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Master Thesis

Thesis Master of Science

The Best Position To Be In –

A Study on the Impact of Club Quality, League Quality, and Playing Position on a Soccer Player's Post-Transfer Performance

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The Best Position To Be In –
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Programme:
Master of Science in Leadership and Organizational Psychology

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Abstract

Today, more and more companies are struggling to develop internal talent at the same speed that the world changes. Therefore, it has become a common practice to search for high-performing talents on the external market. While this sounds simple, research within the field of inter-organizational transfer gives reason to believe that not every high performer will be able to replicate their prior performance right after transfer. Though conclusions have been made that several factors are helpful in aiding a transferee's post-transfer performance, research lacks insights on how the overall difference between job positions can affect it. In this study, we explore how different job positions affect portability in addition to confirming previous research findings. We do so by applying these ideas to the realm of soccer. The soccer industry shows high similarities to organizations outside of sports, and it offers the benefit of providing a high number of transfer occurrences and more easily accessible data. Using a data set of the most valuable soccer transfers in the last decade, we come to conclude that organizational capabilities in terms of the club and league quality impact a player's post-transfer performance. Furthermore, we see the impacts of positional differences on soccer players' post-transfer performances. While we conclude that organizational theory is not perfect in explaining soccer performance after a transfer, it does give reason to believe in the importance of a transferee's position. The insight gained from this study suggests that a job position's effect on post-transfer performance should also be further investigated in organizational research.

1. Introduction

We are living in a world with an ever-rising number of organizations. All of them are united in one goal: generating profit, be it for the sake of capitalism or simply survival in the case of non-profits and NGOs. In recent years, a company's human capital has become an ever more important role in this endeavor. Sourcing the best talent no longer only refers to attracting the brightest graduates, but even more frequently it includes poaching high performing employees from competing firms. Spurred by increasing incentives and a more mobile society, it is not a surprise that the number of employee transfers has skyrocketed. While employee transfers are more attractive than ever to both employers and employees, it comes with distinct downsides.

In the past, both stock market reactions and research studies have shed light on one common issue: a transferee's inability to replicate their pre-transfer performance right after transfer. However, it has also been shown that this finding is in no way a one size fits all application. Several factors have been identified which help mitigate a potential performance drop.

Some of these factors appear rather straightforward; for example, a higher level of similarity between prior and new job roles and industry characteristics can mediate the performance drop. Other factors are more complex; for example, a move to a firm with similar or higher capabilities or a move with former colleagues can also soften the negative effect. One would assume that specific job characterizations also should have a mediating effect. However, while this has been hypothesized occasionally, it has rarely been explored and therefore becomes a main focus in this study.

In research, it is widely accepted that individual performance is based on both portable innate and non-portable organizational factors. An individual's performance drop after transfer is explained by the loss of performance based on the non-portable organizational factors. This theoretical background can also be applied to how different job roles differ and therefore show different sizes of performance drop after transfer. Investigating this theoretical background towards different job roles can increase knowledge and awareness within organizations that not all job roles can be generalized and equal success across them be assumed.

An "industry" well-known for high numbers of transfers is the soccer industry. Every year, hundreds of transfers are taking place both across clubs and leagues. Thereby, many factors mediating a performance drop in the organizational context can also be applied to the soccer industry. Within this study, the main focus lies on investigating how the club and league quality as well as a player's position affect post-transfer performance. Thereby, the soccer industry provides us with unique opportunities by providing uniform data sets across different playing positions. With different soccer positions having different requirements of general and firm-specific skills, they provide a good insight into the relevance of positions.

To come to a conclusion, this study will continue in the following manner. Firstly, the research background and the positioning of the study will be introduced. Secondly, the theoretical argument around the main research points will be built. This includes an explanation of the composition of individual performance and how positional and organizational differences affect the portability of individual performance. Throughout the argumentation, connections between organizational theory and the soccer context will be drawn. Thirdly, the methodology and data sample will be introduced, and the results will be presented. Fourthly, connections between results and theory are discussed. Lastly, limitations and a conclusion are provided.

2. Research Background and Positioning

In today's world, human capital plays an ever more important role in an organization's survival. While many years ago, land, capital and other tangible assets were the most important factors to outcompete competitors, now the possession of highly skilled human capital can be decisive (Gardner, 2002; Weinberg, 2016). It is often these highly skilled employees who contribute the bulk of a company's sales or production (Kang et al., 2018), thus becoming an essential part of their company's value creation chain (Groysberg et al., 2008). However, with the accelerating rate of change, organizations struggle to develop internal talents fast enough. Instead, they turn to the external labor market as they need excellent human capital, and they need it now (Gardner, 2002).

It is often high performers, also referred to as stars, who pique an organization's interest. However, it might be overly optimistic to assume an immediate benefit after hiring a star. Research has shown that these kinds of investments can not only cause a negative market reaction but also real performance consequences. Groysberg et al.'s (2008) study finds that stock price movements after top-level manager buy-ins can show negative trends, indicating that the market does not perceive the buy-in favorably. In addition, research findings also raise concerns about a possible drop in the transferee's post-transfer performance (Campbell et al., 2014; Groysberg et al., 2006, 2008; Groysberg & Lee, 2009; Raffiee & Byun, 2020). While overpaying for a star can pose huge costs for the organization, there can be ramifications for the individual as well. Even when a transferee garners positive returns for the organization, they can still perform below their own potential (Raffiee & Byun, 2020). Personal underperformance can threaten an individual's satisfaction of the ego, which in human relations theory is seen as one of the most significant rewards to an employee (Scott & Davis, 2016). This can manifest into negative physical and mental consequences (Jessurun et al., 2020). While research findings thus indicate that this hiring practice has possible downsides for both employees and firms, it appears as if research findings are not compelling enough to find real application in the workplace. It should therefore be in the mutual interest of both organizations and transferees to better understand the mechanisms underlying inter-organizational transfers. Increased awareness can help maximize the success of talent acquisition and retention practices for organizations and transferees. To date, various streams of research have investigated different organizational factors affecting transfer success (Campbell et al., 2014; Groysberg et al., 2006, 2008; Groysberg & Lee, 2009). Thereby, a large part of this research, referred to as knowledge-transfer research, focuses purely on transferring knowledge between people, without physically moving an individual to a different team in the long-run (see Argote & Guo, 2016; Argote & Ingram, 2000; Nakauchi et al., 2017). This study, however, focuses on physically transferring an individual between organizations, also referred to as inter-organizational transfer, and how their performance built on their knowledge can be affected.

From inter-organizational transfer research, several factors have been identified that enable transferees to maintain more of their performance post-transfer. Some main factors are the similarity between positions, firm capabilities, and industry (Groysberg et al., 2006, 2008). Additionally, the existence of a fully-functioning department is beneficial for a transferee's performance, however its absence can be compensated for by moving with colleagues (Campbell et al., 2014;

Groysberg & Lee, 2009). Using these theories as a foundation, this study seeks to extend these findings by investigating which other factors affect post-transfer performance. Part of our main research focuses on gaining insight into whether different job role characteristics affect performance portability in transfers. While often assumed, it lacks empirical support and may become especially important in samples where previously investigated factors do not apply.

2.1. Contribution to the Inter-Organizational Transfer Research Field

This research contributes to the strategic human resources literature within the field of talent management by confirming prior research and providing novel insight. Additionally, to our knowledge, this study is positioned at the forefront of the application of inter-organizational transfer findings to the realm of soccer. Testing organizational theories on sport samples is quite common, due to the comparative accessibility and uniformity of performance data as opposed to organizational data (Franck & Nüesch, 2008; Weinberg, 2016). Besides these, professional athletes also show high similarities to employees in an organization. Athletes trade their performance for compensation just as knowledge workers trade their knowledge (Lombardi et al., 2019). Furthermore, soccer players do so in fully-functioning businesses, as soccer clubs show all characteristics also found in other organizations (Costa et al., 2018). For these reasons, we have chosen a sample of soccer players.

Applying these theories to the soccer context, we will analyze how a club's capabilities and a player's position impact a player's transfer success. This paper initially shares some similarities with a study conducted by Lombardi et al. in 2019. However, Lombardi et al. (2019) focused on the transfer of players using a framework from the knowledge-transfer literature. This leads them to focus on how a player's knowledge can be operationalized at a new organization, while our focus lies on identifying how a player can maintain their own performance built on their knowledge at a new organization. With the results of this study, we gain insight on three topics. First, we identify the applicability of inter-organizational transfer theory to the realm of soccer. Second, we gain insight into which factors affect post-transfer performance in the realm of soccer. Third, we can use the insights gained from the soccer context to point of research areas of interest in the organizational context. The primary aim of this study is to explore the following research question:

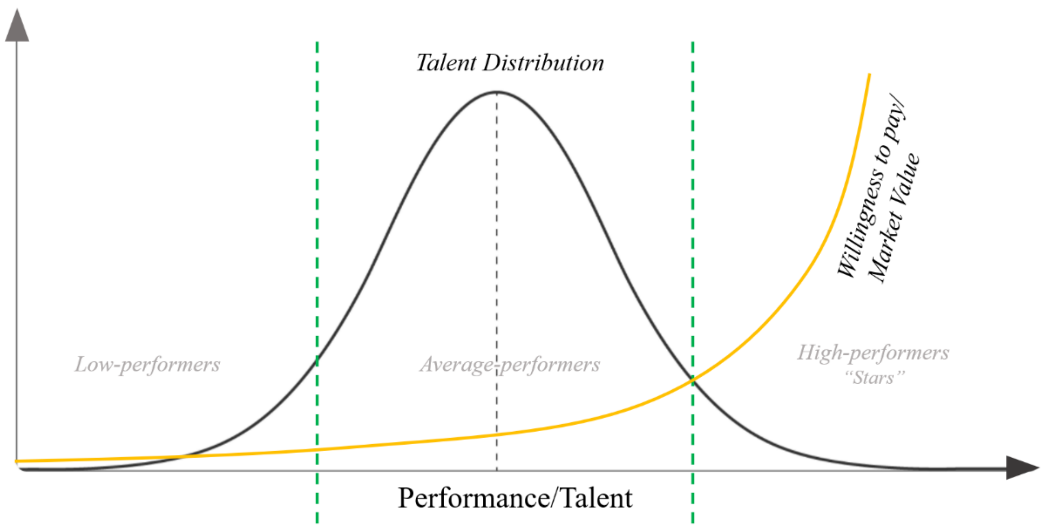
"Which factors impact the portability of an individual's performance after inter-organizational transfer?"

3. Stars

Employees showing superior performance are at the center of attention for transfers. They are often referred to as stars, and we will adopt this convention in this study. Two factors differentiate stars from average performers. First, they are disproportionately more productive and, second, due to their performance they are more visible to the external labor market (Groysberg et al., 2008).

A star's disproportionally high performance is also what increases their monetary value to the market. While representing a small part of the overall organization, stars can account for a disproportional bulk of sales and productivity (Kang et al., 2018). Since, in general, talent in the market is normally distributed, a star's abnormally high talent places them in the right tail of the talent distribution (***Figure 1)***. Due to their scarcity, many people focus their willingness to pay on these talents (Franck & Nüesch, 2008), causing a convex curve of salaries.

Figure 1: *Normal Distribution of Talent of Soccer Players and Exponential Remuneration of Talent (Market Value)*



Therefore, a small increase in talent is rewarded manifold (Lehmann & Schulze, 2008; Rosen, 1981). Groysberg et al. (2008) note that a star's ability and experience can be so unique that it is impossible to replace them with either nonhuman assets or a group of lower-performing individuals. For soccer teams, this consideration is of great importance due to the limitations in overall team size and number of players on the field. This inimitability explains why stars attract such disproportionally high demand and can command a high premium.

This star phenomenon can also be found in the soccer industry. Franck and Nüesch (2008) identify that only a small group of top players received substantially higher compensation in the German Bundesliga. However, within this paper, we must be careful where to draw the line between average and star. Weinberg (2016) has discussed the difficulties in distinguishing between non-stars, stars and superstars. In light of this, we must consider that while the distribution of talent in this data sample shows a normal distribution, in the context of the overall soccer population, we assume most players included in this study to place in the right-end tail of the normal distribution. Since it has been shown that stars possess characteristics which allow them to transfer more successfully (Kang et al., 2018), all players in the sample set might benefit from those characteristics. This also sets the soccer players included in this study on the same level as star employees included in studies by Groysberg et al. (2006, 2008) and Groysberg and Lee (2009).

Though normally salary is tied to star status, in the realm of soccer, market value can be more reflective of high performance than salary. Market value similarly is indicative of the market's willingness to pay for a player (Franck & Nüesch, 2008). However, it is a more widely accessible measure and less biased across leagues and clubs than salary (Frick, 2007). Performance and market value also exhibit the same previously illustrated relationship as talent and salary for stars.

4. Performance

Performance is a critical concept in this study. However, performance itself is a broad term. In the organizational context, performance exists and can be measured at different levels: the organizational, unit, and individual level (Den Hartog et al., 2004). Since all three levels are intertwined, it is difficult to isolate the individual from the organizational and unit-level aspects of performance, both in its measurement and its composition.

While performance can be measured on three different levels, all levels are impacted by the different resources a company possesses. While physical, organizational, and human capital resources impact the organization's performance (Barney, 1991), they also impact the individual's performance (Groysberg et al., 2008). Before diving into how different amounts of resources can impact individual performance, it is essential to discuss how best to describe individual performance.

4.1. Individual Performance

Individual performance is a combination of individual and organizational factors (Groysberg & Lee, 2009). In terms of human capital theory, individual factors are considered general human capital (GHC) while organizational factors are considered firm-specific human capital (FSHC) (Raffiee & Byun, 2020). The base assumption within the strategy literature is that GHC is portable whereas FSHC is not (Becker, 1964).

4.1.1. General Human Capital (GHC)

GHC describes the innate and therefore portable part of individual performance. Skills that are considered GHC include any tacit knowledge which is portable and not specific to a particular firm- it can be innate, or gained through education and experience (Berman et al., 2002; Dokko et al., 2009; Groysberg et al., 2008). As no firm has ownership of their employees, these skills should be fully portable for the transferee (Campbell et al., 2012). It is the performance built on GHC which is of direct value to competing firms.

GHC can also function as an explanation for a star's disproportionally high productivity. Stars and non-star employees are surrounded by similar organizational capabilities, but they still show different performance levels. This disparity reinforces the everyday psychology assumption that some people are simply born with more talent than others (Simonton, 1999). Kang et al. (2018) further support this assumption with the finding that fast advancement of performance in an employee's early career can be a good indicator for performance based on GHC. It can thus be assumed that a star performer bases larger parts of their performance on their GHC, which in turn should also allow them to take a relatively larger share of their performance with them when they transfer.

Applying this theoretical background to the soccer context, we find high similarities. Most soccer players start their career without significant experience, surrounded by many similar-aged children at a local club. However, while all children are surrounded by the same resources, some will be scouted and advance to a higher-level regional club while others drop out or stay at the local level (Verburgh et al., 2014). This pattern continues all the way to the top, with significant differences in performance lessening over time. Looking at this progression, it becomes clear that innate talent plays a big part in the advancement as pointed out by Simonton (1999). A study by Verburgh et al. (2014) shows that already by the age of twelve, there are visible differences in the level of soccer-related skills between amateur and highly talented Dutch youth players.

We can conclude that GHC is portable across company borders and that stars base a larger part of their performance on this portable part. However, as previously mentioned, the individual factors, described here as GHC and portable, are only one part of individual performance.

4.1.2. Firm-Specific Human Capital (FSHC)

FSHC is the second and non-portable part of individual performance, and as such, it impedes perfect portability. FSHC describes the knowledge about organizational procedures, policies, corporate culture, informal norms, and experience with specific management systems, which are needed to apply one's GHC effectively in the organization (Groysberg et al., 2006; Raffiee & Byun, 2020). This firm-specific knowledge is location-specific. Any knowledge and performance based on it is useless at another firm (Campbell et al., 2014; Groysberg et al., 2008). While one would assume that this would hinder employee mobility, it at the very least will impact individual performance (Campbell et al., 2012).

FSHC can be split into two categories: colleague-specific human capital and location-specific human capital (Campbell et al., 2014).

4.1.2.1. Colleague-Specific Human Capital

Colleague-specific human capital is a form of social capital that is created with surrounding colleagues (Campbell et al., 2014). This social capital includes both close and peripheral colleague relationships, and it develops over time through team interaction. Having colleague-specific knowledge includes having role clarity about one's own and others' responsibilities and knowledge. Having this knowledge lowers coordination requirements and moves a team from "task-work", the pure execution of tasks, to "team-work", the most effective execution of tasks (Cannon-Bowers et al., 1993; Salas et al., 2005). This collective understanding of the system under control will be disrupted with a change in membership (Cannon-Bowers et al., 1993). Moving to a new firm, one loses this team-specific knowledge which increases coordination costs for all tasks, lowering overall performance.

4.1.2.2. Location-Specific Human Capital

The other half of FSHC is location-specific human capital. Location-specific human capital describes the possibilities connected to the resources in place. Every firm comes with specific management systems, its own routines, a stock of overall knowledge, a unique corporate culture, and informal norms (Groysberg et al., 2006). Over time, an employee working at an organization will accumulate knowledge of these resources and build their performance upon them. However, a move to a new firm will render this location-specific knowledge useless. This leads to the transferee losing their individual performance based upon this location-specific knowledge, until it is rebuilt at their new firm. A long tenure at the previous firm can add additional hurdles due to rigid habits impeding the adoption of new routines and systems (Dokko et al., 2009).

4.1.3. Concluding Human Capital Transferability

From the above sections, we see that while GHC can be transferred FSHC hinders individual performance portability. FSHC, in both its colleague-specific and location-specific forms, is lost to some degree in the transfer. Justifying the purchase of a star with hopes of an instantaneous high performance would thus assume that a star's entire performance is built on their GHC (Groysberg et al., 2008). From the discussion above, we see that this is improbable. Even when a star's performance is based to a larger extent on their GHC, they may still experience some loss in their individual performance. Their higher GHC may allow them to still contribute net positive effects to the firm (Raffiee & Byun, 2020), obscuring this loss of individual performance to the public. However, this is not always the case as it has also been shown that stars can be outperformed by lower-quality incumbents after a transfer (Raffiee & Byun, 2020).

5. Positional Differences

There is reason to believe that different types of jobs are comprised of different ratios of GHC to FSHC. This would imply that different job positions, or in this study, playing positions, should experience different levels of FSHC loss. However, there is little research done on the proportion of GHC to FSHC contributing to a transferee's performance. The most pertinent study is Glenn et al.'s (2001) work on the firm specificity of Major League Baseball players. Their study examines whether a player's position increases or decreases their likelihood to stay with a team. To analyze the reasons a player stays, Glenn et al. (2001) apply two different models, the FSHC model and the job-matching model, deciding the first better describes a baseball player's tenure. Thus, they conclude that it is more beneficial for baseball players with high team interaction to stay at one club and accumulate knowledge over time than to frequently transfer in search of an optimal fit (Glenn et al., 2001). Specifically, catchers and shortstops, who are more involved in team production, are less likely to move than outfield positions, who rely primarily on GHC (Glenn et al., 2001). Since different playing positions seem to exhibit different turnover behaviors, it implies that they suffer different amounts of firm-specific knowledge loss.

Applying Glenn et al.'s (2001) reasoning in the context of pre- and post-transfer performance, the higher the proportion of skills and tasks using GHC as opposed to FSHC, the more portable a position should be. This reasoning suggests that there should be a difference between the performance of soccer players in different playing positions when transferring between clubs. While Glenn et al.'s (2001) primary focus lies only on differentiating positions based on their involvement in team production, this choice is highly appropriate given the theoretical background applied in this study. Higher involvement in team production requires greater use of FSHC. Contrastingly, having a position with lower involvement buffers the individual from the effects of their colleagues and organization. Their performance, therefore, is more likely attributable to GHC making them more suitable to transfer.

5.1. Positional Differences in Soccer

Soccer positions are no exception, and they can also be based off of more or less GHC as found by Glenn et al. (2001) for baseball positions. Thus, some are expected to be more or less portable. To explore which positions may be more portable, the technical requirements and interdependencies of different soccer players will be examined.

From prior research, we can observe a sharp division between the four main playing positions in soccer. Goalkeepers are often excluded from studies conducted on defenders, midfielders, and forwards (Yi et al., 2018), which immediately gives the impression that a goalkeeper may transfer differently than the other positions due to the uniqueness of the position. These differences can be illustrated in one way through the key performance indicators (KPIs) for the playing positions. Hughes et al. (2012) found that the goalkeepers had a distinct list of KPIs from the other soccer positions, which had many KPIs in common albeit with different weights of importance. A goalkeeper's KPIs were physiologically, tactically, and technically quite different from the others', many involving more individually-based skills and actions like reaction time, short stopping, or throwing (Hughes et al., 2012). This level of separation implies that a goalkeeper should be more highly based on GHC than FSHC. The various types of defenders, midfielders, and forwards shared KPIs including support play, passing, pressing, and tackling (Hughes et al., 2012), which can be looked at as actions that are highly interdependent and connected to team production, and thus more based on FSHC (Glenn et al., 2001).

Though non-goalkeepers were found to have similar performance indicators, it is important to acknowledge that between them, they have different characteristics that may impact their post-transfer performance. The variations in the positions' usage of GHC to FSHC can be viewed through their level of interdependencies, similar to how Glenn et al. (2001) categorized baseball positions. Korte et al. (2019) investigated the amount of involvement per position during a season of German Bundesliga matches, both in general and as a bridging player between other players. They found significant differences between positions for both measures and when considered together (Korte et al., 2019), the trends found in the descriptive statistics from their study provide insights on which positions may be the most interdependent. The various defender and midfielder positions showed overall higher involvement both in centrality and betweenness, with involvement in the range of 34%-47% of plays to acting as bridging players in 18%-34% of plays (Korte et al., 2019). In their systematic review about network analyses in soccer, Caicedo-Parada et al. (2020) echoed the finding that midfielders are the most central players in certain plays. This level of involvement suggests more interdependencies built into these roles, suggesting a higher level of FSHC-based performance.

While specific types of defenders and midfielders showed differences between them in these studies, there was a clear difference in involvement in the two more general groups when compared to both goalkeepers and forwards, who may be based more on GHC. Goalkeepers primarily acted as initiators in play, rather than bridging players (Korte et al., 2019). Forwards, however, were the least involved in plays both generally and as bridging players of the positions in the study (Korte et al., 2019). Based on these findings, goalkeepers and forwards should experience smaller performance losses than midfielders or defenders, who are more highly interdependent on other players and vulnerable to the effects of FSHC. Thus, the following hypotheses are presented:

Hypothesis 1a: "Different positions experience different immediate performance drops after transfer."

Hypothesis 1b: "Goalkeepers experience a lower immediate performance drop than Midfielders and Defenders after transfer."

Hypothesis 1c: "Forwards experience a lower immediate performance drop than Midfielders and Defenders after transfer."

Positions should clearly have some effect on post-transfer performance. Though the composition of a transferee's position can influence one's post-transfer performance, it is not the only determining factor. Glenn et al. (2001) state that while the FSHC model better describes the movement of baseball players compared to the job matching model, due to the unique characteristics of sports, the foundational idea of the job matching model and its relation to soccer should not be ignored. In this study compared to that from Glenn et al. (2001), the impact of fit between the player and the club may have more of a role. Our sample includes multiple countries and leagues, whereas their findings were sourced from Major League Baseball in the United States, of which differences between cities can be presumed to be smaller than differences between countries and league levels. Regardless of position, the transferee is impacted by the surrounding environment, which can greatly differ between firms. Depending on the firm, its capabilities and characteristics can impact transfer success. Next, we will discuss the impacts of the organization on the transfer.

6. Organizational Differences

An organization's capabilities are comprised of its physical, organizational, and human capital resources (Barney, 1991). Every organization has access to a different stock of these resources, some having more and some having less. For an organization with superior access to or a unique combination of the three resource types, a competitive advantage over competitors can be gained. Additionally, so-called socially complex resources, which are advantages based on hardly explainable grounds, often in relation to human capital networks, can produce a competitive advantage (Barney, 1991). Explainable and unexplainable, tangible and non-tangible resources can thus impact how an organization performs. Thereby, these resources do not only affect the organization's but the individual employee's performance as well (Baron & Pfeffer, 1994).

6.1. Firm Capabilities

For a transferee's performance, the level of resources they can base their performance on at a new firm is important. Groysberg and Lee (2009), studied the performance of star managers when hired into a new firm for either exploration or exploitation purposes. An exploitation situation is when a transferee transfers to an established department with a fully functional workstream. An exploration situation, on the other hand, is when a transferee transfers into a department, with a novel workstream lacking experience and resources. Their results clearly showed that managers hired for exploitation reasons showed higher post-transfer performance than those hired for exploration reasons (Groysberg & Lee, 2009). The missing resources in the exploration situation prevent the transferee from fully reaching their potential.

6.2. Firm Capability Quality

In terms of the level of resources to base performance on, it is not only the quantity which matters but also and even more so its quality. In a related study, Groysberg et al. (2008) studied the performance of star analysts after transferring to new firms. They found that analysts moving to firms with higher capabilities do not experience significant effects on their performance. Analysts moving to firms with similar capabilities experience a short-term performance drop. Lastly, analysts moving to firms with lower capabilities show a longer-term performance drop (Groysberg et al., 2008). They again conclude that the drop in performance post-transfer can be mitigated by moving with colleagues, or through "lift-outs," similar to an exploration situation (Groysberg et al., 2008; Groysberg & Lee, 2009).

Identifying "lift-outs" as a mitigation method strengthens the quality argument for human capital. Moving with colleagues not only allows one to maintain a small piece of shared understanding with one's colleagues (Campbell et al., 2014; Cannon-Bowers et al., 1993), but more importantly, it can ensure the quality of the surrounding human capital. This can be important since one rarely possesses a team's full stock of knowledge (Berman et al., 2002). Simply said, one's own knowledge is complemented by one's colleague's knowledge. The quality of knowledge these co-workers have can thus affect one's own performance (Hackman, 2021).

Insights from the study of exploitation and exploration also shed light on the importance of tangible assets to individual performance (Groysberg & Lee, 2009). A firm with higher capabilities is more likely able to provide its employees with better support (Groysberg et al., 2008). This support can mean access to resources which are necessary for the individual to use their GHC efficiently. Without this, an individual may simply be unable to fully capitalize on their GHC (Raffiee & Byun, 2020).

6.2.1. Reputational Effects

In the business world, it is quite obvious in which organizations we expect to find these high capabilities, and this assumption is often self-reinforcing. As a knowledge worker's reputation is often based on or at least influenced by the department or firm they work for (Groysberg & Lee, 2009), working for a reputable firm or department helps the individual to increase their credibility to the outside world. This credibility will help the individual to gain access to external resources which can positively affect the individual's performance (Groysberg et al., 2008). It also helps well-reputed organizations to attract better applicants (Carmeli & Tishler, 2005), increasing the quality of human capital within these firms.

For the individual working at a highly reputable firm, this has multiple benefits. Working with highly capable colleagues increases the quality of peer-training experienced in these firms (Bidwell et al., 2015). This does, directly and indirectly, impact the perceived quality of these employees to the external market (Bidwell et al., 2015). Therefore, these characteristics of highly reputable firms are appealing to job-seekers, as they increase their market value and can benefit their future career progression (Tan & Rider, 2017). These positive effects are especially applicable in the soccer industry.

6.2.2. Person-Organization Fit

While higher capabilities sound favorable, they may not always be necessary if they are substituted by the right capabilities instead. By now it is understood that an individual's efficient usage of their GHC can be hindered by missing resources. However, having the right resources does not ultimately mean having them all. The concept of person-organization fit aptly describes how similarity and complementarity between in-house and incoming human capital, in addition to an organization's general capabilities, can impact the effective exploitation of an individual's GHC (Campbell et al., 2012; Raffiee & Byun, 2020). Therefore, it is possible that a transferee finds more complementary assets at a new organization, allowing them to utilize their GHC in a more efficient way (Campbell et al., 2012; Raffiee & Byun, 2020). This can lead to an equal or higher individual post-performance regardless of the new firm's higher or lower capabilities. Their improved performance is simply a result of their better fit with the new organization.

6.2.3. Position Similarity

Another factor impacting transferee performance lies in the similarity between former and new positions. In a study of General Electric (GE) managers, Groysberg and colleagues found that those transferring within the industry experienced less negative performance than those switching industries. The reason is simple: organizations within the same industry show higher similarity, and with this, firm-specific knowledge retains more value than it would when changing industries (Groysberg et al., 2006). Campbell et al. (2014) come to a similar conclusion by stating that a move between very similar firms can still lead to a performance drop, however, it can decrease the size of this drop and speed up recovery.

From these examples, it can be concluded that more resources are in general beneficial. However, there are situations where fit is more impactful for a transferee. While firm capabilities can thus have some bearing on the success of a transfer, fit can lead to unexplainable effects that result in a transfer being more successful than expected.

6.3. Organizational Differences in Soccer

In the soccer context, the above-explained theoretical background finds good application. We can observe how the quality of club and league can impact the market value the public assigns to a player. On the other hand, the mediating effect of transferring with colleagues is more difficult to capture in the soccer context. While it is unlikely that a club buys two players from the same club simultaneously, it is quite likely that a player will encounter previous teammates from other tournaments. In general, soccer players are highly trained to adapt to new teammates (Campbell et al., 2014), therefore the effect of missing ties to players should be faster eradicated than in the organizational context.

6.3.1. Club Quality Effects

In the soccer context, transferring clubs can impact both the player's performance and how the market views the player. The market can thereby interpret a move of a player to a higher or lower quality club in different ways. In general, higher-quality clubs, as in the organizational context, give rise to positive reputation effects for the player. These reputation effects can be due to generally higher performance and team success in these clubs (Frick & Simmons, 2008; Payyappalli & Zhuang, 2019).

First, a higher-quality club is often accompanied by higher-quality teammates (Weinberg, 2016). Since in the end soccer is a team sport, higher-quality teammates will ultimately increase the team performance in which one partakes. Additionally, higher-quality teammates greatly raise the level of play, increasing both team performance and personal development.

Second, a better club often comes with better facilities and support. These resources include both equipment and support staff. It can make a difference for a player how good training facilities, food, physiotherapists, doctors, and coaches are (Miller & Manner, 2014). A player's performance will thus be affected by the resources surrounding them.

Club reputation is clearly beneficial to the market value of both the player and the club itself. In a small study, Majewski (2016) draws a connection between the club's market value and the market values of its forward players. A better club reputation increases the club's bargaining power in the market, contributing to better conditions for their players (Costa et al., 2018). As in the organizational context, a player's former club can provide useful insights into the player's quality to a potential buying club (Weinberg, 2016). Soccer players are thus also affected by the reputational effects of their current and former clubs further into their careers. Therefore, we assume the following:

Hypothesis 2: "Players transferring to higher quality clubs experience an immediate positive effect on their performance"

6.3.2. League Quality Effects

As with club quality, the league a player plays in can also be a signal of their quality and performance. Thereby, the big five leagues of Europe: Spain's LaLiga, France's Ligue1, England's Premier League, Germany's Bundesliga, and Italy's Serie A are often seen as the most desirable in the industry. There are differences in both characteristics and pay between these leagues, making transfers between the five attractive, but first and foremost, it is attractive to transfer to any of the five (Frick, 2007; Yi et al., 2018). Lago-Peñas et al. (2019) show these transfers to be especially attractive for players from countries with lower-quality domestic leagues. For them, a good national team performance at the FIFA World Cup can provide them the needed attention to secure a contract from a club in the big five leagues. A league transfer like this will augment resources, improve reputation, and increase the quality of play of the player (Costa et al., 2018; Lago-Peñas et al., 2019). Moving to a more prestigious league, like a more reputable firm, can also be a stepping stone for moving to a top club.

Therefore, we assume:

Hypothesis 3: "Players transferring to a higher quality league experiences an immediate positive effect on their performance"

6.3.3. Person-Organization Fit in Soccer

As in the organizational context, we expect a soccer player's performance to be influenced by unanticipated factors. As these effects are unmeasurable, we must accept that some players will not move in the predicted way.

For example, the different leagues, especially within Europe, are known to carry different characteristics. Logistically, the weather and the total number of soccer clubs in each country determine whether there is a seasonal break and how many games are being played (DFL Deutsche Fußball Liga, n.d.). Additionally, the style of play employed by each league carries different archetypes of culture, history, and social factors (Yi et al., 2018). The English Premier League is said to be the most aggressive, while the Italians are seen as more tactically and defensively oriented. The Spanish seem to focus on ball possession, and the Germans and French fall somewhere between the high value placed on physically-able players and more defensive tactics (Yi et al., 2019). Depending on a player's characteristics, it is thus possible that they can exploit their own talent better in one league or another.

Additionally, transfers to lower-level leagues are more common as one ages. For example, elements such as reputation are more highly coveted in different leagues, compensating for decreased playing performance due to age. Especially in recent years, the Chinese Super League has recruited many former top players (Gai et al., 2019). Major League Soccer (MLS) in the US and the Canadian League have also become go-to places for aging players (Lago-Peñas et al., 2019). As these players are clear upgrades for the clubs, they might receive more attention and playing time. Thus, this move may have positive effects on both the players' and clubs' market values, which would not be realized in higher-level leagues. One example of this is David Beckham's move to the MLS club LA Galaxy from Europe. In this case, LA Galaxy both benefitted from his talent in addition to his well-reputed brand and reputation (Harris, 2014). It is these factors related to person-organization fit which are hard to capture and can explain why this study's model will not fit all players.

7. Performance Recovery

A transferee's performance drop does not have to be permanent. While some transferees will not experience a drop, others will recover over the short- or long-term once they have overcome the loss in firm-specific knowledge by acquiring the new firm's firm-specific knowledge. Thus, while the magnitude of a performance drop is determined by the use value of a transferee's firm-specific human capital at the new firm, its recovery is determined by a transferee's ability to acquire new firm-specific knowledge (Campbell et al., 2014). As touched upon earlier, the nature of a position focused on exploitation, in comparison to exploration, can be beneficial towards speeding up the recovery (Groysberg & Lee, 2009). Similarly, a move to a firm with higher capabilities, compared to one with lower capabilities, is favorable (Groysberg et al., 2008).

In the soccer context, we assume players to be accustomed to adapting to new environments and teammates (Campbell et al., 2014). Therefore, we assume their recovery to be faster than it can be seen in the organizational context. Compared to the organizational context we, therefore, assume the overall number of players showing a performance drop to be lower than it would be expected in the organizational context.

8. Methodology

8.1. The Database

The data for this study has been sourced from Transfermarkt.com (Transfermarkt). Transfermarkt is an independent, public German website owned by Axel Springer SE, a European publishing house (Felipe et al., 2020). Transfermarkt provides soccer player data on all major leagues and players over an extensive timeframe, utilizing both expert and crowdsourced judgments (Felipe et al., 2020; Franck & Nüesch, 2008).

8.2. Research Approach

8.2.1. Market Value as a Performance Measure

Many methods of assessing a player's performance have been used within soccer research. A particular challenge relevant for reliability and validity in both the soccer and organizational contexts is the difficulty of fully isolating an individual player's performance from a team's (He et al., 2015). As Lombardi et al. (2019) did in their related research, many researchers use a combination of appearances, goals, and assists to create performance measures for players. However, there is a lack of agreement on which factors should be included in these measures (Franck & Nüesch, 2008; Lombardi et al., 2019). Most also acknowledge that these types of measures disadvantage positions which are less involved in direct scoring, such as goalkeepers and defenders (He et al., 2015), often leading to their exclusion in research. Thus, measures such as these are not impartial and raise concerns as to what type of performance they are measuring.

Instead of creating a new performance measure, we opted to use the frequently utilized performance measure of a player's market value to maintain our research's focus. Additionally, while counter-intuitive, an individual's market value offers a level of content validity higher than that of more limited measures such as goals scored. A player's market value reflects a variety of factors, including those pertaining to that playing position. The main elements contributing to a player's market value are their characteristics, performance, and popularity (Müller et al., 2017). This includes factors such as age, height, footedness, nationality, and position, as well as a player's playing time, goals, passes, dribbles, fouls, yellow and red cards; a player's media presence also influences their market value (Müller et al., 2017). These are factors that are directly related to a soccer player's performance, implying construct validity of the market value measurement. Numerous studies have been conducted to study technical, physical, tactical, and psychological factors' contributions to a player's performance (see Hughes et al., 2012; Yi et al., 2018). So, while the market value could capture other unrelated factors and noise, it offers a more comprehensive and theoretically grounded performance measure than we could create ourselves for the scope of this study. It is an imperfect measure, but it is most fitting as this study aims to examine post-transfer performance changes; it does not aim to determine how to best measure a soccer player's performance.

Transfermarkt provides market values of many players across countries and leagues, offering the benefit of all players being subject to the same overall method of evaluation rather than evaluating each playing position with a different measure. It uses a blend of methods to determine market values: first, it crowdsources values and then allows more experienced users, or "judges," to adjust and finalize the values (Felipe et al., 2020, Müller et al., 2017, Prockl & Frick, 2018). While it cannot be known what exactly users consider every time they submit a market value, the method is built on a reliable fundament. Crowdsourcing is based on the seminal experiment from Galton (1907) in which the averaged guesses of an unbiased crowd were able to determine the correct weight of an ox within a small margin (Prockl & Frick, 2018). Transfermarkt makes use of this "wisdom of crowds" principle by letting hundreds of thousands of users, without any financial incentive, individually evaluate and judge players in the first round (Müller et al., 2017). To avoid emotional or biased opinions from purely crowdsourced data, in the second round, judges weigh in to ensure the quality of the market values (Felipe et al., 2020). This practice does mean a judge's opinion is more highly-valued than a regular participant's, which is helpful to retain quality but can be seen as a breach of democracy (Felipe et al., 2020). Another possible source of bias, however, is that information about and market value estimates of lower-profile players can be more limited (Müller et al., 2017).

Nonetheless, within soccer research, Transfermarkt is an often-used data source, indicating its reliability (Felipe et al., 2020; Franck & Nüesch, 2008; Lombardi et al., 2019; Sæbø & Hvattum, 2015). Another sign of its data quality is that Transfermarkt's market values have been found to be good predictors of actual transfer fees and salaries (Felipe et al., 2020; Herm et al., 2014) as well as its utilization by clubs during real negotiations (Herm et al., 2014). Investigating the reliability of Transfermarkt's market values, Prockl and Frick (2018) find that the market values are a good proxy for players' salaries and that they are driven by a player's skill rather than simply former salaries. They also find that despite Transfermarkt's non-purely democratic method, the market value results adhere to the "wisdom of crowds" principle and can be modeled by the Bass model (Prockl & Frick, 2018).

The conceptualization of a player's performance as their market value is highly relevant to the organizational context. A player's market value describes the value a player provides to the market, and with this, the club's willingness to pay for a player (Felipe et al., 2020; Herm et al., 2014). This willingness to pay is, similar to as in the organizational context, based on the impression the market has about the player's, or in the organizational context the knowledge worker's, qualities.

8.2.1.1. Biases in Market Values

While it is a major benefit that market value is a measurement applicable to all positions, a downside to the market value is that it can be unequally affected by the position of the player and the season of the valuation. Different positions are systematically valued more highly, which can negatively impact validity. Since these are predictable biases, we chose to build the dependent variable as a percentage change and undertake other changes to control for these. With the dependent variable being a percentage change, each player's post-transfer performance is only compared to their individual pre-transfer performance, rather than that of other positions'. To increase across-position comparability, methods to adapt the market value due to inflation and position were used. It is important to note that the changes made do not impact the performance measure in the dependent variable. Since we are using the percentage increase, any inflation adaption does not impact the results compared to the original numbers, since the multiplication coefficients stayed constant. The changes thus only affect the model's independent variables by providing a measure of potential performance.

A clear increase in the market's willingness to pay for a player over the recent decade can be observed in both the literature and the data (He et al., 2015). Besides a difference between soccer seasons, we are also aware that the market values various positions to differing degrees, forwards most highly, then midfielders, defenders, and goalkeepers (He et al., 2015; Müller et al., 2017). These changes can be attributable to different sources; while the game and demands on players have changed, soccer's fanbase has simultaneously grown. With an increasing fanbase, the market's willingness to pay for a player increases, which can explain increasing market values and transfer fees besides actual changes in the player's performance. Therefore, we assume two average players from the 2010/2011 and 2019/2020 seasons to be objectively similar in performance despite the 2019/2020 player's higher market value. The discrepancy in the market values between these two comparable players is simply due to the market's higher willingness to pay in the 2019/2020 season on top of the indirect effect of inflation on salary. We argue that this logic holds not only between seasons, but also between positions. Forwards are more visible on the playing field, and thus garner the most attention from the market (He et al., 2015). However, in performance level, an average forward should be objectively as good as an average goalkeeper in their respective positions when playing on the same team.

Since this study both runs across ten seasons and all four positions, we decided that ignoring these systematic biases would wrongly impact the predictions of this model. Including a player's un-adjusted market value or transfer fee would inaccurately represent the relationship between a player's pre- and post-transfer performance. Within the literature, we were not able to find a study trying to account for a similar bias. However, two sources have created their own versions of a transfer price index, the Tomkins Times and the Totally Money website (*About TTT*, n.d.; Totally Money, n.d.). The Tomkin Times, originally a blog started by a former columnist for Liverpool FC, created their transfer price index to provide directly comparable transfer values by applying the same reasoning as the Retail Price Index (RPI), a UK inflation measure (*About TTT*, n.d.). Though their exact calculations are not made publicly available, there are insights that the index is based on both the overall market changes but also the individual's transfer history, assigning individual or team-based inflation factors to each player (Wilkinson, 2018).

Despite the lack of details, the existence of these resources gives credence to the need to inflation-adapt both the market values and transfer fees. Similar to The Tomkin Times' basing their transfer price index on the RPI, our inflation adaptation practice is based on the Consumer Price Index (CPI) of the US. The CPI describes how much the same basket of goods costs in a specific year compared to a base year, of which the percentage change is the consumer price inflation (Oner, 2012). One can apply the logic of the CPI also to smaller groups of goods (Oner, 2012). Based on the data available, we can designate the average market value per playing position and season as a "basket". Thus, the "basket" in this application contains the 250 most valuable transfers per position each season, which should be comparable enough as a group between the years to comprise the fixed basket for this inflation calculation. One could assume averages to increase in seasons after major events like the FIFA World Cup or UEFA European Championship. In our research, this occurs in the 2018/2019 season, but we do not find this to be reoccurring for other event years.

The changes between market value averages per position and season to the base year, the season 2019/2020, represents the price inflation for soccer players' market values. As a first step, we thus multiplied each player's market value and transfer fee with the coefficient for their position and season to "inflation-adapt" their market value. As a next step, we calculated the systematic difference between positions, with the forward player being the base group, and multiplied each player's inflation-corrected market value and transfer fee with their positional factor (see Appendix A). Comparing the inflation-adapted transfer fees after only the season factors, we find similarities to the Totally Money's Transfer Index adapted transfer fees, especially in their trends.

With this adjustment, every player is assigned a market value and transfer fee which is brought up to the market value level of a forward player in the season 2019/2020. We are aware that this rather easy way of equalizing market values to a non-discriminating performance measure can be criticized. However, we see this as the best and simplest method to create a performance indicator free of systematic biases obscuring a player's potential value.

8.3. Data Collection

Transfermarkt does not provide downloadable Excel files with the needed data points. Therefore, to collect data from a large number of seasons and across multiple web pages, we wrote and utilized Python code to source data from Transfermarkt's website. The Python code was written using Python 3.8, relying heavily on the Python library Beautiful Soup 4.

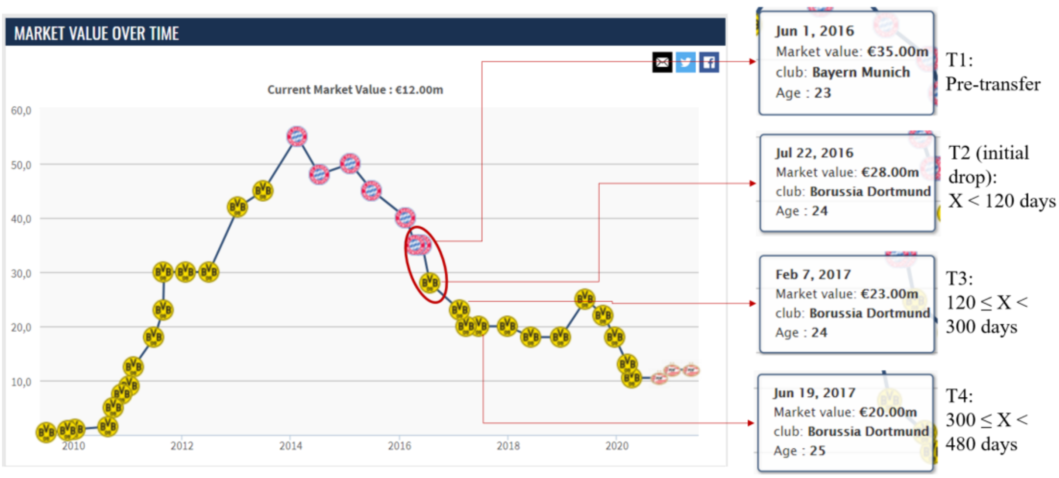
This study's data set includes extensive information to build the necessary variables with the goal to answer the research question. As a starting point, the data collection is based on the 250 most valuable transfers per season by the four main positions: goalkeeper, midfielder, forward, and defender (hereafter referred to as top 250 list). The top 250 list per position is provided by Transfermarkt, but it unfortunately only provides data on 1000 of the most valuable transfers per season. However, using the top 250 lists is beneficial as its structure allows automation to be used in the data extraction with a low error rate.

Additionally, since it captures roughly 1000 transfers, the top 250 list also provides a list of players with a wide range of market values and is thus not limited only to the players with the highest values. A total of 6,378 soccer player transfer occurrences were included in the study's sample, with roughly 30% of the transferring players being defenders, 29% being midfielders, 30% being forwards, and 11% being goalkeepers. The transfer occurrences were of players between the ages of 16 and 38, with the average player being a bit older than 24 at the age of transfer. After inflation-adapting the market values, we find the lowest market value to be 80,000 Euros, the highest market value 254.626 million Euros, and the mean market value to equal 13.070 million Euros.

After investigation, we found this data source to reach back in a reliable fashion until the season 2010/2011, with seasons prior to this often lacking complete market value data for many players. Prockl and Frick (2018) found a similar trend in the market values for American Major League Soccer players in their study, where market value availability greatly increased after 2011. Starting from the top 250 list for each season and position, the code collected data from all entries in the chart, then it opened each player's individual player profile page, and from there, their transfer chart and market value graph. In total, four webpages were used for data extraction for each player listed on any of the 10 seasons' and 4 positions' top 250 lists. From the top 250 list, the code was programmed to pull the market value of the player at the time of transfer, the season, the names of the former league and club, the names of the new league and club, the transfer fee, and the age at the time of transfer. Additionally, the code sourced details of the player's transfer history from their transfer chart. Using the transfer fee, the former club, the new club, the market value at the time of transfer, and the season from the top 250 list, the correct transfer entry was located in order to extract the exact date of transfer.

This date of transfer was utilized to extract a maximum of three additional market value measurements from the market value chart if values existed that met our criteria (see ***Figure 2***). The code was written to extract a T2 value if the market value measurement was more than 0 days but fewer than 120 days after the date of transfer. This timeframe provided an acceptable number of cases while still providing a measurement close enough to transfer for a post-transfer comparison. After that, the time spans encapsulate a window of 6 months, as not all players are measured at the same frequency. As such, the acceptable date range for T3 was more than or equal to 120 days and fewer than 300 days after the date of transfer. For T4, the acceptable date range was more than or equal to 300 days after transfer and fewer than 480 days after the date of transfer.

Figure 2: *Player's market value taken from Transfermarkt, showing the points extracted for T1, T2, T3, and T4*



The number of available market values for each player can vary widely, as due to the system of crowdsourcing, a high number of assessments for each player must be reached. This naturally is reached faster for more prominent than non-prominent players (Felipe et al., 2020). If there were multiple eligible market value measurements recorded within a single time frame, the first and earliest point in the time frame was extracted. These fairly narrow time frames were selected with consideration for the relative brevity of a soccer season, and the nature of the soccer sample allows for this in comparison to an organization, where performance measurements especially before and after an inter-organizational transfer are not conducted as frequently or in a standardized manner across firms.

8.3.1. Data Extraction Challenges

Occasionally, Transfermarkt showed discrepancies in the spelling of club names. For example, Dinamo was spelled Dynamo depending on the page. This occasionally led to transfer occurrence listed on the main transfer record page not being found, as this relied on a positive match of the club's name. The exact number of occurrences for this error is unknown, but it was noted it occurred in a few Chinese clubs in addition to the one Russian club previously mentioned. Best efforts were given to reduce any error sourcing from spelling or special characters, however, if Transfermarkt's spellings were inconsistent, these errors were inherited by our data set, leading to the data entry being deleted.

All data extracted from Transfermarkt via Python were stored in separate Excel files. Further details about the different variables generated based on extracted information will be given.

8.4. Data Cleaning

In the first step, all forty Excel sheets were merged into one singular Excel file. After this step, the data has been cleaned in the following manner. First, any players lacking a functioning profile link, market value chart, or matching transfer entry on their transfer chart on Transfermarkt were noted in the file at the time of data extraction and subsequently deleted. Second, deletion took place based on whether a market value for the time point T1 was in place. Since this T1 market value is crucial to create any of the three dependent variables, players missing this value were without use. Third, each player had to have at least one market value at a later time point (T2, T3, T4) value besides T1. Since one of these time points is needed to create at least one dependent variable, the absence of these lead to a player's deletion. This cleaning, based on the above-described steps, eliminated most players with irregularities in their documentation from our data set. Lastly, players with missing values for league or club belongingness were checked individually. If their information could not be identified, they were deleted from the sample set. In total, data cleaning reduced the number of player observations from N=8536 to N=6378.

8.5. Variables

Variables for this model were directly extracted from Transfermarkt or created in Excel based on the extracted data.

8.5.1. Dependent Variables

%ΔT2 / %ΔT3 / %ΔT4: The analysis uses three different dependent variables. These variables capture a player's change in performance at three different time points after transfer. As described above, market value is used to measure performance in this study, and these terms will be used interchangeably hereafter.

There are two ways one can account for a player's change in performance: the absolute or relative percentage change in performance. We decided to use the relative percentage change (hereafter percentage change). The percentage change provides several benefits for this study. It provides a measure to compare a player's post-transfer performance in relation to their pre-transfer performance. Thereby, it must be noted that due to its nature the percentage change over-represents the performance increase of players starting with low market values compared to players with high market values. Since theory suggests that marginally more talent is remunerated disproportionally highly (Weinberg, 2016), we see the percentage change to capture this theory better than the absolute change. Using the absolute change would over-represent the performance change of high market value players. Since their slightly higher performance is already remunerated disproportionally, the absolute change would over-represent their performance change even more. An additional factor advocating for the percentage change within this study is the use of the above-described data smoothing. Using the percentage change, players are compared against themselves. As the change in the market's willingness to pay has not increased significantly between the measurements taken for each player, a player's percentage change in performance is unaffected by both discrimination over position and season. When using the absolute difference, we would have to apply the inflation adaption to the dependent variable to account for the biases across seasons and positions.

We created the percentage change in performance by calculating the differences between T1 and T2, T3, and T4 and divide them by the player's T1 market value. Any positive value shows a percentage increase in performance, a value of 0 shows no change in performance and a negative value shows a drop in performance. In total, we are able to predict the following number of cases for each dependent variable: %ΔT2, n=3542; %ΔT3, n=5700; %ΔT4, n=4977.

8.5.2. Independent Variables

Club Quality (CQ): This variable is created to test whether a change in organizational capabilities affects transfer success, based on Groysberg et al. 's (2008) argumentation. To test this, we extracted each player's former and new club from Transfermarkt. To capture whether a player moves to a more, equally, or less reputable club, we created a club ranking.

Table 1: Club Quality Groups

Group	MV Bracket (mil €)
1	> 700
2	400-700
3	250-400
4	150-250
5	100-150
6	50-100
7	30-50
8	15-30
9	7.75-15
10	< 7.75

To rank all clubs, we data scraped the market values from Transfermarkt's list of the 100 most valuable clubs per association football confederations (AFC, CAF, CONCACAF, CONMEBOL, OFC, UEFA). Next, we compared them against all clubs in our data set. All clubs present in both lists were consolidated in one Excel sheet. These clubs were then ranked based on their market values. In total, 10 groups were created with decreasing market value brackets (***Table 1***) and each club was assigned the corresponding group number in the data set. Several clubs were not listed within the club lists available on Transfermarkt. This was especially true for the European UEFA league since the list only shows the highest-ranking clubs of their leagues. The highly valuable UEFA league makes it harder for its clubs to be ranked on this list. Therefore, we inspected cases of unranked clubs individually. For those in one of the big five European leagues, market values for each club were easily identifiable allowing us to place them in the right group. For clubs in leagues outside of the big five and second-tier league clubs, market values were harder to retrieve. Therefore, we looked at the direction in which a player was moving to assign them the right group; this will be described more in detail below.

The groups are deliberately covering smaller changes in groups of market value for two reasons. First, we assume diminishing returns with increasing market values. Second, there is increasing density towards the lower end, therefore a player's transfer between two low-end clubs can still present a significant increase to the player. The full table of club groupings can be found in Appendix B.

As a next step the variable accounting for an up-, even-, or down-grade was created by filtering the ten different groups against each other. When a player upgraded to a better group, thus a lower group number than their former club, they were assigned a 1. When they stayed in the same group, they were assigned a 0. When they downgraded to a lower club group, thus a higher group number, they were assigned a -1. Since it is most important with this variable to capture an upgrade, downgrade, or an equivalent move instead of placing a club 100% accurately into the right group, we decided to continue with the few players whose clubs' market values were not retrievable in the following manner. We assumed players moving from one of the big five countries' second league clubs to another one of the big five countries' first league clubs to be an increase in club value, and so we assigned them a 1. After this step, there were very few cases left lacking information on both their former and new clubs. We decided to label those with a 0, representing no quality change between the clubs.

League Quality (LQ): Like a club change, a league change can also have reputational effects and involve changes in quality or capabilities. For every player, their former and new league were extracted and included in our data set. To rank whether a player moves to a more reputable league, we again consulted different sources. First, we looked at the stated market value for the league on Transfermarkt. Second, we used the UEFA association club coefficient over the last years to rank the European leagues (UEFA, 2021). Third, we used the FIFA ranking of Latin American soccer teams (FIFA, 2021). Based on this information, we did our best to group the 115 different leagues, which included mostly European and Latin American first-, second-, third-, youth-, and regional-tiers. We created five groups in total. Due to their world-renowned status, we defined the major five leagues as the first group, thus the leagues with the highest possible reputation. The second group includes some of the strongest other European as well as Latin American leagues. We chose to rate a country's second-tier league always one group below the country's first-tier; a third-tier or junior league, always two groups below the country's first-tier. All regional leagues are assigned to the lowest group, group five. We assigned each player a ranking for their former and new league from 1 to 5. A full list of the league grouping can be found in the Appendix C. As a next step, the variable accounting for an up-, even-, or down- grade was created by filtering the five different groups against each other. When a player upgraded to a better league, they were assigned a 1, when they stayed in a similar quality league, they were assigned a 0, and when they downgraded to a lower-quality league, they were assigned a -1. Since the grouping of leagues can be perceived differently, we made sure to check the direction of any questionable transfers between leagues. The main goal with this variable is to capture a possible difference in reputation and capabilities when changing between leagues, it is less important in which exact group a league is placed, but rather that the reputational effects of a player's movement between leagues are correctly accounted for. Therefore, since we only concentrate on moving up, equal, or down but not the size of this movement, a misplacement in groups can still account for the right reputation movement.

Transfer Fee (TF): A player's transfer fee represents a club's definite willingness to pay for a player. It is often said that a transfer fee, therefore, represents a player's real performance from the perspective of the buying club (He et al., 2015). It is the monetary cost of buying a player out of their contract with another club for immediate transfer rather than waiting until their current contract expires. A player's transfer fee is impacted by their market value, however, the final fee can vary between clubs based on how valuable the player is to the specific club. This data set excludes loan fees since these are said to be significantly lower than the transfer fee a player could achieve (Payyappalli & Zhuang, 2019). Due to the limited amount of loans in this data set, we do not account for them. As both market values and transfer fees discriminate over position and season, we accounted for this by adjusting the transfer fee by the previously-described method.

Under 21 (U21): Youth players can be hypothesized to base more of their performance on GHC instead of FSHC due to their lower experience. When a youth player enters the adult soccer market, both their real performance and the attention they receive increases. This can cause their market values to skyrocket. For this study, youth players are considered those under the age of 21 as there are competitions dedicated for those in this age group. Additionally, from our data set, we observe that most youth players seem to receive their first real contract and serious market value estimation at an age between 18 and 21. Thus, we account for this by assigning a 1 for a player under the age of 21 and a 0 for older players.

Age: Age at transfer influences a player's performance. First, aging's effects on the human body must be considered when using a sample of athletes, which leads to an inverted U-shaped curve of performance with increasing age (Lehmann & Schulze, 2008). Secondly, as one ages, one's mental flexibility declines and rigidities set in. Thus, age is accompanying by rigidities and fatigue. A soccer player is said to increase in performance until the age of 25.4, after which they begin to decline in performance (Lehmann & Schulze, 2008). The data set includes every player's age at the time of transfer extracted directly from Transfermarkt.

Positions (Goalkeeper (GK), Defender (D), Forward (F), Midfielder (MF)): A main goal of this study is to identify whether the characteristics of a position can impact its performance portability. In the case of soccer, this can be easily operationalized by controlling for the position in which a player plays. Therefore, four dummy variables for the four different positions are included. The dummy variable takes a value of 1 for the position the player plays in and 0 for the other positions. Some players occasionally switch positions, however most switches happen within the sub-position under the main four groups. He et al. (2015) found in their study that though there were significant differences in the market values between the four position categories, differences between sub-categories within the four positions were insignificant. For this reason, we chose to categorize players into goalkeepers, defenders, forwards, and midfielders, rather than specific types within these positions.

MV Pre-Transfer (MV T1): A club's interest in a player is based on the player's performance before transfer. The higher a player's market value is, the higher their performance should be. With a higher market value, there is reason to believe their performance is built on more portable factors, differentiating them from their team member. For this reason, we control for the market value a player had before the transfer. Since the market value is included in the model in an absolute form, we inflation adapt this variable as described previously.

Bottom 5% (B5%): The players with market values in the bottom 5% of the overall sample often show abnormally high percentage changes in performance. This is due to two reasons. First, the players start with a very low market value, allowing them to multiply their initial value easily with a low increase in their absolute value. Second, players included in the top 250 list with very low market values are likely to have been underrated beforehand. Due to the lack of earlier attention, the market did not evaluate their performance correctly. With a transfer these players receive greater attention, leading to a substantial increase in their market values. We use a dummy variable to control for this. A value of 1 is assigned to any player in the bottom 5% of this sample set, based on their adjusted market value at T1.

Interaction Variable Between Under21 and Bottom5% (U21B5%): Besides accounting for Under 21 players and players in the bottom 5%, the interaction between these two variables creates a separate, non-correlated group. While some youth players are departing from a reputable youth club to their first big club and with this have received considerable attention already at a young age, others are coming from less visible youth clubs and have not received this attention, while potentially showing the same real performance. In those cases, their market value prior to transfer is extremely low, placing them in the bottom 5% of market values. These players are thus a very specific group which have been undervalued both based on their age and their former club. Often, these players will show very high increases in market value after transfer due to their severe undervaluation.

Interaction Variables Between Club Quality and Positions (CQGK, CQD, CQMF, CQF): The concept of firm/club quality affecting transfer success is a main argument in the existing literature. Within this research, we additionally explore the factor of positions on transfers. Combining both variables provides theoretically interesting insight into whether club quality also shows unequal effects depending on positions. To create these variables, we build interaction terms between the club quality variable and each of the four positional variables.

8.6. Model Specifications and Empirical Testing

All empirical testing in this study was performed using the statistical software IBM SPSS Statistics 27.

8.6.1. Regression Analysis

The main interest of this study lies in identifying how different factors affect the performance of a player after transfer. To do so, we apply multiple linear regression analysis. As described above we use three different dependent variables to show the initial impact (T2/T1 = Model 1) on performance, and the recovery over two subsequent time points (T3/T1 = Model 2; T4/T1 = Model 3). Thereby, the initial change in performance (Model 1) is of the highest interest. After consideration, we chose to assess two models. Regression A includes all independent variables excluding the interaction variables between the positional variables and club quality. Regression B includes all independent variables.

Regression A:

$$\Delta\%\, T_i/T_1 = \beta_1 + \beta_2 CQ + \beta_3 LQ + \beta_4 TF + \beta_5 U21 + \beta_6 Age + \beta_7 GK + \beta_8\, D + \beta_9 F + \beta_{10} MF + \beta_{11} B5\% + \beta_{12}\, MV\, T1 + \beta_{13} U21B5\% + \varepsilon$$

Regression B:

$$\Delta\%\, T_i/T_1 = \beta_1 + \beta_2 CQ + \beta_3 LQ + \beta_4 TF + \beta_5 U21 + \beta_6 Age + \beta_7 GK + \beta_8\, D + \beta_9 F + \beta_{10} MF + \beta_{11} B5\% + \beta_{12}\, MV\, T1 + \beta_{13} U21B5\% + \beta_{14}\, CQGK + \beta_{15}\, CQD + \beta_{16}\, CQMF + \beta_{17}\, CQF + \varepsilon$$

We run both regressions with all three dependent variables, leading to six regression models in total (Model 1A/B; Model 2A/B; Model 3A/B).

All six models show significance (p= 0.00) in their predictive power. Since the sample size with n > 3000 is considered large, and the data was gathered through random selection from a natural population, the Central Limit Theorem applies. Therefore, the requirement of normality does not apply, enabling us to ignore both the abnormal skewness and kurtosis factors for all dependent variables. The model was tested for autocorrelation using the Durbin-Watson Test. With all values lying between 1.73-1.95, there is a slight positive autocorrelation, however, these are within an acceptable range and do not pose any significant problems. Further, we tested for multicollinearity by using bivariate correlation statistics and the variation inflation factor (VIF) values. The bivariate correlation statistics show no significant highly correlated variables. The VIF scores also show values below five for all variables, thus only low to moderate correlations exist. Therefore, all variables are suitable predictors in this model.

All models show good predictive power for a study of this nature. Model 1A and 1B show the highest explanatory power both with a value of adjusted R^2 = 0.349 and 0.35 respectively (Model 2A/B, adj. R^2=0.231; Model 3A/B, adj. R^2=0.214).

8.6.2. ANOVA Analysis

We used ANOVA analysis to test for significant differences in the dependent variables between specific groups. To conduct ANOVA analysis, we created factors designating season and position.

Since the different factor groups show varying numbers of observations, we conducted the Levene's test for homogeneity. For both factors, season and position, and all three dependent variables, we find p<0.05, therefore the assumption of homogeneity is rejected for both factors. As a result, we run a robust test for equality of means by using the Welch test and the Games-Howell test as post-hoc tests.

The ANOVA analysis for differences between seasons shows significant differences between groups for all dependent variables. Analyzing the post-hoc test, it is mainly the season 2018/2019 which differs significantly from the other seasons (Appendix D). Considering the season's mean performance change score being the highest, it explains why the other seasons are considered different. This abnormality could be due to the 2018 FIFA World Cup. However, it is not a reoccurring phenomenon for the other seasons that had either a World or European Championship. We find it to have a very limited impact after testing to control for it in the regression models, and therefore we decide to proceed without controlling further for this.

The ANOVA analysis for positions shows there are significant differences between positions only for the initial percentage drop in performance, or Model 1 (Appendix E). Since the different positions are a main focus of this study, they are, as described above, included in the regression analysis as dummy variables.

8.6.3. Multivariate Multiple Regression

As a last step of analysis, we run a multivariate multiple regression. This method allows us to model multiple dependent variables against the same set of independent variables. Using this analysis, we can identify which independent variables have the largest effect size on the combined set of dependent variables. We run this multivariate multiple regression using our Regression B model. This means all interaction variables are included as independent variables. As dependent variables, we use all three time point percentage change variables (%ΔT2 / %ΔT3 / %ΔT4). We use the Pillai's trace statistics for interpretation, as this statistic is said to be most robust to any violation of assumptions.

9. Results

In order to interpret the results correctly, we have to consider the nature of the data set and the focus of this study. The main objective is to identify how the variables impact the initial change in performance (Model 1A/B). The later time points are used as a reference to see how the same variables impact recovery (Model 2A/B; Model 3A/B). The dependent variable is constructed as the percentage change in performance. Within the context of this study with the dependent variable indicating a monetary value, the percentage change has a lower bound of -1, in which a person loses 100% of their performance. Anything lower than -1 would not make sense, as players cannot have negative market values. However, there is not an upper bound on the performance increase based on the nature of the variable. An increase in performance can thus have a larger impact on the models than a decrease in performance. For Model 1, we see in total that 22% of the sample set (n=3541) experienced an initial loss in performance, 14% retained their performance, and 64% increased their performance. On average, the performance increased by a factor of 0.741. Since the dependent variable is computed in percentage change, this is equivalent to an increase of 74.1%-points. This increase of 74.1%-points is relative to the individual player's prior performance. For the later time points, we see increased sample sizes (Model 2: N=5698; Model 3: N=4972), and while the mean of the dependent variable falls to 0.656 for Model 2, it increases again to 0.903 for Model 3. For both models, the percentage of players increasing in performance is slightly lower than in Model 1 (Model 2: 53%; Model 3: 56%), while the percentage of players decreasing in performance increases (Model 2: 28%; Model 3: 33%).

When interpreting the coefficients, we thus note a few crucial elements for these results. Each coefficient presents an explanation for a positive or negative effect on the dependent variable. This means every independent variable influences the constant increasing or decreasing the final dependent variable outcome. Each individual factor alone can thus not predict whether a player will have a negative change in performance, no change in performance, a performance change equal to average, or an above-average performance change since all variables must be considered together to make the conclusion. We will interpret variables as explaining for an increase or decrease of x-factor or x%-points towards the overall effect. Each variable's effect is interpreted as a percentage change, however, the percentage is always in relation to that specific player's initial performance. Thus, the absolute value of the change will differ between players.

9.1. Regression A: Post-Transfer Performance Model with Club Quality as an Overall Effect

Regression A considered all independent variables with the exclusion of the club quality and position interaction variables. For Regression A, we find the highest predictive power in Model 1A (adj. R^2=0.349), and lower but still significant predictive power for Model 2A (adj. R^2=0.231) and Model 3A (adj. R^2=0.214). From these three models, we see that Model 1A can better describe the performance change taking place initially after transfer than Model 2A and 3A can describe subsequent performance changes.

In Model 1A, we find all independent variables to be significant ($p<0.05$). First, we find that a transfer to a higher-quality club can be beneficial for a player by explaining for a 10.9%-points increase in their performance compared to a transfer to an equal club. On the other hand, a transfer to a lower-quality club comparably explains a loss of 10.9%-points in their performance. This effect remains similar when moving towards Model 2A (0.078) and Model 3A (0.132). Second, a similar but stronger pattern can also be found in the context of a league quality change. In Model 1A, a transfer to a higher quality league can explain an increase in a player's performance by 19.6%-points compared to an equal league transfer and a decrease of 19.6%-points for a transfer to a lower quality league. This effect increases slightly in Model 2A (0.226) and Model 3A (0.24). Therefore, we find support for both Hypothesis 2 and 3, that an increase in either the club or league quality shows a positive effect on the transferee's performance.

Third, we find prior performance, in terms of transfer fee and market value before a transfer, to show opposite effects. The transfer fee variable shows a small positive coefficient of 0.023 (2.3%-points). This means a player benefits with a positive effect on their performance for each million € in inflation-adapted transfer fee. On the other hand, each million € in inflation-adapted market value can explain a decrease of 3.7%-points (-0.037) in performance. Since the values of transfer fee and market value lie close to each other (MV T1 μ= 13.070 mil €; TF μ=14.452 mil €), their total effect is limited. This means the effect prior performance has on post-transfer performance is limited in this study.

Fourth, age-related effects observed in this study align with prior findings of age effects on a soccer player's performance. The pure consideration of a player's age at the time of transfer shows a negative coefficient of 0.051 per year of age, which may seem small. To put this in perspective, the youngest player in this dataset is 16 years of age, thus age can account for a post-transfer loss of 81.9% for this player. An average-aged player (24.38) loses 124.34%-points, and the oldest player (38) loses 193.8%-points. Thus, the most important insight is the effect on differently aged individuals. An older player experiences a higher loss in performance after transfer compared to a younger player.

While we observe a direct linear relationship between age and performance change, the Under 21 variable offers more insight. It shows that being under the age of 21 can explain this player's performance increase by 26.7%-points after transfer. Thus, performance change after transfer also seems to show an indication of a u-shaped relation between age and performance change. We find for both variables that their impacts remain similar in Model 2A (Age: - 0.055, Under 21: 0.276), however in Model 3A they further intensify (Age: -0.094, Under 21: 0.424).

Fifth, the Bottom 5% variable seems to aptly capture the statistical artifact of our dependent variable: the propensity of initially lower-valued players to show larger percentage increases. The variable's coefficient shows that being in this group can explain a performance increase by 240.1%-points initially after transfer (Model 1A), and even higher increases at later points of time (Model 2A, 3.277; Model 3A, 4.262). The interaction variable combining the Bottom 5% and the Under 21 variables explains an additional increase of 342.6%-points for these players at time T2, and lower but significant impacts later on (Model 2A, 1.447; Model 3A, 1.8). From both variables, we see that abnormally high percentage changes in performance after transfer can be explained by the players' low initial market values which allows them to increase significantly percentage-wise without showing a large absolute change in market value.

Sixth, we observe that all four positions only show significant effects in Model 1A. Within Model 2A and Model 3A, only being in the goalkeeper position shows a significant effect. This outcome is in line with the results of the conducted ANOVA analysis, where Model 1A also is the only one to show significant differences between all positions. With these results, we find support for Hypothesis 1a by showing that different positions experience different impacts on their performance initially after transfer. In Model 1A, the forward position is excluded from the regression, as is normal when using dummy variables. This makes the forward position the neutral reference category, meaning that being a forward in Model 1A has no further effect on the outcome. Compared to being a forward, being a goalkeeper explains for a decrease by 96.4%-points of their performance change, being a defender explains for a loss of 15.9%-points in

Table 2 - Regression Results

	1. Percentage Change T2/T1 (%ΔT2)		2. Percentage Change T3/T1 (%ΔT3)		3. Percentage Change T4/T1 (%ΔT4)	
	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B
(Constant)	1.954**	1.83**	1.898**	1.894**	2.979**	3.055**
	(0.284)	(0.285)	(0.267)	(0.267)	(0.382)	(0.386)
Club Quality	0.109**		0.078*		0.132*	
	(0.038)		(0.036)		(0.052)	
League Quality	0.196**	0.194**	0.226**	0.226**	0.24**	0.238**
	(0.045)	(0.045)	(0.044)	(0.044)	(0.064)	(0.064)
Transfer Fee	0.023**	0.023**	0.027**	0.027**	0.028**	0.028**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Under 21	0.267*	0.274*	0.275**	0.276**	0.424**	0.422**
	(0.106)	(0.106)	(0.105)	(0.105)	(0.151)	(0.151)
Age	-0.051**	-0.051**	-0.055**	-0.055**	-0.094**	-0.094**
	(0.011)	(0.011)	(0.01)	(0.01)	(0.015)	(0.015)
Goalkeeper	-0.964**	-0.925**	-0.673**	-0.663**	-0.876**	-0.98**
	(0.111)	(0.123)	(0.101)	(0.112)	(0.146)	(0.159)
Defender	-0.159*				0.079	
	(0.072)				(0.102)	
Forward		0.1	0.056	0.057	0.103	0.05
		(0.08)	(0.07)	(0.077)	(0.104)	(0.113)
Midfielder	-0.24**	-0.1	-0.075	-0.066		-0.067
	(0.073)	(0.083)	(0.07)	(0.079)		(0.114)

Table 2 - Regression Results (Continued)

	1. Percentage Change T2/T1 (%ΔT2)		2. Percentage Change T3/T1 (%ΔT3)		3. Percentage Change T4/T1 (%ΔT4)	
	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B
Bottom 5%	2.401**	2.435**	3.277**	3.275**	4.262**	4.274**
	(0.169)	(0.169)	(0.174)	(0.175)	(0.245)	(0.246)
MV T1	-0.037**	-0.037**	-0.039**	-0.039**	-0.043**	-0.043**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Under 21× Bottom 5%	3.426**	3.408**	1.447**	1.448**	1.801**	1.795**
	(0.260)	(0.26)	(0.268)	(0.268)	(0.387)	(0.387)
Club Quality × Goalkeeper		0.346**		0.062		0.233
		(0.13)		(0.115)		(0.163)
Club Quality × Defender		0.02		0.087		0.158
		(0.067)		(0.063)		(0.09)
Club Quality × Midfielder		0.065		0.066		0.127
		(0.065)		(0.062)		(0.091)
Club Quality × Forward		0.17**		0.086		0.085
		(0.061)		(0.06)		(0.088)
F	165.873	130.962	148.533	116.649	119.804	94.143
Adjusted R^2	0.349	0.35	0.231	0.231	0.214	0.214
Observations	3382	3382	5400	5400	4801	4801

Values in parenthesis are standard errors.

$^{*}p < 0.05$

$^{**}p < 0.01$

comparison to the forward, and being a midfielder explains for a loss of 24%-points in comparison to the forward. This shows that simply the fact of being a goalkeeper can explain why a goalkeeper only reaches a post-performance level that is 96.4%-points lower than if they would have been a forward. The goalkeeper is also the only position which continues to perform consistently and significantly lower than the other positions (Model 2A, -0.673 compared to a defender; Model 3A, -0.876 compared to a midfielder). From the results we reject Hypothesis 1b and support Hypothesis 1c. While the assumption that goalkeepers will experience a lower negative effect on their performance is rejected, this hypothesis is supported for the forward position.

9.2. Regression B: Post-Transfer Performance Model with Club Quality as a Position-Specific Effect

Regression B is differentiated from Regression A by the inclusion of the four club quality and position interaction variables. The inclusion of these interaction variables does not change the predictive power for any of the three models compared to the use of Regression A by more than 0.001. Furthermore, the effect the change has on most of the independent variables is minimal, besides two changes which will be described next. First, the club quality variable is eliminated. At first glance, this is against expectations since one would interpret the interaction variables in relation to the main effect. However, when further investigating how the interaction variable is built, it becomes evident that the interaction variables and the main effect of club quality function as dummy variables. This means the four interaction variables together can describe the fifth variable: the main effect of club quality. While one might assume the interactions therefore to be highly correlated with the main effect, this is not the case. We can see that with this regression that only the goalkeeper remains significantly different from the reference group, the defender, in all the three models (Model 1B, -0.925; Model 2B, -0.663; Model 3B, -0.98). A further specification is that club quality only appears to have a significant effect on two positions and only in Model 1B. It shows that a move to a higher-quality club for a goalkeeper can explain a positive effect on their performance change by 34.6%-points compared to an equal club quality transfer, and a performance loss of 34.6%-points when moving to a lower-quality club. This effect is also shown for a forward player with a factor of 0.17. For the other two positions, a change in club quality does not show any significant impact on their performance change. From these results, it seems that a change in club quality affects a player differently based on their playing position.

9.3. Multivariate Multiple Linear Regression of Performance Measurements at Three Time Points

In the multivariate multiple linear regression analysis, we use the Pillai's trace values to identify which variables show the highest effect size on the dependent variables. We can find significant effects on all dependent variables for seven of the independent variables. All factors lie between 0.004 and 0.083. This means that even the variable with the highest effect, the Bottom 5% variable, has only a small overall effect on all three models. We conclude the independent variables are good at explaining each model individually but are not the strongest in explaining the combined models.

Table 2: Multivariate Multiple Regression Results - Pillai's Trace Values

	Dependent Variables: %ΔT2 / %ΔT3 / %ΔT4
(Constant)	
League Quality	0.004*
Transfer Fee	0.037**
Under 21	0.007**
Age	0.018**
Bottom 5%	0.083**
MV T1	0.061**
Under 21× Bottom 5%	0.048**

Note: Only significant variables displayed.

*$p < 0.05$

**$p < 0.01$

10. Discussion

From our analysis, we find several factors to impact the portability of an individual's performance after inter-organizational transfer. The data set, besides being based on the 250 most valuable transfers per season and position, shows a normal distribution of talent as Franck and Nüesch (2008) found in their study of players in the German Bundesliga. Thus, while looking at a sample set of high-performing soccer players, we are not exclusively looking at superstars.

In the organizational context, various researchers stress the difficulties for star transferees to replicate their prior performance initially after transfer (B. A. Campbell et al., 2014; Groysberg et al., 2006, 2008; Groysberg & Lee, 2009; Raffiee & Byun, 2020). Looking at our sample set of star soccer players, we only find partial support for this hypothesis. From our study, we find the players' post-transfer performance initially after transfer to be on average higher than their pre-transfer performance. Sixty-four percent of players in this sample set increase in their performance after transfer, as observed from Model 1A. Therefore, we assume three factors to impact this outcome.

First, the level of uncertainty about a transferee's skill is lower in soccer than in the organizational context. Since in soccer performance, data is more uniform and accessible (Franck & Nüesch, 2008; Weinberg, 2016), clubs benefit from having a better understanding of a player's qualities than employers would in the organizational context. Therefore, while star soccer players and star employees show many similarities in their characteristics, soccer clubs compared to organizations may be able to base their purchase decision on more objective performance data and with this, avoid an ill-advised purchase to a larger extent. Therefore, soccer players from high-quality clubs, who do not show promising pre-transfer performance, are likely to either acquire low-value contracts or no contract at all, and therefore are not captured in this data set.

Second, soccer players are highly trained to adapt to new teammates (Campbell et al., 2014). Therefore, their post-transfer performance may suffer less from a loss in colleague-specific knowledge compared to organizational transferees.

Third, Groysberg et al. (2008) show that organizational capability differences between a former and new firm can affect a transferee's performance. We find this concept to be highly relevant in the context of soccer, by finding clear support for the benefits of higher-quality clubs on a player's performance post-transfer. However, counter to Groysberg et al.'s (2008) focus on firm capabilities, we also assume reputational effects to be a main contributor to this mechanism. In their work, Groysberg and Lee (2009) describe a knowledge worker's reputation to be based on the department or firm in which they work. Since the performance measure of market value is based on crowdsourcing, we expect contributors to be prone to change their perception of a player when they associate them with a different club. Therefore, when a player moves to a higher-quality club, this can be perceived by the crowd as a sign of quality, stemming from their trust in a buying club's judgment of a previously undervalued or unknown player. On the other hand, a move to a lower-quality club can be interpreted as a decrease in a player's quality, since their prior club seems to no longer value them as highly as before.

Besides the effects of a club quality change, we find the same pattern in league changes. Thereby, we identify a move to a more reputable league to also show a positive effect on the player's market value. In prior research, it has been noted that especially for Latin American players, a move to a big five European league can be very beneficial (Frick, 2007). From these insights, we think that a change in reputation can have at least the same amount of impact on a player's performance as a change in capabilities in the field of soccer. Based on the sample set, we cannot generalize this to a larger population than the soccer industry, however, it appears to be a factor worth investigating further in other contexts.

Another main factor investigated in this study is the impact of position on post-transfer performance. We thereby find different positions to indeed experience different immediate performance drops after transfer, however, the overall effect is lower than expected. Thereby, one main insight is that counter to our assumption, the goalkeeper does not benefit from being in the most isolated position. Rather, we find the goalkeeper to be the most disadvantaged position in their post-transfer performance. Thus, we assume that the nature of market value measure as performance impacts this finding. As goalkeepers are valued least by the market and are the least visible on the playing field, we assume goalkeepers to be of lower interest for the crowd. In comparison to other positions, a goalkeeper's valuation by the market differs also differs due to their longer careers. Additionally, as there are few players reaching star status, this accomplishment can be seen as evidence of quality in and of itself. We can find support for this assumption when considering the effect of a change in club quality based on position. From this analysis, we see that for a goalkeeper, the effect of transferring to a better or worse club is larger than for any of the other positions. As a goalkeepers' quality may not be as temperamental in the eyes of the market, it can be understood how a change of club could be a disruptive surprise to the otherwise stable valuation. This might be connected to the fact that each club has a lower number of goalkeepers compared to other positions. Thereby, one player often takes the responsibility as the main goalkeeper. Thus, the reputational effects on a player's market value can be especially evident when a goalkeeper moves to a higher-quality club, where the smaller market size makes it harder to play for a top club. On the other hand, a move to a lower quality club shows the same reputational effect, as there is a larger negative effect on the goalkeeper's performance.

From these insights, we conclude that an individual's position impacts post-transfer performance, possibly indirectly. Thus, while the application of organizational theory showed its limitations in explaining for differences between the soccer player positions, the insights we gained do support the main argument that differences between positions exist. Considering this, further research could investigate positional differences in the realm of soccer. These insights provide good reason to believe positional differences also appear in the organizational context.

Besides these two main factors, we also find other factors making smaller impacts on post-transfer performance. As in the organizational context, we find age to affect post-transfer performance though the nature of this effect might be different. In the organizational context, as age and tenure increase, an individual's performance is expected to rely more heavily on firm-specific human capital, hindering adaption to new routines (Dokko et al., 2009). In the soccer realm, the natural effects of aging also lead to performance losses (Lehmann & Schulze, 2008), which we find support for in this study. Simultaneously, we also identify young players to perform better after transfer. This finding can be attributed to two factors. On the one hand, as in organizational theory, high performance at an early career stage can be a sign of performance highly-based on general human capital (Kang et al., 2018). On the other hand, especially in the case of soccer, we assume young players to be undervalued. This initial undervaluation allows their market values to skyrocket after their first transfer to a fully professional elite club. Age effects on performance portability between the organizational and soccer context are thus differentiated but share a similar overall declining trend with increasing age.

Besides these identified factors, we assume other unknown factors to play a role. Based on the results, we see that the model does not perfectly describe the performance change after transfer. Since soccer is a team sport and different soccer styles are being played across clubs, we thereby assume person-organization fit to play a significant role in a player's post-transfer performance as well. The better the player fits with the coach and team, the better we expect them to perform. Additionally, we anticipate factors such as a change in country to affect a player's performance. A change in culture, environment, and language can have effects both on the direct performance, but also on the subconscious well-being of a player, thus indirectly affecting a player's post-transfer performance.

In terms of performance recovery, we begin by reiterating that the initial post-transfer performance change is positive. Next, we identify performance to take a small dip in T3 and increase again towards T4. This trend is identified on the aggregate level, as our study does not follow the progression of an individual player's career. We also find that the effects of club quality are not consistent over time. It initially shows high importance, decreases somewhat towards T3, and then increases again by T4. Groysberg et al. (2008) discussed the sometimes negative effects of a manager buy-in on the stock price, as the market views the buy-in as less favorable than does the buying firm. In observation of temporary dips in both performance and importance of club quality between T2 and T4, connections to Groysberg et al.'s (2008) statement can be drawn. We assume that a player's initial post-transfer market value benefits from the reputational effect the club change has on the player's market value. However, by T3 this first spark fades, and the crowd becomes more critical in whether the player's performance actually lives up to the expectations created from their club upgrade. Therefore, the values of some players will be lower due to real performance declines, and others will lose market value due to the crowd being underwhelmed by their actual performance. We find this reflected in our descriptive statistics, which shows that immediately after transfer, 64% experienced a positive performance change, whereas only 53% of the sample set experienced this by T3. After this, the player has time to rebuild their performance in the eyes of a crowd. This concept is reflected in our sample set, where the percentage of players experiencing positive performance changes increases back up to 56% by T4. This could be a possible explanation for the observed aggregate trend, however, each individual player's progression is different, and overall, most players increase their performance over time.

From our analysis, we can see that there are various factors affecting a player's post-transfer performance. Thereby, while the study has been conducted in the realm of soccer, we believe that factors of reputation and position have shown to be worthwhile for exploration in the organizational context as well.

11. Limitations

Inevitably, this study encountered limiting factors. First, our choice of market value as a measure of performance presents a limitation to this study. A more direct measure of performance that is available and standardized for many players across positions would be preferable. Furthermore, the choice to use the percentage change in performance decreases comparability between players, as each individual's performance is compared to their prior performance. This measure does also allow some low-valued players to substantially increase their performance in percentage change, though their absolute value of their performance increase is comparably smaller than others'.

Furthermore, the chosen data set only includes the top 250 players per position. Additionally, the method of data extraction limited the measurement of possible variables of interest. Better methods of data extraction could exist which would enable more operationalization opportunities and the collection of a larger data set, allowing for higher external validity.

Additionally, we see room for improvement in the inflation-adaption of seasons and positions. While the used sample was already large in size, an even larger sample could provide more accurate inflation factors for seasons and positions and with this, improve the quality of this study. Lastly, the club and league ranking groups could be constructed differently, thus potentially providing additional insights.

12. Conclusions and Future Research

From this study, we conclude that a player's position, quality of the club and league to which they are transferring, age of the player, pre-transfer performance, and youth player status are influential on a player's post-transfer performance. We acknowledge that organizational theory does not fully explain these variables in the realm of soccer, as the spectator sport of soccer involves an emotionally-rich landscape in contrast to the organizational context. However, in combination with soccer research, organizational theory offers a unique glimpse at the similarities between a soccer club and an organization.

We also see avenues for further investigation in addition to those previously mentioned within our discussion. Unexplored in this study, nationality could be of interest in future studies. In this study, we opted not to attempt to disentangle any possible effects of nationality on post-transfer performance. The challenge with this population is the frequent movement of players between countries, especially those in Europe, the holding of multiple citizenships, and involvement in different national teams. However, nationality could be of renewed interest as there are maximum caps on the number of foreign players for leagues, such as the Chinese Super League, who are trying to grow domestic talent (Yu et al, 2020).

Additionally, this study included a wide range in age of players. Introducing more age brackets may be of interest to explore the possible differences in post-transfer performance of individuals at different ages.

Ultimately, with insights gained from this research, we hope to shed light on the differences between position and the illusive effects of reputation. We hope that further research will contribute to clarify how different positions and transfers are affected, in order to provide more positive transfer experiences to both individuals and organizations.

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Appendices

Appendix A

Table A: Inflation Adaption Coefficients by Season and Position

		Goalkeeper	Defender	Midfielder	Forward
Season	19/20	1.000	1.000	1.000	1.000
	18/19	0.948	1.364	1.332	1.402
	17/18	1.564	1.414	1.754	1.567
	16/17	1.611	1.924	1.785	1.974
	15/16	1.834	1.985	1.990	1.730
	14/15	1.527	1.949	2.301	2.162
	13/14	2.090	2.356	1.762	1.811
	12/13	1.903	2.415	2.094	2.126
	11/12	1.268	2.236	2.148	2.383
	10/11	2.623	2.704	2.392	2.416
	Positional Factor	3.263	1.663	1.192	1.000

Appendix B

Table B: Club Quality Groups

Group 1 **> 700 mil €**	**Group 2** **400-700 mil €**	**Group 3** **250-400 mil €**	**Group 4** **150-250 mil €**	
Atlético Madrid	AC Milan	Ajax Amsterdam	ACF Fiorentina	Sporting CP
Bayern Munich	Arsenal FC	AS Monaco	Athletic Bilbao	Stade Rennais FC
Chelsea FC	Borussia Dortmund	AS Roma	Brighton & Hove Albion	Torino FC
FC Barcelona	Everton FC	Aston Villa	Cagliari Calcio	TSG 1899 Hoffenheim
Liverpool FC	Inter Milan	Atalanta BC	Crystal Palace	US Sassuolo
Manchester City	Juventus FC	Bayer 04 Leverkusen	Eintracht Frankfurt	Valencia CF
Manchester United	Leicester City	Borussia Mönchengladbach	Fulham FC	VfB Stuttgart
Paris Saint-Germain	RB Leipzig	FC Porto	Getafe CF	VfL Wolfsburg
Real Madrid	SSC Napoli	LOSC Lille	Hellas Verona	Villarreal CF
	Tottenham Hotspur	Newcastle United	Hertha BSC	Zenit St. Petersburg
	Wolverhampton Wanderers	Olympique Lyon	Leeds United	
		Real Sociedad	OGC Nice	
		Sevilla FC	Olympique Marseille	
		SL Benfica	PSV Eindhoven	
		Southampton FC	Real Betis Balompié	
		SS Lazio	Shakhtar Donetsk	
		West Ham United	Sheffield United	

Appendix B

Table B (continued)

Group 5		**Group 6**	
100-150 mil €		**50-100 mil €**	
1. FC Köln	Granada CF	AS Saint-Étienne	Red Bull Bragantino
AFC Bournemouth	Levante UD	Atlanta United FC	RSC Anderlecht
AZ Alkmaar	Montpellier HSC	CD Cruz Azul	Santos FC
Bologna FC 1909	Norwich City	Celtic FC	Santos Laguna
Brentford FC	Parma Calcio 1913	CF América	São Paulo Futebol Clube
Burnley FC	RC Strasbourg Alsace	CF Monterrey	Sport Club Corinthians Paulista
Celta de Vigo	Red Bull Salzburg	Club Atlético Boca Juniors	Sport Club Internacional
Club Atlético River Plate	SC Braga	Club Atlético Vélez Sarsfield	SV Werder Bremen
Club Brugge KV	SC Freiburg	Clube Atlético Mineiro	Tigres UANL
Clube de Regatas do Flamengo	Sociedade Esportiva Palmeiras	Deportivo Guadalajara	
CSKA Moscow	Spartak Moscow	FC Nantes	
Dynamo Kyiv	UC Sampdoria	Fenerbahce SK	
FC Augsburg	Udinese Calcio	Galatasaray SK	
FC Schalke 04	West Bromwich Albion	Grêmio Foot-Ball Porto Alegrense	
Feyenoord Rotterdam		Inter Miami CF	
FK Krasnodar		KRC Genk	
GNK Dinamo Zagreb		Los Angeles FC	

Appendix B

Table B (continued)

Group 7 **30-50 mil €**		**Group 8** **15-30 mil €**		
Al-Ahli Jeddah	Club Tijuana	Al-Ain FC	Club Cerro Porteño	Nagoya Grampus
Al-Duhail SC	Columbus Crew SC	Al-Ettifaq	Club Necaxa	New York Red Bulls
Al-Hilal Riyadh	Defensa y Justicia	Al-Gharafa SC	CSD Colo Colo	Olimpia Asunción
Al-Ittihad Jeddah	Fluminense Football Club	Al-Jazira (Abu Dhabi)	Deportes Tolima	Philadelphia Union
Al-Nassr FC	Minnesota United FC	Al-Rayyan SC	Deportivo Toluca	Puebla FC
Al-Shabab Riyadh	Nashville SC	Al-Sadd SC	El Ahly Cairo	Pyramids FC
Asociación Atlética Argentinos Juniors	New England Revolution	Al-Wahda Mekka	Esperance Tunis	Querétaro FC
Atlas Guadalajara	New York City FC	Atlético Nacional	Esporte Clube Bahia	Real Salt Lake City
Beijing Sinobo Guoan	Orlando City SC	Barcelona SC Guayaquil	FC Dallas	San Jose Earthquakes
CF Pachuca	Portland Timbers	Botafogo de Futebol e Regatas	FC Tokyo	Sanfrecce Hiroshima
Club Athletico Paranaense	Racing Club	CA Peñarol	Gamba Osaka	Sharjah Cultural Sports Club
Club Atlético Banfield	Seattle Sounders FC	CD América de Cali	Independiente Santa Fe	Shenzhen FC
Club Atlético Independiente	Toronto FC	CD Universidad Católica	Jeonbuk Hyundai Motors	Shimizu S-Pulse
Club Atlético Lanús	UNAM Pumas	Ceará Sporting Club	Junior FC	Sport Club do Recife
Club Atlético San Lorenzo de Almagro		Cerezo Osaka	Kashima Antlers	Sporting Kansas City
Club Atlético Talleres		Chicago Fire FC	Kashiwa Reysol	Ulsan Hyundai
Club de Regatas Vasco da Gama		Club Atlético Colón	LDU Quito	Vancouver Whitecaps FC
Club Estudiantes de La Plata		Club Atlético Huracán	Los Angeles Galaxy	Vissel Kobe
Club León FC		Club Atlético Newell's Old Boys	Mamelodi Sundowns FC	Yokohama F. Marinos
Club Libertad Asunción		Club Atlético Rosario Central	Millonarios FC	Zamalek SC

Appendix B

Table B (continued)

Group 9 **7.75-15 mil €**				**Group 10** **< 7.75 mil €**
Al Qadisiyah FC	Club de Gimnasia y Esgrima La Plata	Independiente del Valle	Suwon Samsung Bluewings	CD Motagua Tegucigalpa
Al-Arabi SC	Club Deportivo Godoy Cruz Antonio Tomba	Independiente Medellín	Unión Española	Club Africain Tunis
Albirex Niigata	Club Nacional	Ismaily SC	Universitario de Deportes	Club Athlétique Bizertin
Al-Faisaly Harmah	Club Sportif Sfaxien	Jeju United	Urawa Red Diamonds	El Gouna FC
Al-Raed	Club Universidad de Chile	Júbilo Iwata	Vegalta Sendai	El Masry SC
Al-Wasl Sports Club	Coritiba Foot Ball Club	Kaizer Chiefs	Wydad Casablanca	El Mokawloon SC
Arsenal Fútbol Club	Cruzeiro Esporte Clube	Liverpool FC Montevideo		Enppi SC
Associação Chapecoense de Futebol	CS Emelec	Omiya Ardija		FAR Rabat
Audax Italiano	Daejeon Hana Citizen	Once Caldas		FUS Rabat
Avaí Futebol Clube (SC)	Dalian Professional	Orlando Pirates		Ittihad Alexandria
Bolívar La Paz	Deportivo Cali	Pakhtakor Tashkent		Kawkab Marrakech
CD La Equidad Seguros SA	Deportivo Cuenca	Paradou AC		Masr El Makasa
CD O'Higgins	Envigado FC	Persepolis FC		Olympique Beja
CD Universidad Católica	Esteghlal FC	Pohang Steelers		Olympique Khouribga
CF Atlante	Etoile Sportive du Sahel	Renaissance de Berkane		Stade Tunisien
Changchun Yatai	FC Baniyas	Sagan Tosu		US Monastir
Club Alianza Lima	FC Seoul	Seongnam FC		
Club Atlético Tigre	Hokkaido Consadole Sapporo	Sepahan FC		
Club Atlético Unión	Huachipato FC	SuperSport United		

Appendix C

Table C: League Groups

Group 1

1. Bundesliga		
LaLiga		
Ligue 1		
Premier League		
Serie A		

Group 2

2. Bundesliga	Liga MX Mexico	Série A
Bundesliga	Liga NOS	Serie B
Championship	Ligue 2	Süper Lig
Eredivisie	Premier Liga Russia	Superliga
Jupiler Pro League	Premier Liga Ukraine	Superligaen
LaLiga2	Premiership	

Group 3

1. Division	Keuken Kampioen Divisie	Primera División Chile
1. HNL	League One	Primera División Paraguay
1. Lig	Liga 1 Romania	Primera Nacional
2. Liga	Liga Dimayor	Professional League
2ª B - Spain	Liga Expansión MX Cl.	Protathlima Cyta
3. Bundesliga	Liga Portugal 2	Proximus League
Allsvenskan	Ligat ha'Al	Série B
Beloften Eredivisie	MLS	Serie C
Championnat national	NordicBet LIGA	Super League 1
efbet Liga	Persha Liga	Super liga Srbije
Ekstraklasa	Premier League 2	Swiss Super League
Eliteserien	Premyer Liqasi	U19-Bundesliga Süd/Südwest
J1 League	Primavera Italy youth	UAE Gulf League

Group 4

1 CFL	League Two	Primera División Uruguay
2. HNL	Liga 1 Peru	Prva Liga
2. Lig Turkey	Liga Leumit	Prva Liga
A Lyga	LigaPro Serie A	Prva liga Makendonia
Challenge League	Ligue I Pro	Serie D
China Superleague	MSFL	Stars League
Crystalbet Erovnuli Liga	National 2 - Grp. D	Superettan
DStv Premiership	NB I.	Thai League
Egypt Premier League	OBOS-ligaen	Torneo Clausura
Fortuna Liga	Persian Gulf Pro League	U19 Premier Liga
J2 League	Premier Liga Kazachstan	Veikkausliiga
K League 1	Premijer Liga	Vysheyshaya Liga

Table C (continued)

Group 5		
1 Liga	Friendlies	Paulistão A1 - Primeira fase
A-League	K League 2	Promotion League
Botola Pro Inwi	League Two North	Regional League Central
China League One	Liga II - Seria II	Regionalliga Germany
Divizia Nationala	NB II.	Segunda División
FNL	NPFL	Swiss U18 Elite League
Football League		

Appendix D

Table D: ANOVA Post-Hoc Analysis with Factor Seasons

		Different from Season	Mean Difference	Std. Error	Sig.
Season	18/19	16/17	0.456	0.142	0.046
		15/16	0.468	0.139	0.028
		14/16	0.500	0.134	0.008
		11/12	0.674	0.129	0.000
		10/11	0.667	0.151	0.000
	17/18	11/12	0.467	0.125	0.008

Note: Only significant variables plotted.

Appendix E

Table E: ANOVA Post-Hoc Analysis with Factor Positions

		Different from Position	Mean Difference	Std. Error	Sig.
Position	Goalkeeper	Defender	-0.364	0.090	0.000
		Midfielder	-0.118	0.073	0.374
		Forward	-0.366	0.094	0.001
	Defender	Goalkeeper	0.364	0.090	0.000
		Midfielder	0.246	0.081	0.012
		Forward	-0.002	0.100	1.000
	Midfielder	Goalkeeper	0.118	0.073	0.374
		Defender	-0.246	0.081	0.012
		Forward	-0.248	0.086	0.020
	Forward	Goalkeeper	0.366	0.094	0.001
		Defender	0.002	0.100	1.000
		Midfielder	0.248	0.086	0.020