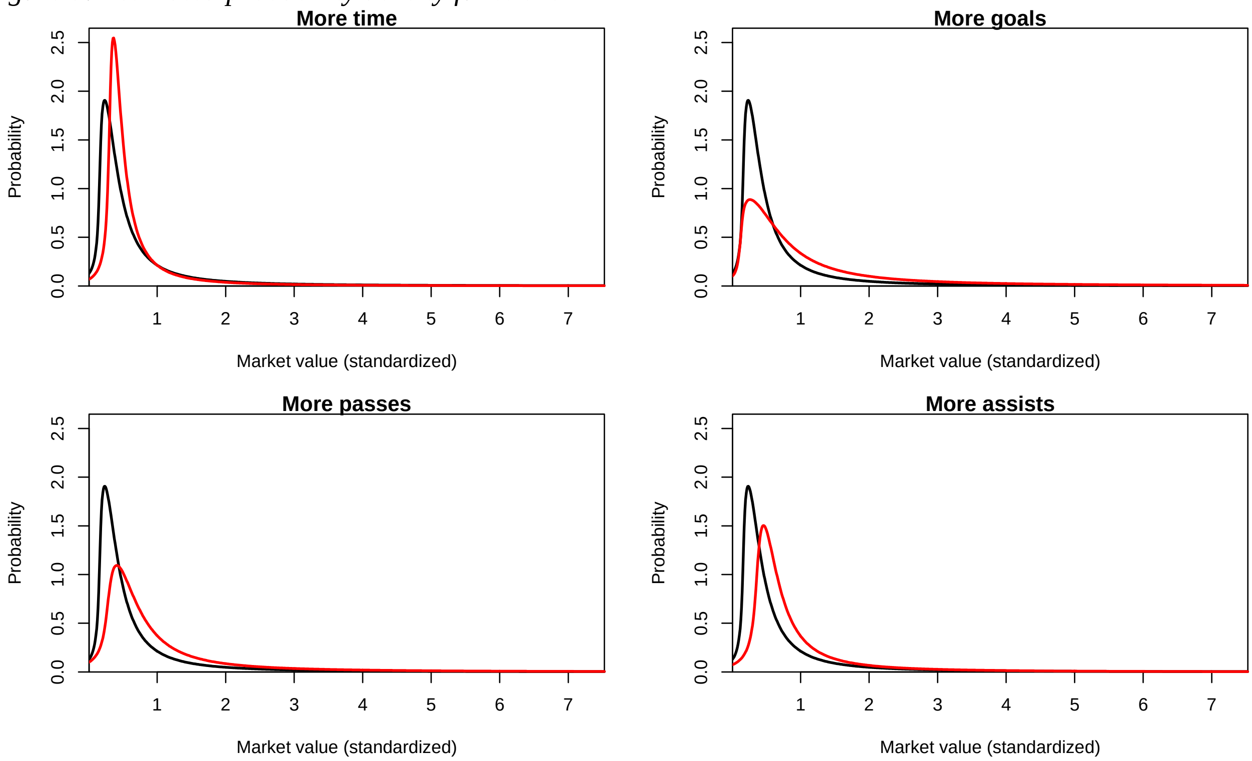


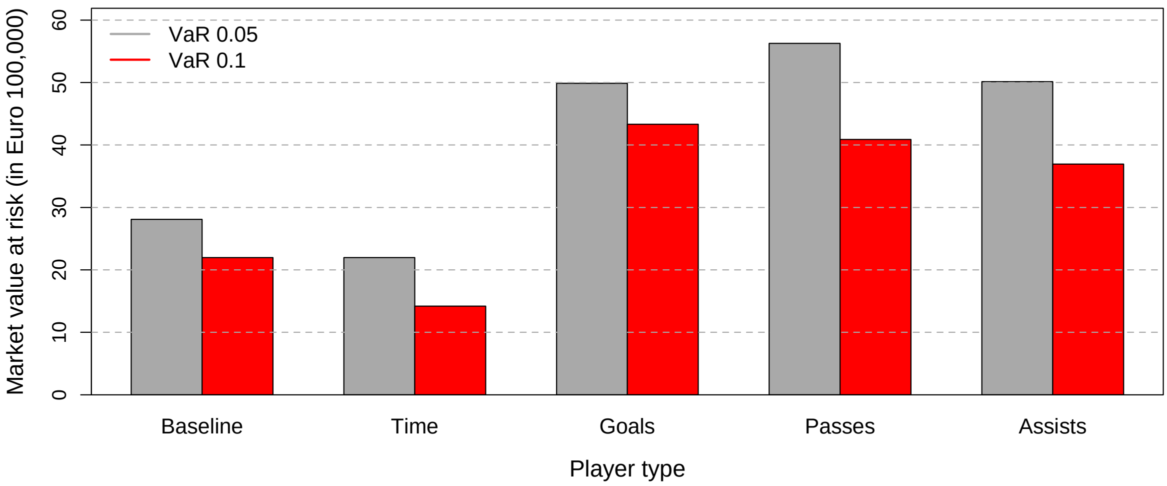
Figure 3 shows that an increase in the time played mainly shifts probability mass from the lower end to the center part of the estimated probability density function of market value. As we can see time played hardly affects the upper parts of the probability density function of market value. More goals scored and more passes, in turn, have a comparatively small effect at the lower end of the probability density function of market value, but rather shift probability mass from the center of the distribution to its upper parts. Similarly, more assists shift the estimated probability density function to the right but tend to have a relatively stronger effect at the lower end of the probability density curve of market value than goals and assists. Finally, we observe a very small probability of a very large market value, consistent with a superstar phenomenon (Rosen 1981).

Figure 3 also sheds light on a drawback of the skew t-distribution in the context of our empirical analysis: the distribution does not account for the fact that the player market value is a non-negative number. While the probability density functions, we plot in Figure 3 illustrate that this drawback of the skew t-distribution is not a serious problem (because only a small probability mass is allocated to the negative part of the real line), we shall present below (see Figure 8) results for an alternative statistical model that explicitly accounts for the fact that player market values in our sample are positive numbers.

Figure 4 summarizes the results that we obtain when we use the estimated probability density function of market value to calculate the market value at risk for the five different player types.

We calculate the market value at risk by subtracting from the market value of the five types of players as predicted by our quantile-regression model the market value implied by the lower 5% and 10% quantiles of the estimated probability density functions estimated for the five player types (we assume that the current market value of the five types of players is equal to the market value of an average player of a given type evaluated at the mean).[ix] The market value at risk, therefore, represents the maximum loss a club incurs with a probability of 5% and 10%. The market value at risk, hence, is larger when we look at the lower 5% quantile of the estimated probability function of market value than at the lower 10% quantile. Moreover, the market value at risk is larger relative to market value at risk that we calculate for a player of the baseline type when we look at a player who scores comparatively more goals, plays more successful passes, and has more assists. The performance parameter time played, in turn, tends to lower the market value at risk because, as Figure 3 witnesses, an increase in the time played reduces the probability mass allocated to very low market values.

Figure 4: Market value at risk



Investments in players are of course associated with risks, but no club would invest in a player from whom it did not expect a corresponding benefit – under uncertainty, of course (e.g., Leifheit and Follert 2021). A manager of a football club may therefore not only be interested in the „downside“ potential of market value, but rather also in its upside potential. For this reason, we plot in Figure 5 the market value at hope, that is, the increase in market value that will not be exceeded with a probability of 5% and 10%. As expected, we measure the smallest value at hope for a player who plays for a longer period than the baseline player, while we observe the largest value at hope for a player who scores more goals than the baseline player.

Figure 5: Market value at hope

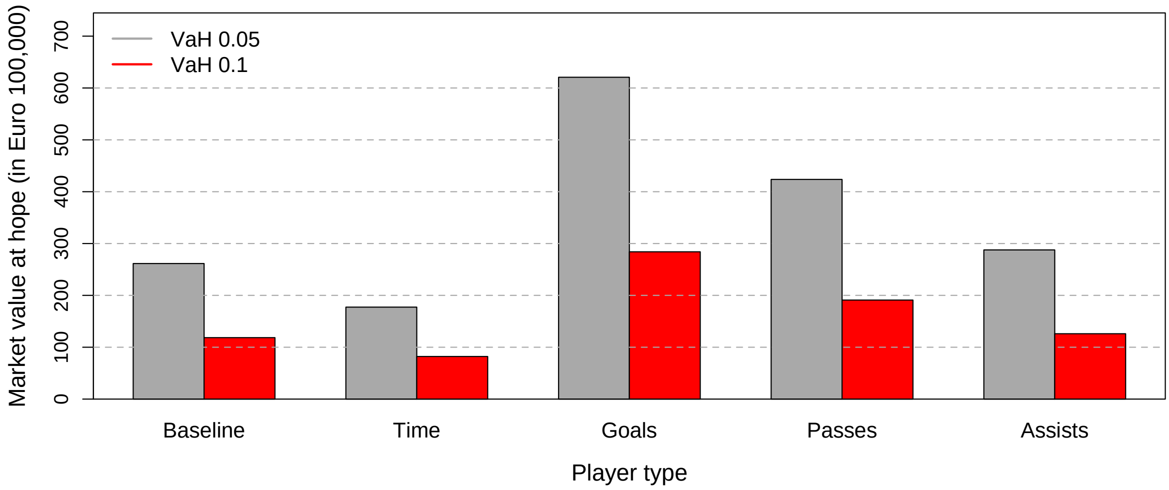
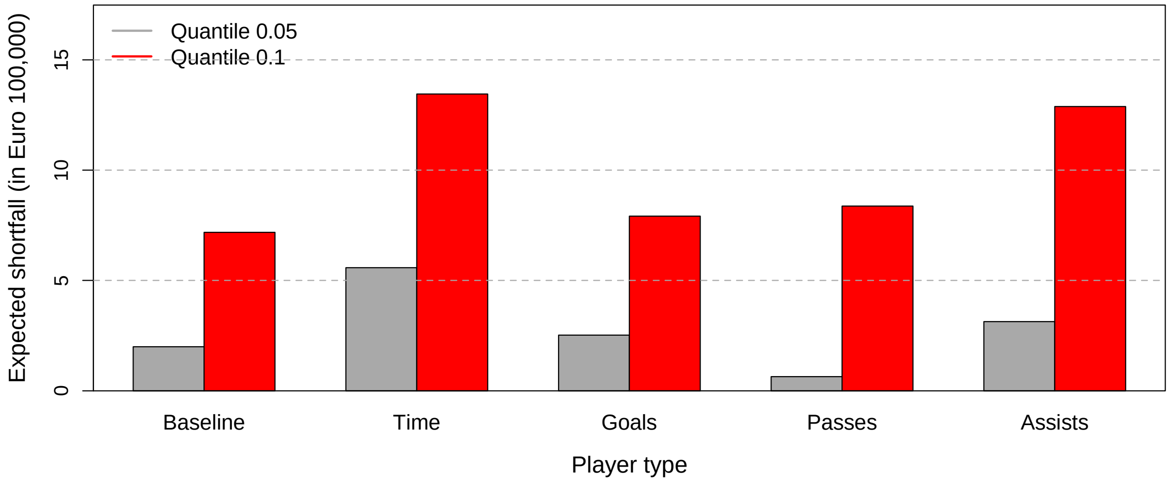


Figure 5 plots the expected shortfall of market value, that is, the expected value of market value given that a loss in market value exceeds the lower 5% and 10% quantiles of the estimated probability density curves. Naturally, the expected shortfall is larger for the 10% than for the 5% quantile. A player who spends comparatively much time on the pitch has a relatively small market value at risk and, because playing time shifts the probability density function of market value to the left, a high expected shortfall when compared to the baseline player type. Conversely, a player that scores more goals than a baseline player has a comparatively high market value at risk and, because goals scored mainly affect the right tail of the probability density function of market value, the expected shortfall for such a player is not much different from the expected shortfall of a player who is of the baseline type.

Figure 6: Expected shortfall



It is interesting to study how our risk-management tool performs in an out-of-sample analysis. To this end, we proceed as follows. First, we delete every 7th observation from our dataset (that is, a total of 5475 observation, or approximately 15% of the data) and reserve these deleted observations for our out-of-sample analysis. Second, we estimate our core quantile-regression model on the remaining data. Third, we use our estimates to predict the 5%, 25%, 75%, and 95%

quantiles of the conditional distribution of market value for the out-of-sample data. Third, we fit a skew t-distribution to the quantiles predicted for every out-of-sample observation. Fourth, we use the fitted skew t-distribution to compute the probability integral transform (PIT) for the out-of-sample data, which Diebold, Gunter, and Tay (1998) advocate as a key instrument to assess the quality of density forecasts. They show that a well-behaved PIT should be uniform and independent and identically distributed.

Figure 7 depicts a histogram of the PIT along with the autocorrelation function of the PIT and the squared PIT. The histogram shows that the hypothesis that the PIT has a uniform distribution cannot be rejected (Kolmogorov–Smirnov test: p-value: 0.79; Anderson–Darling test: p-value 0.43). The autocorrelation functions, in turn, do not provide much evidence against the hypothesis of independence (Ljung-Box test: p-value 0.34; Ljung-Box test applied to the squared PIT: p-value 0.12). Finally, application of a structural break test provided no evidence against the hypothesis that the PIT is identically distributed (Andrews QLR test: p-value: 0.3).[x] In sum, our empirical model has a reasonable out-of-sample performance.

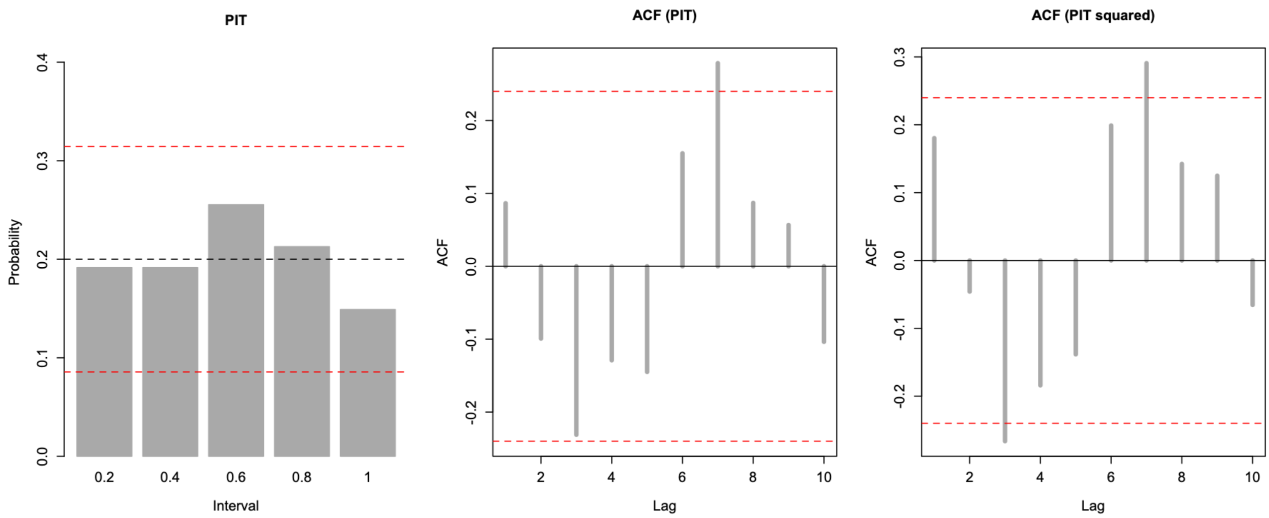
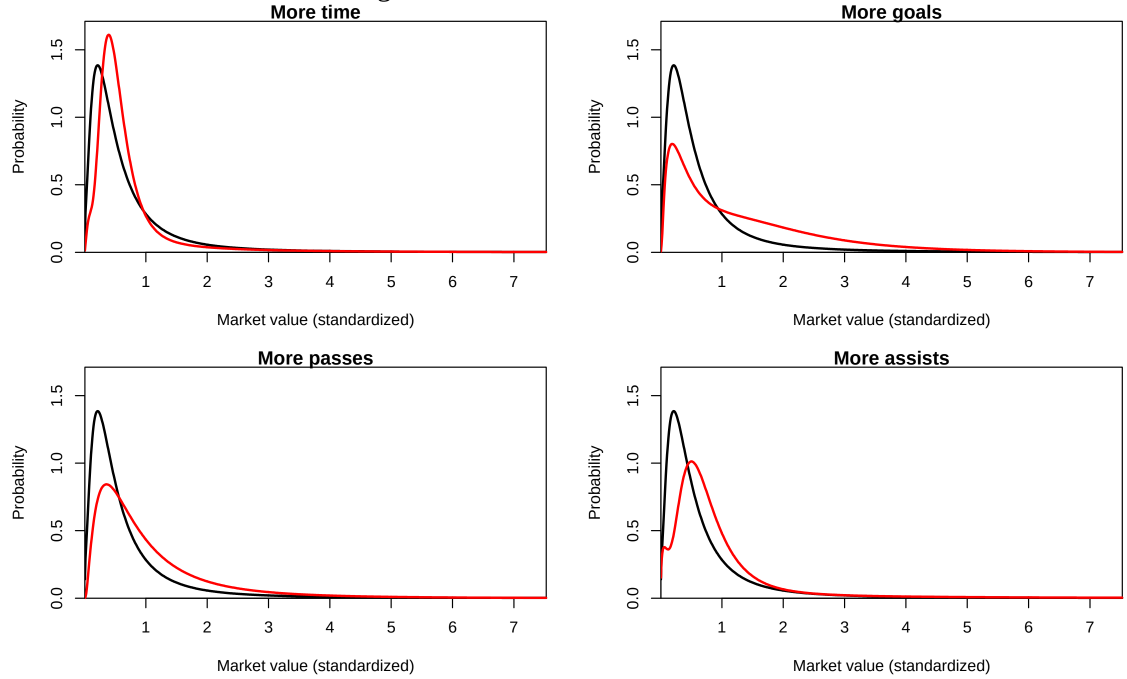


Figure 7: Properties of the PIT

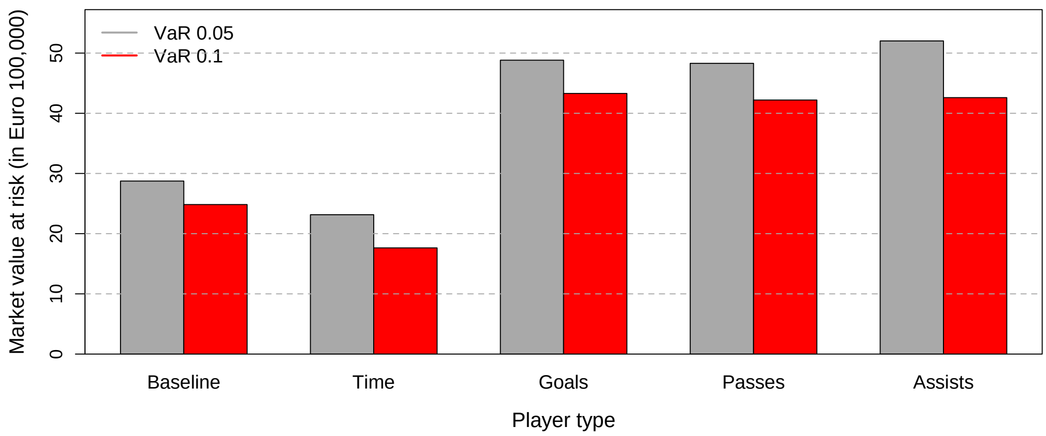
Finally, it is interesting to check how the results for the player value at risk and expected shortfall change when we replace the skew t-distribution with an alternative probability density function. To this end, we use the 5%, 25%, 0.5%, 75%, and 95% quantiles implied by our core model (estimated on the full sample of data) to estimate the five parameters (two means, two standard deviations, and one weight) of a mixture of two log-normals model.[xi] The mixture of log-normals model has the advantage that it explicitly accounts for the fact that the player market value is a non-negative variable.

Figure 8: Results for the mixture of log-normals model

Panel A: Estimated mixture of log normals



Panel B: Market value at risk



Panel C: Expected shortfall

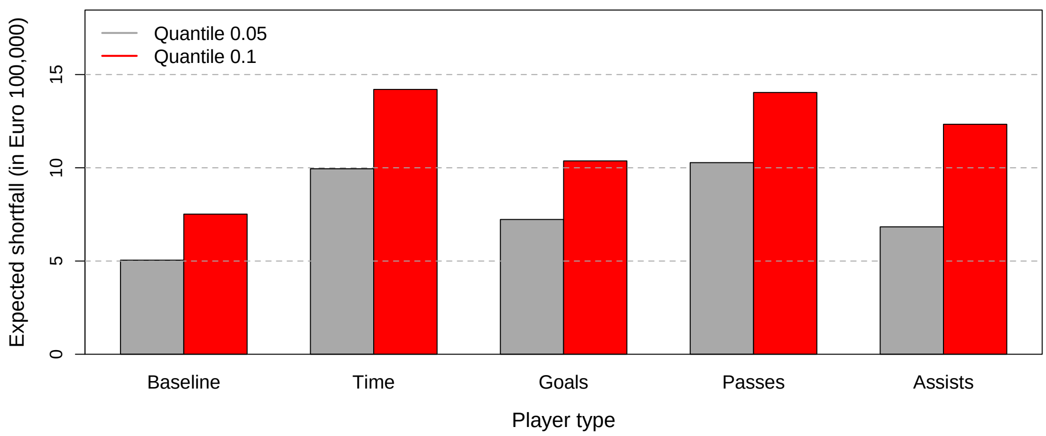


Figure 8 depicts the results for the estimated probability density functions and the market value at risk of the player market value for the five different types of players. The key message to take home from Figure 8 is that, while the exact values of the market value at risk, as one would have expected, depend on the probability model being used, the results for the mixture of log-normals model are qualitatively like the results for the skew t-distribution model.

4 Concluding remarks

The right to use a player is an intangible asset that significantly determines the degree to which the objective of the club to maximize sporting success is achieved. Signing a player is an investment that, in the best case, generates benefits over the contract period that exceed the costs of the investment. Every investment involves opportunities and risks, and risks cannot be completely avoided. Rather, it is critical that a club's human capital be managed in a systematic and data-driven process. In this respect, a key task for managers of football clubs is to monitor, to control, and to expand the human capital of a football club. This task comprises two interlinked dimensions. One dimension concerns the quality of the football team. Upon recruiting new players and selling other players to other clubs, mangers of football clubs must attempt to increase the overall quality of a football team and, thereby, to improve sporting performance. We see here, that "at the beginning" (when market value is still low), time on the pitch, i.e., quantity, is more important, while quality components play a greater role as the market increases. For team managers is important to balance those different types of players in his team portfolio. The second dimension is economically in nature and concerns the management and monitoring of the market value of individual players and of the whole team. The market value of players depends on key performance parameters (like the number of goals scored) and on other factors (like injuries, which show up as the statistical error of our empirical model). While sports economists have done much significant empirical research to recover the links between player market value and key performance parameters, we have built on recent research by Adrian et al.(2019) to show that the insights of this earlier research can be easily used to build a straightforward risk-management tool that helps the management of a football club to monitor and control risks that their club confronts due to the unavoidable random fluctuations of the market value of the players of the team that they manage. Risk management for a team manager can also mean that a balanced strategy for selling a player must be considered. Here the strategically favorable (in the sense of the time) sales of a player could be more important for some clubs than for others, so that the basic conditions of the club also play a role for the risk evaluation and thus club specifics exhibit called, to sell could be for some clubs a more important component than for others. Therefore, one of my arguments would be that the framework of the clubs play a role and / or the management strategy in one club.
While the list of predictors that we have studied in this research comprises standard performance parameters often used in earlier work (see, for example, Wicker, Prinz, Weimar, Deutscher and Upman 2013), one could think of additional predictors that affect market value like, for example, whether a club participates in international competitions (Partosch 2015) and whether a player is a member of the national team (Serna Rodríguez, Ramírez-Hassan, and Coad 2019). Because Frenger et al. (2019) or Majewski (2021), for example, also consider public interest and popularity as variables influencing a player's market value, future research cold address potential reputational risks that may decrease a player's marketability. It is straightforward to extend in future research the risk-management tool that we develop in this research to include such additional predictors.

In future research, it also is interesting to apply the risk-management tool that we have described in this research to study the market value of players of other major football leagues. It is also interesting to use case studies of successful and less successful football clubs as an instrument to backtest the risk-management tool that we have laid out to trace out in which dimension the tool should be extended to further improve its usefulness for managers of football clubs.

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[i] Duffie and Pan (1997, 8) define the value at risk generally as follows: „For a given time horizon t and confidence level p, the value at risk is the loss in market value over the time horizon t that is exceeded with probability 1 – p".

[ii] In contrast to the value at risk, the expected shortfall does not measure the smallest loss, but the average loss within a given period, e.g., Tasche (2002).

[iii] Hermes, as sleeve sponsor in the season under study, had published a large amount of data for each player in each match of the Bundesliga. The database is currently no longer available online, but the collected data can be viewed. The authors understand there are other providers that make performance data available. For example, Kicker or the Bundesliga site itself, where often only aggregated data (e.g., total kilometers) or a selective range of data is available.

[iv] See Carmichael et al. (1999) for an in-depth analysis of player attributes that affect the probability of a transfer or the magnitude of the transfer fee.

[v] A representative assignment is defined by the fact that there are evaluations for this player in the kicker in the form of a grade. A player receives a Kicker grade if he was on the pitch for at least 30 minutes. Short-term substitutions are left out. If a player has never received a Kicker grade in a season (= no representative use), he is excluded from the analysis.

[vi] We used the R language and statistical programming environment (R Core Team 2019) to compute this histogram and all other empirical results that we present in this research.

[vii] We used the R package „quantreg" (Koenker 2020) to estimate the quantile-regression models.

[viii] We used the BFGS algorithm implemented in the R package „optimx" (Nash and Varadhan 2011; Nash 2014).

[ix] See Miller (2018) for an introduction to value at risk and other techniques of quantitative risk management.

[x] See Rossi and Sekhposyan (2014) for an in-depth discussion of various statistical tests useful for studying the properties of the PIT.

[xi] The mixture of log-normals model features prominent in the empirical finance literature as a description of the distribution of financial-market prices. See, e.g., Melick and Thomas (1997).