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Salary Discrimination in the Sports Labor Market: An Evidence from Major League Soccer

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SALARY DISCRIMINATION IN THE SPORTS LABOR MARKET: AN EVIDENCE FROM MAJOR LEAGUE SOCCER

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ABSTRACT

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Since Gary Becker's (1971) discrimination theory, which provided the groundwork to investigate various forms of discrimination based on individuals' demographic characteristics, wage discrimination has been a long-standing issue in labor economics and sport management. With this knowledge, it is of interest to examine whether sports labor markets offer equal financial opportunities. Although a growing body of literature has examined and uncovered evidence of pay discrimination in various sports settings, relatively little attention has been paid to Major League Soccer (MLS) because of its short history. In addition, there is a need to understand salary discrimination among superstars in MLS amid the adoption of the Designated Player rule, commonly known as David Beckham rule, to acquire star players as a strategy to achieve attendance and revenue goals. Despite the important role of superstars in improving the league and making MLS more competitive, it is unclear thus far whether superstars are discriminated against based on their demographic characteristics. This dissertation therefore aims to explore the existence of pay discrimination in MLS and the degree to which superstars are discriminated against based on their origin of birth.

Using 4,280 observations of MLS players' salary data from the 2007-2019 seasons and performance statistics from the 2006-2018 seasons, the results of both

ordinary least squares estimation and quantile regression showed that there is salary discrimination in MLS—regular players from North America are paid less than comparable players from other areas. Findings also revealed possible evidence of discrimination among superstars where Asian superstars are favored, while South American superstars are discriminated against in certain salary distributions. This study contributes to the literature by providing possible evidence of and a new perspective on pay discrimination among MLS regular players and superstars, respectively, while combining discrimination theory and superstar theory in the context of professional sports. It also provides implications for MLS so that it can operate better, benefit from diversified superstars, and become a high-profile and competitive worldwide soccer league.

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An arduous and long Ph.D. journey has come to an end, and it would not have been possible without the support of many individuals to whom I am grateful. I have had various hardships and challenges during the past four years, and I am fortunate to be surrounded by people who are always ready to help.

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ABBREVIATION	
AFC	Asian Football Confederation
AP(s)	All Player(s)
BIC	Bayesian Information Criterion
CAF	Confederation of African Football
CBA	Collective Bargaining Agreement
CONCACAF	Confederation of North, Central America and Caribbean Association Football
CONMEBOL	South American Football Confederation
DP(s)	Designated Player(s)
DPS	Designated Player Status
DV	Dependent Variable
EEOC	Employment Opportunity Commission
EPL	English Premier League
ESL(s)	European Soccer League(s)
FIFA	Fédération Internationale de Football Association
GSL	German Soccer League
HCT	Human Capital Theory
ISL	Italian Soccer League
IV(s)	Independent Variable(s)
MLB	Major League Baseball

MLS	Major League Soccer
MLSPA	Major League Soccer Players Association
MPL	Marginal Product of Labor
MRP	Marginal Revenue Product
NASL	North American Soccer League
NBA	National Basketball Association
NFL	National Football League
NHL	National Hockey League
OFC	Oceania Football Confederation
OLS	Ordinary Least Squares
RP(s)	Regular Player(s)
SSL	Spanish Soccer League
UEFA	Union of European Football Associations
UN	United Nations
VIF	Variance Inflation Factor

CHAPTER I

INTRODUCTION

The issue of wage discrimination has received significant attention in labor economics since Gary Becker's (1971) work, which pioneered discussions regarding discrimination based on individuals' demographic characteristics (e.g., gender, race, nationality, and origin of birth). Over recent decades, the United States has experienced a vast influx of immigrants. In 2018, for example, the U.S. employed 28.2 million foreign-born workers, for a total of 17.4% of the entire labor force (U.S. Bureau of Labor Statistics, 2020). Therefore, the issue of discrimination has been widely discussed in the neo-classical era to examine the degree to which various groups receive different wages for equal work (Wells, Allen, Morisset, & Pirnia, 2001). In addition, the Equal Pay Act of 1963 and the Civil Rights Act of 1964 outlawed any type of discrimination based on race, color, gender, religion, and national origin. For this reason, the issue of discrimination has been a socially unacceptable norm.

The sports labor market, which acts as a microcosm of society (Holmes, 2011), provides a novel testing ground for wage discrimination because it is a diverse community in terms of race, nationality, and birth country. Since Jackie Robinson, the first African American Major League Baseball (MLB) player, broke the color barrier in 1947 (Dorinson & Warmund, 1998), various racial and national groups have flourished in the professional sports market, and the proportion of minority groups has gradually increased. By 2018, the percentage of players of color had increased to over

70% in the National Football League (NFL), 80.7% in the National Basketball Association (NBA), and 42.5% in MLB (Tower, 2018). The increase in players' diversity in professional sports provides a reasonable testing ground for examining whether athletes are discriminated against by race or nationality (Kahn, 2000). With this knowledge, pay discrimination in professional sports has been a long-standing issue (Kahn, 1991; Yang & Lin, 2012); thus, an extensive amount of research has examined the evidence of discrimination, especially in wages (Reilly & Witt, 2007).

In addition to the sporting world's diverse groups of players, detailed information on players' performance statistics offers a reasonable testing ground for salary discrimination. Unlike the general labor market, where a worker's productivity is difficult to measure, the professional sports world provides detailed information regarding players' productivity over a long period of observation (Holmes, 2011). Thus, the problem of unobservable variables is not a major issue in the sports labor market. The data on detailed observations of individuals and organizations over a long period of time provide a strong opportunity for sports economists to analyze the extent of pay discrimination:

> Professional sport offers a unique opportunity for labor market research. There is no research setting other than sports where we know the name, face, and life history of every production worker and supervisor in the industry. Total compensation packages and performance statistics for each individual are widely available, and we have a complete data set of worker-employer matches over the career of each production worker and supervisor in the industry. These statistics are much more detailed and accurate than typical

microdata samples such as Census or the Current Population Survey (Kahn, 2000, p. 75).

The study of discrimination in professional sports therefore indicates whether the sports labor markets offer equal economic opportunities for every group (Eitzen & Sage, 1982). Accordingly, wage discrimination and salary determination have been a focal area of research in sport management and labor economics because they serve to provide advice to sports organizations, leagues, and managers (Forrest & Simmons, 2002; Szymanski & Kuypers, 1999; Zimbalist, 2002), and payroll costs may be sports organizations' largest expense.

Research Background

Association football (hereafter soccer), commonly known as "soccer" and "football" in the U.S. and Europe, respectively, may be regarded as the most popular professional and amateur worldwide sport (Dunning, 1999; Stubbe, Schmikli, Van de Port, & Backx, 2015). In Europe, for example, where soccer is a pastime with a history of more than 100 years, there are 36 professional leagues with 950 clubs (European Leagues, n.d.); worldwide, there are approximately 250 million players in over 200 countries and 3.5 billion fans (Das, 2020). It has been less successful in the U.S. compared to soccer leagues in Europe, however, because of its short history (Coates, Frick, & Jewell, 2016) and various alternative professional sports leagues, including MLB, NBA, NFL, and National Hockey League (NHL).

In an attempt to create a high-profile soccer league in North America, Major League Soccer (MLS) has adopted a "Designated Player" (DP) rule, which allows each team to acquire up to three players outside of the salary cap as a management strategy to encourage the development of MLS franchises. This DP rule was

introduced as a marketing strategy for boosting attendance and improving the prosperity of the league (Bradbury, 2020) because sports fans are attracted to on-field performance success driven by marquee players' well-executed performances (Scully, 1974). Previous studies have focused on whether the presence of a DP has contributed to higher attendance across MLS, providing evidence that designated players (i.e., superstars) are positively associated with attendance (Jewell, 2017; Parrish, 2013) and team revenue (DeSchriver, 2007; Lawson, Sheehan, & Stephenson, 2008). It was also found that superstars could generate and strengthen brand loyalty, as well as having the potential ability to enhance brand awareness and brand affiliation for the league as a whole (Shapiro, DeSchriver, & Rascher, 2017). For this reason, the existence of superstars plays an important role for MLS to become a high-profile soccer league.

Despite the importance of designated players in MLS, there is a significant wage differential between the DPs. For example, Carlos Vela, a former player at Real Sociedad, was paid $6.3 million at Los Angeles FC in 2019 while Gyasi Zardes, an American soccer player at Columbus Crew SC, received $2.3 million in 2019 (Fleming, 2019). Of course, not all DPs (i.e., superstars) have the same impact (Bradbury, 2020) in that Carlos Vela is considered to be an international superstar while Gyasi Zardes is a local superstar. However, this wage gap cannot be completely explained when considering the difference in performance statistics between the two players: Carlos Vela scored 14 goals in 28 games in 2018 while Gyasi Zardes scored higher goals, 19 goals in 33 games in 2018. Although the wage differential may be due to the player's popularity to some extent (Adler, 1985), the above example certainly suggests the possibility of wage discrimination among DPs, and little research has been conducted as to whether DPs are discriminated against. If salary discrimination by origin of birth is found in MLS, superstars are more likely to choose

to play in other leagues, such as those based in Europe, because of their better reputation and higher financial rewards (Prockl & Frick, 2018b). In this case, MLS may not attract as many talented and popular players as needed to achieve its attendance and revenue goals. In what ways this could adversely affect MLS attendance and revenue?

Some people may argue that discrimination is inevitable in the labor market (although it is a socially unacceptable norm) and players from certain regions are either favored or discriminated against. As discussed above, however, the issue of salary discrimination is especially important for MLS because the league could acquire more potential fans with the existence of diversified superstars. This argument is based on the following facts: the U.S. becomes more ethnically and racially diverse and continues to diversify with the influx of immigrants from around the world (Schelhas, 2002). Fans, of course, have a strong preference and are willing to pay a higher price for their favorite players (Becker, 1971) and previous literature found evidence of fan preference (e.g., Burdekin, Hossfeld, & Smith, 2005; Jones, Nadeau, & Walsh, 1999; Kahn, 1992; Kerr, 2019; Ruihley, Yu, & Hardin, 2017). Kahn (1992), for example, stated that “players make more money the greater the representation of their race in the local population” (p. 307). Based on this reasoning, MLS teams could attract more fans by having diversified high-profile superstars from all over the world.

Within the wage determination literature, most previous research focuses on two different threads: discrimination by race/nationality (Becker, 1971) and superstar effect (Adler, 1985; Rosen, 1981). As a result, a vast range of literature has been dedicated to the exploration of whether athletes encounter salary discrimination by race, nationality, or origin of birth and whether superstars experience a salary premium in professional sports. Although these two threads have been widely studied

and discussed, little attention has been paid to the earnings equation that links discrimination and the superstar effect. In particular, it is still unclear whether salary discrimination also exists for superstars.

There are two related studies that consider migration and superstardom in the ISL (Bryson, Rossi, & Simmons, 2014) and in multiple European soccer leagues (Kleven, Landais, & Saez, 2013), but neither study directly investigates the existence of discrimination for superstars. To my knowledge, this dissertation is only the second paper exploring the existence of salary discrimination among superstars, after the work of Prockl and Frick (2018b), who found evidence of pay discrimination for superstars. However, their study was limited to showing the existence of salary discrimination in MLS while using a small sample size. In addition, they put more emphasis on the effect of league regulation than players' origin of birth. Therefore, there is a research gap in understanding whether superstars are discriminated against based on their demographic characteristics while focusing on discrimination theory.

In addition to salary discrimination and superstar effect, the salaries of professional athletes are influenced by factors that pertain to human capital (e.g., age, skill, experience, education, and physical attributes) in ways that are similar to other occupations (Bryson, Frick, & Simmons, 2013; Frick, 2011). Most of the research on salary determination and discrimination, however, has focused on the narrow pay-performance relationship. Thus, there is limited research on the extent to which players' compensation can be influenced by individual demographic characteristics in the presence of different human capital factors. Moreover, most studies on the effect of human capital on players' compensation have centered on American sports leagues (i.e., NFL, MLB, NBA, and NHL) and professional European Soccer Leagues (ESLs) (e.g., English Premier League (EPL), German Soccer League (GSL), Italian Soccer

League (ISL), and Spanish Soccer League (SSL)); little research has been conducted on sports markets with short histories, such as MLS. Thus, further investigation is needed to determine which factors, human capital-related or otherwise, influence players' salaries in the professional sports labor market. This study focuses on MLS labor market to investigate salary discrimination as well as human capital factors.

Purpose

Although it is important to understand the existence of salary discrimination among superstars in the context of MLS, it has been rarely discussed and studied. Understanding whether superstars are discriminated against based on their demographic characteristics (especially origin of birth) would therefore help us to better understand recent salary discrimination by players' origin of birth and provide implications for MLS. The purpose of this dissertation is therefore to explore the existence of salary discrimination and the degree to which superstars are discriminated against by demographic characteristics (i.e., origin of birth). This dissertation builds on the existing sports discrimination and superstar literature by pursuing the following research questions and hypotheses.

Research Questions

Q1 Is there any salary discrimination by origin of birth among players in MLS?

Q2 Is there any salary discrimination by origin of birth among superstars in particular?

Q3 Is there any salary discrimination by origin of birth among regular players in MLS?

Q4 Does superstar status have an effect on players' salaries? Do designated players (i.e., superstars) make significantly more money than other players?

Q5 Do players' human capital factors impact their compensation? What factors contribute to players' salaries in MLS?

Research Hypotheses

H1 There is salary discrimination by players' origin of birth in MLS.

H2 There is a positive relationship between superstar status (i.e., designated player status) and compensation.

H3 There is salary discrimination by players' origin of birth among superstars.

H4 A player's salary is positively associated with his experience.

$H5_a$ A player's salary is positively associated with his age.

$H5_b$ A player's salary is negatively associated with his squared term of age.

H6 A player's salary is positively associated with his innate skills or scarce talent.

H7 A player's salary is positively associated with his physical attributes (e.g., height).

$H8_a$ A player's salary is positively associated with individual performance factors (i.e., the number of goals scored).

$H8_b$ A player's salary is positively associated with individual performance factors (i.e., the number of assists scored).

$H9_a$ There is a positive relationship between a player's salary and the number of games played as a starting member.

$H9_b$ There is a negative relationship between a player's salary and the number of games played as a benchwarmer.

H10 A player's position influences his salary.

Rationale

The reasons that MLS merits a study of salary discrimination among superstars are as follows. First, unlike soccer leagues in Europe where player salaries generally remain confidential, MLS salary data are readily available from Major League Soccer Players Association (MLSPA). Second, MLS considers itself the most diverse league among the five major team professional sports leagues in the U.S. (Major League Soccer, 2018), providing a reasonable testing ground for examining

the existence of salary discrimination (see Table 1.1). Third, unlike other professional sports leagues in which the definition of "superstar" can be somewhat arbitrary (Jewell, 2017), MLS offers a relatively objective definition of superstars because of the DP rule that was introduced in 2007; the provision for DPs whose salaries do not count against the salary cap is an exceptional feature of MLS. Fourth, MLS operates as a single-entity structure, which indicates the presence of monopsony (Kesenne, 2015; Twomey & Monks, 2011) and could potentially suppress labor costs to below the marginal product of labor (MPL) (Barr & Roy, 2008). In this structure, salary discrimination and the superstar effect may work differently.

Table 1.1

Diversity of Professional Team Sports Leagues in North America

League (Season)	# of Players	# of Players Born Abroad	% Born Outside U.S. & Canada	Countries Represented
MLS (2018)	637	315	49.4%	72
MLB (2017)	1,087	326	29.9%	24
NHL (2017-2018)	779	225	28.8%	22
NBA (2017-2018)	496	96	19.4%	47
NFL (2017)	2,104	57	2.7%	26

Notes: Diversity is determined by player's birthplace.

The findings of this dissertation could contribute to both managerial and academic issues in terms of discrimination in MLS and other professional sports leagues. First, understanding the degree to which players' compensation is affected by their origin of birth would help how MLS would operate. If MLS turns out to be a discriminatory organization, MLS teams could attract more fans by having diversified fan-favorite high-profile superstars from all over the world to meet soccer demand in the U.S. On the other hand, MLS could promote itself as the most diverse and non-discriminatory league if it turns out to be a non-discriminatory organization. Understanding the existence of salary discrimination would provide implications for

MLS in either way. Second, the results of this dissertation are not limited to the MLS labor market; they could provide more generalizable implications to the less popular or newly established leagues, similar to MLS. Those leagues may consider recruiting superstars for the success of the league given that fans are more likely to visit sports venues when there are superstars. The newly established leagues and less popular leagues may benefit from the findings of this study to operate their teams more efficiently.

Organization

In summary, this dissertation endeavors to investigate the existence of salary discrimination in MLS and the degree to which superstars are discriminated against by demographic characteristics (i.e., origin of birth). The remainder of the dissertation is as follows. Chapter 2 provides a thorough review of literature related to discrimination theory, superstar theory, and human capital theory and their applicability in the professional sports labor market. Chapter 3 describes the methodology, including data variables, data description, and the production of data analysis. Chapter 4 addresses the results of the empirical estimation used to answer the research questions and relevant hypotheses. Chapter 5 provides a discussion of the findings and concludes with contributions, implications, limitations, suggestions, and directions for future research.

CHAPTER II

REVIEW OF LITERATURE

Introduction

Chapter 1 discussed the importance of understanding the degree to which superstars are discriminated against by origin of birth within the professional soccer league in the U.S. Discrimination by individuals' demographic characteristics (e.g., race, gender, nationality, and origin of birth) is prohibited; relatively little attention, however, has been paid as to whether top players (i.e., superstars) are discriminated against in the sports labor market. The goal of this chapter is to establish a theoretical background and framework for both discrimination and superstar effect within MLS context.

This chapter presents basic information about the contextual setting (i.e., MLS) and a thorough review of extant literature that is relevant to players' salaries. The first part is an explanation of MLS context. It includes MLS's league history, changes in league size and popularity, and the uniqueness of its league structure, playoff format, closed system, and players' compensation system. The second part is a review of discrimination theory, which guides this dissertation. The third part is a review of superstar theory explaining how superstars' salaries are affected by their performance and popularity. With discrimination theory and superstar theory as the foundation of this dissertation, the fourth part is a review of human capital theory, as it suggests that human capital factors also influence players' salaries. In the last part

of the literature review, additional salary determinants in MLS (i.e., performance statistics, league appearance, and position) are discussed.

Contextual Setting

MLS is a high-profile professional soccer league sanctioned by the United States Soccer Federation (Kivlehan, 2019). Soccer, however, has been considered in North America to be relatively inferior (in terms of popularity) to traditional professional sports leagues such as the NFL, NBA, MLB, and NHL (Heitner, 2015). MLS was officially formed in February 1995 and launched the following year with 10 teams in its inaugural season. As the league is relatively new compared to other professional sports leagues in North America, MLS has expanded multiple times, and several teams have relocated or been abolished.

The regular season usually begins in March and continues until October (the 2020 season started on February 29th). Each team plays 34 games throughout the season: a team plays two games (home and away) with its opponents within the same conference, for a total of 24 games, and plays one game with 10 out of 13 opponents in the other conference, for a total of 10 games. MLS is divided into two conferences (Eastern and Western) based on geographical location. The team with the highest record throughout the regular season is awarded the Supporters' Shield; however, the top seven teams (out of 13) in each conference are eligible to clinch the playoff spots to be the ultimate champions of the year. MLS's postseason is from November to December, when the ultimate champion is decided; this is unlike the European Soccer Leagues, where the team with the best regular season record becomes a league champion. MLS team with the best record (i.e., highest number of points) throughout the regular season reaches the semi-finals, while the second through seventh best teams play against one another from the first round during the postseason.

Major League Soccer History

The history of professional soccer in the U.S. dates to the mid-1960s, when the North American Soccer League (NASL) began. By 1975, the number of soccer teams in the NASL was 20, and soccer's popularity has been growing ever since. Of particular note, the New York Cosmos, the most successful team in the NASL, recorded an average of 40,000 spectators per game after signing the Brazilian soccer star Pelé (Ellsworth, 2019). This led other clubs to recruit international superstars who would likely bring more spectators. By this time, the U.S. soccer league had witnessed a peak in popularity with the addition of another four teams—a total of 24 teams in the league and an average of 14,400 fans per game led to stability in the 1980s. By 1984, however, the league had trimmed down to only nine teams because of its overspending and overexpansion, as small markets faced profitability problems.

After two years of planning and almost doubling the number of league teams, MLS was newly launched in 1996 as the successor to the NASL with an agreement with Fédération Internationale de Football Association (FIFA), the governing body of recognized international soccer, to host the 1994 World Cup. Ten teams made up MLS in 1996: D.C. United, the New England Revolution, the New York/New Jersey MetroStars (now the New York Red Bulls), the Tampa Bay Mutiny, the Columbus Crew, the Dallas Burn (now FC Dallas), the Colorado Rapids, the Kansas City Wiz (now Sporting Kansas City), the Los Angeles Galaxy, and the San Jose Clash. The league began the season at San Jose's Spartan stadium, recording 31,683 attendees, where the San Jose Clash had defeated D.C. United. To avoid the pitfalls encountered by the NASL, which tended to attract star players without suppressing the associated costs (Mendelsohn, 2003), MLS structured itself as a single limited-liability company. As a single entity, MLS could ensure its stability and lure potential investors with less

financial risk, as team operators do not own the entire franchise—the league owns at least 50% of each team (Francis & Zheng, 2010; Twomey & Monks, 2011).

League Growth (Popularity and Size)

With the 1996 advent of a professional soccer league in North America, there was some doubt as to whether soccer could survive and be successful within the U.S. Despite some initial skepticism, MLS recorded an average annual attendance of 17,406 in its inaugural season, with over one-quarter of total games attracting more than 20,000 spectators (Woitalla, 2010). One notable attendance number is that L.A. Galaxy attracted 69,255 spectators to the Rose Bowl stadium on April 13th, 1996, when the team defeated the New York/New Jersey MetroStars. Following its inaugural season, MLS has experienced attendance fluctuation during its early years; during the 2018 season, however, the league saw an average attendance of 21,875 per game, which was almost 4,000 more than that of the NBA (17,830) and NHL (17,446), indicating its growth in popularity. Figure 2.1 shows MLS's average attendance history. Despite showing a slight downturn in 2013, 2018, and 2019 in the 2010s, the attendance numbers have gradually increased, which indicates that MLS seems to be becoming more popular year by year.

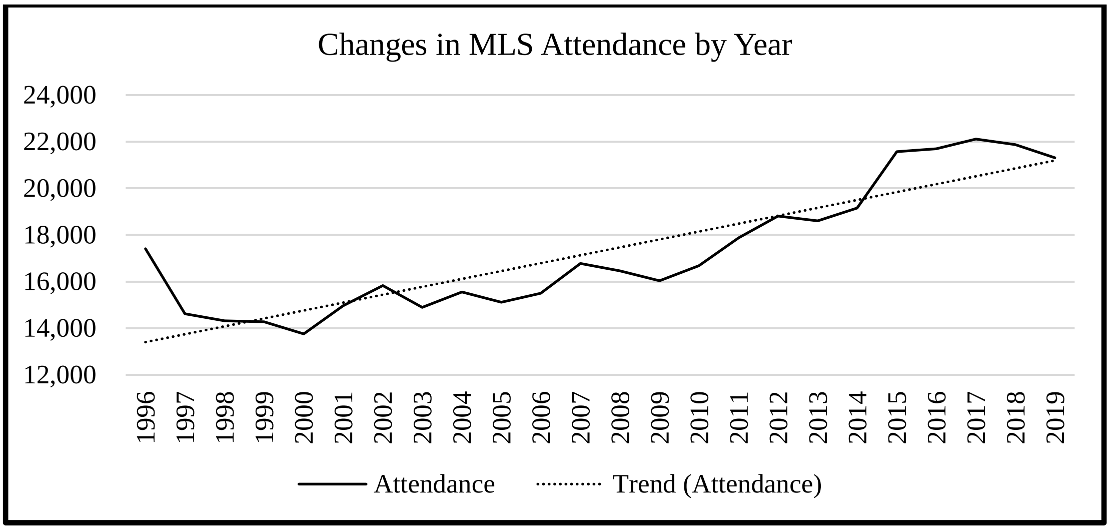

Figure 2.1. Changes in MLS Attendance by Year.

From the perspective of TV contracts, MLS's growth seems apparent. Fox Sports, ESPN, and Univision currently have media rights in an eight-year agreement (2015-2022 seasons) worth $90 million per year. A total of $90 million per year is a stark upsurge compared to the previous broadcasting contract, when MLS received an annual average of $18 million for the 2007-2014 seasons (Ourand & Botta, 2014). MLS commissioner, Don Garber, said of the current contract: "This is the most comprehensive media rights partnership in the history of soccer in our country. That's something we're very proud of. It's a statement about where the soccer market is and where MLS and U.S. Soccer fit into the paradigm" (Ourand & Botta, 2014).

In addition, since 2007, MLS has been implementing aggressive league-expanding policies (Bradbury, 2020); the league has gradually expanded from 10 to 24 franchises (Bogert, 2019). Los Angeles and Cincinnati participated in the league in 2018 and 2019 as the 23rd and 24th franchises, respectively. Moreover, Miami and Nashville were selected as the 25th and 26th MLS franchises, joining the league in 2020; Austin, Charlotte, St. Louis, and Sacramento were recently selected as the 27th, 28th, 29th, and 30th franchises and are expected to play in either 2021 or 2022. MLS began with 10 teams in 1996 and tripled to 30 teams within 25 years, indicating its rapid growth in league size. Figure 2.2 shows the changes in the number of MLS teams.

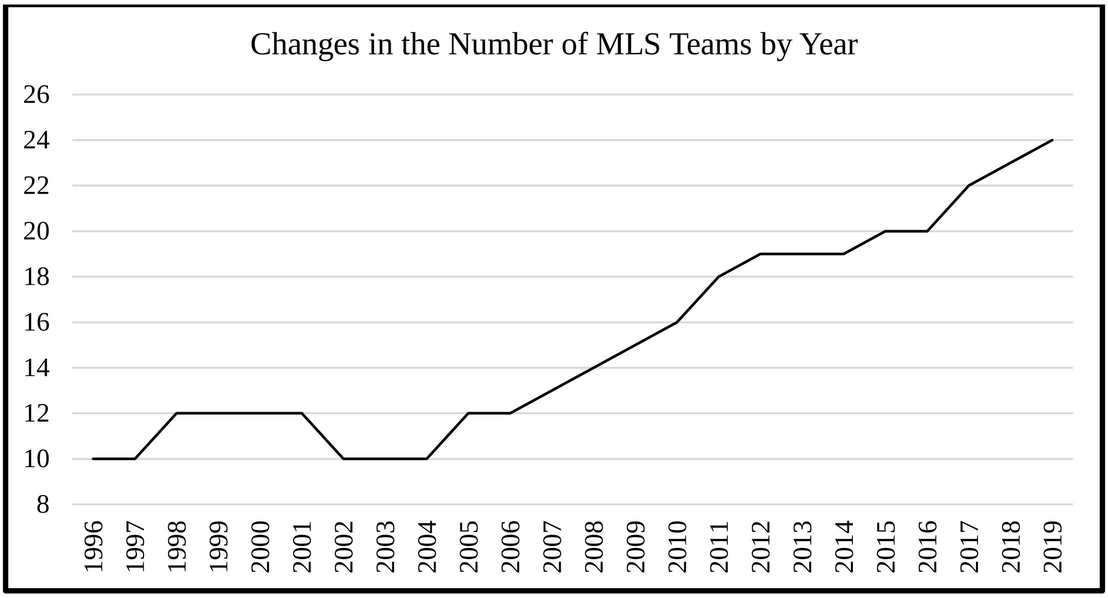

Figure 2.2. Changes in the Number of MLS Teams by Year.

Uniqueness

MLS is unique in terms of its league structure, playoff format, closed system, and salary system, and is thus very different from professional soccer leagues in Europe. The commissioner believes that the uniqueness of the league makes soccer fans more excited: “I think people are intrigued by our structure, this unique system we have with salary caps, union agreements, and strict revenue-sharing, this partnership among owners who are competitors on the field. That has created a lot of buzz and it's something for us to be excited about" (Slater, 2015). In order to better comprehend the professional soccer labor market in North America, it is important to understand how MLS is structured.

League structure (single entity). The first unique characteristic of MLS is that it operates as a single entity. This indicates centralized leadership of MLS, which allows the league to control each team and player. Under the syndicate structure, player contracts are determined by the league, not by an individual team, and all sponsorship and broadcasting agreements are controlled by the league (Jewell & Molina, 2005). For this reason, individual teams are not permitted to participate in

arms races to sign high-profile players to their rosters. MLS adopted its unique structure due to the fact that the previous professional soccer league (i.e., NASL) in part failed due to its overspending on international superstars. This structure allows the league to limit individual teams' overspending on hiring well-known players and limit market size problems, given that small-market teams have much less financial power than larger-market teams (Francis & Zheng, 2010). The purpose of single entity structure is thus to not meet the same fate as the NASL and to bring long-term prosperity to the league (Jewell & Molina, 2005).

The single-entity structure, however, indicates the presence of monopsony (Kesenne, 2015), and could potentially suppress labor costs to below MPL (Barr & Roy, 2008). According to demand and supply theory, the equilibrium moves when there is a limited number of suppliers (i.e., a monopoly). In MLS, there is only one consumer (i.e., MLS), while there are more than 600 providers (i.e., players) in the market, and this negatively affects athletes' wellbeing (Kesenne, 2015). For example, MLS spends only about a quarter of its total revenue on players' compensation, while other professional sports leagues spend more than half of their revenue on players' salaries (Twomey & Monks, 2011). The unique league structure of MLS has thus been the subject of debate for a long time.

Playoff format. The second unique aspect of MLS is its playoff system. Within the European Soccer Leagues, the league champion is decided by the team with the highest number of points over the regular season. In the 2018-2019 season of the EPL, for example, Manchester City became the ultimate champion, recording 98 points through 32 wins, four losses, and two ties throughout the 38 games. In most ESLs, the team with the best record during the regular season becomes the champion.

MLS, however, functions differently. As in other professional sports leagues in the U.S., the ultimate champion is determined in the playoffs. MLS Cup Playoffs is MLS's annual postseason tournament. In the 2019 season, seven teams in each conference (Eastern and Western) reached the playoff berth, for a total of 14 teams. The team with the most points in each conference gets a bye, while the remaining six teams starts the playoffs from the first round. For example, Toronto FC and Seattle Sounders FC played MLS Cup on November 10th, and the latter became the 2019 MLS champion. While the ultimate champion is decided during MLS Cup, MLS awards the Supporters' Shield to the team with the best record during the regular season. This, however, is different from the ultimate champion in the season, so MLS fans may think of the regular season and postseason separately (Bradbury, 2020).

Closed system. The third unique aspect of MLS is its closed system with no promotion and relegation, indicating that low-performing teams in Division 1 (i.e., MLS) will not be relegated to Division 2 (i.e., United Soccer League Championship) or Division 3 (i.e., United Soccer League One & National Independent Soccer Association), nor will high-performing teams in Divisions 2 and 3 be promoted to MLS (Galarcep, 2019). This is similar to other professional sports leagues in the U.S., in which promotion and relegation are not permitted. As MLS commissioner has stated, "Just because there is promotion/relegation in other leagues that were founded on different principles doesn't mean that it would make sense in Major League Soccer" (Galarcep, 2019). He believes that not every team in Division 2 can have the national revenues to play in Division 1.

By contrast, European Soccer Leagues have a promotion and relegation system. For example, in the EPL, teams can be transferred between the eight different divisions. The bottom three teams in the first division (i.e., Premier League) are

relegated to the second division (i.e., English Football League Championship) based on their performance. On the other hand, the top two teams in the second division are directly promoted to the first division, while the next four teams compete for the third promotion spot. The structure of a closed system without promotion and relegation is therefore unique to MLS.

Salary system. The fourth unique aspect of MLS is its salary system. Since its inaugural season, MLS has controlled players' salaries with a salary cap to ensure a competitive balance among franchises. According to MLS (Major League Soccer, 2020), its salary cap is set at $4.24 million and $4.9 million for a senior roster of up to 20 players, occupying the first 20 slots in 2019 and 2020, respectively. A single player included in the senior roster cannot be paid over $612,500.

Similarly to the National Basketball Association, this salary cap is considered to be a "soft cap" given that exceptions exist. MLS introduced the DP rule in 2007, which allows each team to contract up to three players whose salaries do not count against the salary cap. MLS has adopted the DP rule, which is commonly known as the "David Beckham rule," as a way of boosting attendance and improving the prosperity of the league, because sports fans are attracted to the participation of star players. In addition, the compensation for the players on the supplemental roster (slots 21-30) do not count against teams' salary constraint. A single player included in the supplemental roster cannot be paid less than $81,875 for players in the 21-24 slots, $63,547 for players in the 25-28 slots, and $63,547 for homegrown players in the 29-30 slots.

Discrimination Theory

Introduction

Discrimination by individuals' demographic characteristics (e.g., gender, race, nationality, and origin of birth) has received a great deal of attention since Gary Becker's (1971) work. Discrimination, or the unequal treatment of employees for identical work, can affect various professional facets, such as salaries, hiring, retention, promotion, and occupational positions. Studies have found that the motivation for such unequal treatment results from employer, employee (co-worker), and customer prejudice (Arrow, 1973; Becker, 1971; Darity & Mason, 1998). A vast range of economics and business literature has been devoted to exploring racial discrimination in a variety of settings (Schuman, Steeh, Bono, & Krysan, 1997); still, discrimination theory has received little attention in the professional sports labor market. The purpose of this section is therefore to use discrimination theory to explain the degree to which MLS players, including both regular and superstar players, are discriminated against based on their origin of birth. This section endeavors to not only extend the existing literature on discrimination in the sports industry but also seeks to provide fundamental theoretical frameworks for various types of discrimination.

Theoretical Framework

The concept of discrimination dates back a century; economists have discovered a variety of motivations for and forms of discrimination. The neo-classical theory of discrimination originated in the 1920s, when it was first stated by Edgeworth (1922); most of the work around racial discrimination in labor economics, however, was influenced by Becker's "The Economics of Discrimination" in 1971. There are two dominant theories in discrimination literature: statistical discrimination and associational discrimination.

The first discrimination theory, statistical discrimination, was developed by Phelps (1972) and Arrow (1973). According to statistical discrimination theory, discrimination against individuals' demographic characteristics is attributed to the fact that economic agents (e.g., employers) do not have perfect information about the workers with whom they interact. Statistical discrimination theory posits that inequality exists and further persists between majority and minority groups not because economic agents are irrationally prejudiced but because they have imperfect information about individuals and thus rely on previous statistics. If the employers perceive that a minority group is not as productive as the majority group in the initial stage, each individual in the minority group will be regarded as inferior (i.e., less productive) than the majority group. Discrimination then arises and persists. For example, if employers have experienced that women workers are initially poorer at math, every woman will be seen as inferior in math because, without perfect information on current female workers' math abilities, employers employ statistical information from the past. This type of discrimination may therefore seem rational when economic agents are unable to evaluate work productivity, which is difficult to observe, instead using the process of information-gathering.

The second discrimination theory, associational discrimination, was pioneered by Becker's "The Economics of Discrimination" in 1971. Unlike statistical discrimination, which posits that economic agents discriminate based on previous information, association discrimination theory posits that people discriminate because they have a specific taste for certain demographic characteristics. Under Becker's taste-based discrimination model, minority workers are likely to be paid a lower wage than majority workers for identical productivity because of their demographic characteristics. This leads to a question why certain groups are discriminated against

despite their equal work productivity. According to Becker (1971), the labor market's discrimination against minorities can result from three possible "taste for discrimination" sources: employer prejudice, employee (co-worker) prejudice, and customer prejudice.

Becker's (1971) first type of discrimination is employer prejudice, leading non-favored groups to receive only a fraction of the compensation given to favored groups (Hamilton, 1997). Black people, for example, may be discriminated against in the labor market simply because the employer may prefer to hire white people, or vice versa. In this case, there is no reason to discriminate because each group has identical productivity, but discrimination arises only because the employers wish to do so. When an employer has a taste or preference in hiring one group of workers over another, "he must act as if he were willing to pay something, either directly or in the form of reduced income" (Becker, 1971, p. 14). For this reason, in a competitive market, employer discrimination will bring lower monetary profits (Szymanski, 2000), and, as a result, this form of discrimination will disappear from common practice (Hellerstein, Neumark, & Troske, 2002).

Becker's (1971) second type of discrimination is employee (or co-worker) prejudice. Co-worker discrimination occurs when members of dominant or favored groups are prejudiced against members of minority or non-favored groups and dislike working with them (Lang & Lehmann, 2012). This friction often results in discord amongst team members and reduces performance overall (Burnett & Van Scyoc, 2015). In this case, the owners may pay more to majority groups (e.g., white players) or discriminate against minority players (e.g., black players) to prevent a reduction in game performance, thus resulting in salary differentials. Using the same reasoning that employer discrimination will not persist in the highly competitive labor market,

employee discrimination will not exist, in theory, because this practice will bring economic loss.

Becker's (1971) third type of discrimination is consumer (or fan) prejudice. Unlike employer and employee discrimination, where any type of discrimination (e.g., wages) is unlikely to persist in the competitive labor market (Kahn, 1991), customer discrimination is not likely to be mitigated by market forces (Nardinelli & Simon, 1990). Broadly, in the labor economics literature, wages of employees are equal to worker's marginal revenue product (MRP), which refers to the change in revenue by hiring one additional unit of labor (e.g., employee). In a sports context, MRP can be defined as "the ability or performance that he [the athlete] contributes to the team" (Scott, Long, & Somppi, 1985, p. 52); thus, a player is anticipated to earn his expected MRP in wages (Scully, 1974), according to the MRP theory. In this case, wage discrimination may exist because, in the customer discrimination model, fans have a strong preference and are willing to pay a higher price for fan favorite products (Holmes, 2011). To appease prejudiced fans, teams may hire players at a salary premium or reduction based on skin color; fan preference leads to higher MRP for favored (e.g., white) players and lower MRP for non-favored (e.g., black) athletes in the market (Kahn, 1992). A salary premium for white players, who are more favored by prejudiced fans, would then be offset by customers' increased investment, thus increasing the individual player's MRP in the sports labor market (Kahn, 2000). As long as fan prejudice exists in sports that are closely tied to fan-based service, pay discrimination will be pervasive (Kahn, 1991). The persistence of discrimination found in wages as a result of customer discrimination has therefore been an important issue and an empirical question in professional sports.

Given that discrimination in wages will persist to the degree to which customer prejudice exists (Nardinelli & Simon, 1990), substantial range of professional sports literature has examined wage differentials among minority groups based on customer prejudice. However, as Hill and Groothuis (2017) stated, “it is often impossible to separate the motivation behind discrimination through empirical observation (p. 206)” and researchers have not reached a consensus as to whether discrimination results from fans. For this reason, instead of investigating who is acting upon these preferences in MLS, this study focuses on whether there is evidence of salary discrimination, about which little is known thus far.

Forms of discrimination. Various forms of discrimination exist against minority players in professional sports. These forms of labor market discrimination can include salary discrimination (unequal pay for equal work), hiring discrimination (or entry discrimination), positional segregation (restriction of position), and retention discrimination (career length). Discrimination also manifests in other forms, such as reduced endorsement income, lower bonuses, exclusion from executive and managerial positions after a playing career, reduced speaking engagements, and the presence of quota systems. While there are various forms of discrimination in professional sports, the focus of this dissertation is salary discrimination among players; thus, this section will provide a thorough review of salary discrimination that have been studied in the professional sports leagues.

***Salary discrimination*.** Among various forms of discrimination in professional sports, the study of salary discrimination between different groups of players has received great attention in academia (Kahn, 2000). Salary discrimination can be described as the payment of different wages to players with similar productivity based on their demographic characteristics (Hamilton, 1997). Existing

literature has stated that “in professional athletics, black and white [players] of similar abilities are paid vastly differing salaries” (Edwards, 1969, p. 22); thus, “minority workers earn less than majority workers of identical productivity” (Autor, 2003, p. 5). Among various forms of discrimination in wages, racial pay discrimination has been widely studied to examine whether black players are paid less than white players. The existence of salary discrimination has been examined in a variety of professional sports settings, and I will thoroughly review the related literature for each sports league, including the NBA, MLB, NFL, ESLs, and MLS.

National basketball association wage discrimination. Since Wataru Misaka first joined the National Basketball Association in 1947-1948 as the first player of color, the proportion of international players and players of color has increased (Chow, 2019). According to the Institute for Diversity and Ethics in Sport, 74.3% of players in the 2015-2016 NBA season were black and 81.7% were players of color (Spears, 2016). Owing to its racial diversity, the NBA has long been a testing ground for salary discrimination and past scholars have put forth a growing collection of literature concerning racial discrimination in wages between black and white players.

Early National Basketball Association research using data before the 1980s concluded that black and white players were paid equally for their work, indicating no racial discrimination in wages (Mogull, 1979, 1981; Rockwood & Asher, 1976; Scott et al., 1985). However, since the samples used in the above studies were limited and not random, the findings of the empirical analysis are less reliable (Jenkins, 1996). When scholars used larger samples, several studies reported that black NBA players were paid less than white players during the 1980s (Brown, Spiro, & Keenan, 1991; Kahn & Sherer, 1988; Koch & Vander Hill, 1988; McCormick & Tollison, 2001; Wallace, 1988).

Wallace's 1988 study, which included the 1984-1985 National Basketball Association season and 227 players, tested whether human capital variables (e.g., original draft position, first-year selection to the All-Rookie team, and years in the league), performance productivity variables (e.g., points, rebounds, blocks, and offensive and defensive proficiency ratio), and structural variables (e.g., team salary, player mobility, and race) play a role in explaining players' compensation. The author found that black players who demonstrated equal on-court performance with white players were paid 14-16% less. He also noted the irony in the fact that black players are discriminated against in the NBA, where black athletes comprise 75% of all players. While the findings of the study were interesting, the author did not explain why black players experience significant discrimination in the NBA although they are the majority in the league.

Subsequent studies on this matter, however, have supported Becker's 1971 theory, which argued that salaries will be equalized over time due to the pricing out of discriminating clubs. There was no significant evidence of racial pay discrimination in the National Basketball Association during the 1990s (Bodvarsson & Brastow, 1998; Dey, 1997; Groothuis & Hill, 2004; Guis & Johnson, 1998; Hamilton, 1997; Jenkins, 1996). In particular, Guis and Johnson (1998) tested NBA racial wage discrimination using a log-linear salary equation and Chow test. By examining the data of 328 players who played in the 1995-1996 NBA season and salary data from the 1996-1997 season, they found that there was no significant relationship between race and players' compensation. They suggested that instead of players' race, factors influencing players' compensation include performance statistics, free agency, experience, and draft status, indicating that wage discrimination is no longer a concern in the NBA.

In assessing the 1985-1991 National Basketball Association seasons, Bodvarsson and Brastow (1999) also explored the existence of salary discrimination among racial groups. They confirmed that racial pay discrimination had greatly declined by the early 1990s because of the 1988 negotiation of a collective bargaining agreement (CBA), which decreased the owners' monopsony power, a key source of pay discrimination. Further studies also revealed that there was no significant pay discrimination against black NBA players from the 1990s onwards (Groothuis & Hill, 2013; Kahn & Shah, 2005; Robst, VanGilder, Coates, & Berri, 2011).

While earlier research examined race's effect on compensation, more recent work has examined salary discrimination by nationality (Burdekin & Van, 2018; Eschker, Perez, & Siegler, 2004; Hill & Groothuis, 2017; Hoffer & Freidel, 2014; Yang & Lin, 2012), as the NBA's minority groups are not limited to black players. In the 1996-1998 NBA seasons, scholars suggested that foreign players enjoyed a salary premium because there were only a few international players present; as more foreign players joined the league, however, the premium disappeared (Eschker, et al., 2004).

Yang and Lin (2012) tested the existence of nationality discrimination as well as the effect of market size of players' home countries by using unbalanced panel data for the 1999-2008 seasons. They determined that the majority of foreign-born players were paid less than U.S-born players, but international players who were from a larger home country market experienced preferential treatment. Hoffer and Freidel (2014), however, found that by the 2010-2011 NBA season, international players' salaries matched those of domestic players, and that they experienced an average of salary premium of $900,000, indicating reverse discrimination. They further explained that reverse discrimination may be attributed to the development of an international

scouting system and an increase in demand for talented and popular foreign-born players.

Most recently, Hill and Groothuis (2017) tested whether new international players in the National Basketball Association experience either pay discrimination or salary premiums. Dividing the 1989-2013 seasons into two different sections (1989-1999 seasons and 2000-2013 seasons), they found that foreign players with no college basketball experience in the U.S. were favored in salary in the first era (1989-1999 seasons) but that this trend vanished in the second era (2000-2013 seasons). The authors noted that foreign-born players experienced market preference in the first era because there were only a small portion of international players, but this preference was cancelled out as this portion become larger.

Major league baseball wage discrimination. Similarly to the National Basketball Association, an extensive amount of literature has examined the existence of racial pay discrimination because of diversity in MLB players' race/nationality. Scully (1974) conducted one of the first notable studies on this topic when he uncovered salary discrimination against black MLB players. He revealed that black hitters received lower salaries than white hitters with equal on-court performance and argued that "racial wage discrimination is a feature of the baseball labor market" (Scully, 1974, p. 267). Subsequent studies, however, revealed either small differences in wages or non-discrimination (Hill & Spellman, 1984; Irani, 1996; Kahn, 1993; Medoff, 1975; Mogull, 1979; Raimondo, 1983). Further study of racial pay discrimination in MLB stalled in the 1980s and 1990s because scholars seemed to have reached a consensus that racial pay discrimination no longer existed in the baseball labor market. Kahn (1991, 2000) reviewed professional sports literature on salary discrimination and stated that "regression analysis of salaries in baseball and

football have not found much evidence of racial salary discrimination against minorities" (Kahn, 2000, p. 85).

Research conducted in the 2000s, however, verified racial pay discrimination in MLB and suggested the need for further study. Parmer and King (2006) tested whether unequal pay for equal play was still a problem in the 2000 season. The authors used a regression model to test the observable salary differential between white players and players of color while controlling for individual player performance factors. They demonstrated that black and Hispanic players are discriminated against in the lowest salary distribution, but not in the average or higher-level groups. This showed the possibility of discrimination against minority groups of players in the lower salary ranges even when "equal pay for equal work" is generally preserved.

Holmes (2011) found a similar result when testing MLB 1998-2006 seasons. The author explained previous studies' pitfall of using least squares regression and noted, "if only a particular salary class of players are subject to discrimination, or if the size of the discrimination is small at the average, then least-squares techniques will struggle to identify discrimination" (Holmes, 2011, p. 320). To avoid this oversight, he used quantile regression and weighted least squares regression and found a salary premium of up to 25% for white and Hispanic players for the bottom wage group. Similarly to the findings of Parmer and King (2006), these results demonstrate the importance of using quantile regression to investigate whether there is an invisible market preference in certain salary distributions.

National football league wage discrimination. Similarly to MLB, relatively little attention has been paid to potential racial pay discrimination in the National Football League, as prior literature found little evidence of it (Kahn, 2000). Mogull (1973, 1981), for example, failed to observe a significant relationship between

players' race and compensation in the 1970s; the samples, however, were collected by players, which resulted in a response bias. In both studies, he suggested that NFL teams do not racially discriminate in rewarding player performance.

Kahn (1992), on the other hand, used data from the 1989 National Football League season and applied a regression model with a reliable sample of over 1,000 players. The author found that white players enjoyed a salary premium of 4.1% over black players, which is insignificant, and supports Mogull's (1973, 1981) findings. In addition, Kahn suggested the possibility of fans' preference for players of their own race because both white and non-white players received more money in metropolitan areas where, respectively, more white and non-white fans reside. Team owners would pay more to the players who are favored by fans, as they bring more spectators to the stadium and thus contribute more to team revenue.

More recent research, however, indicates evidence of unequal pay for equal work in the National Football League in the 1990s and 2000s. Guis and Johnson's (2000) study, for example, used 938 players to test whether there is a significant relationship between race and compensation. They found that players' race as well as their experience, draft status, position, and percentage of games started affected players' salaries in the 1996 NFL season. Specifically, they found reverse discrimination in that white players were paid approximately 10% less than non-white players. The findings of their study are different from those of previous literature because Guis and Johnson (2000) used data from the 1990s, while prior literature used data from the 1970s and 1980s.

Berri and Simmons (2009) also examined National Football League racial discrimination in wages but focused on the quarterback position between the 1995-2006 seasons. They uncovered that neither black nor white quarterbacks were

financially rewarded for extra yards they achieved by running despite black quarterbacks showing better running statistics. They also verified the evidence of salary discrimination in that black quarterback players received far less money than comparable white players when they reached median and above-median salary distributions.

Similarly, Keefer (2013) assessed the presence of racial discrimination against 1,575 linebackers using both ordinary least squares (OLS) regression and quantile regression with data from the 2001-2009 National Football League seasons. The author reported that, all else being equal, black linebackers faced salary discrimination. The OLS estimation suggested that non-black (i.e., white) players experienced a salary premium of 10% over comparable black players, indicating evidence of salary discrimination. The quantile analysis also demonstrated that white players experienced market preference of 10.7% and 11.4% in the 0.1 and 0.25 quantiles, respectively.

Nevertheless, Burnett and Van Scyoc (2015), following Keefer's (2013) work, discovered no wage discrimination for offensive linemen or linebackers. Restricting the sample to players in rookie years—when the market is not fully efficient compared to both restricted and unrestricted free agents—they failed to find evidence of salary discrimination other than for offensive linemen in the lower 0.25 salary distribution. The reason the results were different from Keefer's is that Burnett and Van Scyoc included players who joined the league after the 2000s, when the NFL attempted to remedy racial discrimination, while Keefer (2013) used data on players who had joined the league before the 2000s. These contradicting results leave room for further exploration as to whether non-white players face racial pay discrimination in the football labor market.

Soccer wage discrimination. The soccer labor market—the contextual setting of this dissertation—has also received a great deal of attention due to its global popularity and the diversity in its players' race and nationality. The proportion of players of color has gradually increased in the EPL, in that the proportion of players from black, Asian, and minority ethnicities increased from 16.5% in the 1992-1993 season to 33% in the 2017-2018 season (Fraser, 2017). Despite the increase in diversity in the most well-known professional soccer leagues, racism seems epidemic in that players of color face verbal abuse from fans not only on the field but also online (Smith, 2019). For example, Antonio Rudiger, a black defender playing for Chelsea FC, complained to a referee that he was subjected to a racist "monkey" chant from the fans of the opposing team, Tottenham Hotspur (Steinberg, 2020). As such, ESLs have had a conspicuous racism problem in recent years (Fuller, 2019).

In accordance with the problem of racism among fans of the European Soccer Leagues, racial pay discrimination has also been examined in a variety of professional soccer leagues. Szymanski (2000), for example, using data from the EPL 1978-1993 seasons, proposed a market test to investigate whether black players face racial discrimination in salaries. The author found empirical evidence of wage differentials between whites and blacks and confirmed that pay discrimination results from the owners' preferences. It was also found that teams in England that hired black players in lower numbers than below the league average tended to perform more poorly than other clubs, indicating that owners paid a penalty in the form of reduced performance.

Similarly, Reilly and Witt (2007), using a single season with a sample of 361 MLS players, tested whether players face racial discrimination by allocating players into three different groups: white, black, and mixed. The authors failed to find any pay disadvantage for non-white players but suggested that black players who were not

born in the U.S. are paid less than other groups. The lack of racial pay discrimination indicates that MLS has performed effectively in reducing the wage gap between players due to its single entity structure. In a similar context, Medcalfe (2008) examined whether black players are discriminated against in the English soccer transfer market, but failed to find evidence of unequal treatment, suggesting that there is little racial discrimination in the transfer market.

In contrast to racial pay discrimination, relatively little attention has been paid to salary discrimination by players' origin of birth. As the international sports labor market becomes more ethnically diverse, the examination of racial discrimination does not fully capture the existence of discrimination against individuals' demographic characteristics. The United States Employment Opportunity Commission (EEOC) has announced guidance on national origin discrimination. National origin discrimination refers to "discrimination because an individual (or his or her ancestors) is from a certain place or has the physical, cultural, or linguistic characteristics of a particular national origin group" (EEOC, 2016).

With this knowledge, scholars have explored the existence of pay discrimination by origin of birth and found evidence of discrimination in the European Soccer Leagues. Frick (2006), for example, discovered that players from Eastern Europe, Western Europe, and South America experience salary premiums of 15%, 30%, and more than 50% over comparable German players in the Bundesliga. Frick reached a similar conclusion when he updated his study in 2011, revealing that South American and Western European players are paid more than players from North America, Eastern Europe, Africa, Asia, and Australia. The author noted that these results were not surprising given that players from the first two regions are able to attract a larger number of fans (Wilson & Ying, 2003) and contribute more to team

revenue (Kalter, 1999). This indicates that players are paid based on their MRP, not simply their performance statistics.

Frick's research is consistent with the findings of Pedace (2008) and Lehmann and Schulze (2008), whose studies both indicate that, all else being equal, players from South America enjoy a salary premium in the Premier division, implying that players of a certain nationality or origin of birth are favored in the professional soccer labor market. Pedace explained that they experience market preference in wages because a team with additional players from South America experience an attendance increase of approximately 900 fans each season. According to Becker's (1971) discrimination theory, higher salaries for favored players appears to be rational given that a team signs a fan-favorite player at a salary premium due to their higher MRP from the fans' preference.

As for MLS, little research has been conducted to investigate pay discrimination in the league, since soccer has a short history in North America (Coates et al., 2016). To my knowledge, there have been six studies on salary discrimination by origin of birth in MLS (Celik & Ince-Yenilmez, 2017; Kerr, 2019; Kuethe & Motamed, 2010; Medcalfe & Smith, 2018; Prockl & Frick, 2018b; Wooten, 2013). Among these, the work of Celik and Ince-Yenilmez (2017) and Kerr (2019) focused on the effect of players' origin of birth and ethnicity on players' remuneration.

Celik and Ince-Yenilmez (2017) examined salary discrimination by players' origin of birth in the 2007-2016 MLS seasons using the generalized least squares estimation. They found that players' origin of birth was the most significant factor in explaining individuals' compensation. Players from Western Europe, Northern Europe, and South America experienced favorable market treatment, earning salaries

65.4%, 44.6%, and 24.6% higher than those of North American players. In contrast, players from the Caribbean earned salaries 20% lower than those of North American players, indicating salary premiums and reductions based on players' origin of birth. Their study was different from previous MLS studies in that it included performance statistics from the previous season instead of the current one, differentiated between games started and substituted, and considered the transfer dummy to control the effect of a new contract.

Kerr (2019) recently showed empirical evidence of market preference for players from South America with a specific focus on Chivas U.S.A., a former MLS club that played from 2005 to 2014. The author found that Hispanic players were paid above their market value because the club was located in Los Angeles, where many Hispanic fans reside. This evidence supports the existence of salary discrimination in MLS in that players who are favored by the fans are paid more because of their higher MRP. Kerr further noted that there is a strong negative relationship between a team's performance and the proportion of on-field Hispanic players, indicating that discriminatory teams pay for their discrimination.

Unlike other professional sports leagues, which demonstrate mixed evidence of salary discrimination by race, nationality, and origin of birth, literature on the European Soccer Leagues and MLS seems to reach a consensus that salary discrimination exists and prevails in the soccer labor market. Consistent with the findings of the previous literature on the effect of origin of birth on players' compensation, it is expected that the non-favored group(s) of players earn less money than the favored group(s) (Becker, 1971). The first hypothesis is therefore as follows:

H1 There is salary discrimination by players' origin of birth in MLS.

Other forms of discrimination. In addition to salary discrimination, which is the main focus of this dissertation, various forms of discrimination exist against minority players in professional sports. While the focus of this dissertation is wage discrimination, this section will briefly provide a review of other forms of discrimination.

After salary discrimination, the second form of discrimination is exit discrimination, which can be defined as "the involuntary dismissal of workers based on the preferences of employers, coworkers, or customers" (Hoang & Rascher, 1999, p. 69). In professional sports, player turnover rates are high as new players join the league while existing players retire. One question regarding this turnover rate is whether there are certain demographic factors (e.g., race or nationality) that influence players' duration of career length. If black players are found to have a shorter career length than comparable white players, *ceteris paribus*, there is evidence of discrimination in terms of retention. It is therefore of interest to examine whether black players have a relatively similar period of career length to white players.

The third form of employment discrimination is hiring (entry) discrimination. Entry discrimination can be defined as a "failure or refusal by an employer to engage a qualified applicant as an employee due to the existence or consequence of disability" (McMahon, Hurley, Chan, Rumrill, & Roessler, 2008, p. 133). Entry discrimination occurs when an employer is prejudiced and prefers to hire favored group players over non-favored group players. This can take two forms: (a) a minority group faces higher performance standards than the majority group (Kahn, 1991), and (b) if players demonstrate equal performance, employers are more likely to hire those from a favored group (Autor, 2003).

The fourth form of discrimination is positional segregation. This indicates that players of a particular race are either disproportionately overrepresented or underrepresented in certain positions because they are believed to be suited (or not suited) for these positions. In the NFL, for example, people in general formerly believed that black players were not intelligent enough to become leaders (Reid, 2019). For this reason, the roster spot of quarterback was given only to white players, who were believed to be more equipped to lead a team. Positional segregation is in line with co-worker (i.e., employee) discrimination in that players from the majority group may not prefer to follow orders from players from minority groups. Nevertheless, if black players, or any other players from minority groups, are underrepresented in a specific position because of their demographic characteristics, it should be considered to be a form of discrimination.

In addition to the forms of discrimination mentioned above (salary inequality, hiring discrimination, positional segregation, and exit discrimination), sports literature also addresses other potential manifestations of prejudice, such as income from endorsements and speaking engagements (Govan, 1971; Olsen, 1968), bonuses (Aikens, 1971; Mogull, 1975), the quota system (Bouton, 1970), the likelihood of becoming a manager (Cutler, 2016; Stone, 2015), and the probability of being benched (Volz, 2017). With the exception of discrimination driven by fan prejudice, discrimination is unlikely to be sustainable in a perfectly competitive market, because non-prejudiced organizations are likely to experience an economic benefit over prejudiced ones (Arrow, 1973). Nevertheless, discrimination still exists in certain forms, in particular in the sports labor markets. It is therefore important to explore the existence of racial discrimination as well as how inequality manifests.

Superstar Theory

Introduction

Within the salary determination literature, discrimination theory and superstar theory have received a great deal of attention. I explained discrimination theory and the related literature in the previous section and will discuss superstar theory in this section. Understanding the effect of superstar status on players' compensation is necessary in order to answer the main research question of this dissertation: Is there salary discrimination among superstars?

Following Adler (1985) and Rosen (1981), who developed the theoretical framework on the superstar, previous research has inquired into three distinct aspects of the superstar: superstar status and compensation (Bryson et al., 2014; Feess, Frick, & Muehlheusser, 2004; Franck & Nüesch, 2008, 2012; Frick, 2006; Garcia-Del-Barrio & Pujol, 2007; Kiefer, 2014; Kuethe & Motamed, 2010; Lehmann & Schulze, 2008; Lucifora & Simmons, 2003; Prinz, Weimar & Deutscher, 2012; Treme & Allen, 2011), the effect of superstars on fan demand (i.e., attendance and television audience ratings) (Berri & Schmidt, 2006; Berri, Schmidt, & Brook, 2004; Brandes, Franck, & Nüesch, 2008; Humphreys & Johnson, 2017; Burdekin & Idson, 1991; Feddersen & Rott, 2011; Jane, 2016; LeFeuvre, Stephenson, & Walcott, 2013; Lewis & Yoon, 2018; Mullin & Dunn, 2002; Rivers & DeSchriver, 2002; Scott et al., 1985), and the effect of superstars on team revenues (Franck & Nüesch, 2012; Hausman & Leonard, 1997; Lawson et al., 2008). This dissertation follows the line of the above literature by focusing on the effect of superstar status on compensation and expanding the literature on superstars and discrimination in MLS.

A growing body of literature has investigated the relationship between superstars and salary within European Soccer Leagues and American sport leagues

such as the NFL, NBA, MLB, and NHL, but not MLS. Moreover, it is important to understand the superstar effect in MLS because attracting star players from across the world is a key growth strategy—such players are positively related to increased attendance (DeSchriver, 2007) and ticket sales (Lawson et al., 2008). Thus, there is a need to determine whether superstar status plays a significant role in explaining variation in MLS players' compensation. The purpose of this section is therefore to use the superstar theory to explain the degree to which superstars are paid more than regular players (RPs) and whether there is salary discrimination among superstars. This section endeavors to extend not only the existing literature on superstar theory in the sports industry but also the literature that links superstar theory and discrimination theory.

Theoretical Framework

What makes a small portion of athletes in a given occupation superstars? Why do some professional athletes earn far higher salaries than others? Within the superstar literature, the dominant and competing theories of superstar formation explain that superstars earn high salaries based either on their talent (Rosen, 1981) or on their popularity (Adler, 1985). Both theories agree on the need for large economies of scale, but the driving forces for high salaries for superstars are different.

The first theory of superstar formation is Rosen's (1981) theory, which suggests that a marginal difference in talent between the players is the key factor in explaining the large differences in salary: that is, superstars enjoy market preference due to their scarcity of talent (i.e., talent superiority). In his seminal work, "The Economics of Superstars," Rosen (1981) explains how "small differences in talent become magnified in large earnings differences" (Rosen, 1981, p. 846) when there is a convex relationship between a player's talent and compensation (Figure 2.3).

According to Rosen (1981), imperfect substitutability of talent leads to this convex relationship based on the reasoning that quality cannot be replaced by quantity. Sports fans are more likely to be satisfied with a superstar than with several RPs (Rosen, 1981). In this case, they prefer to consume high-quality performances within a budget constraint. The inequality in salary for superstars can therefore be attributed to their marginal difference in talent and spectators' higher willingness to pay for them.

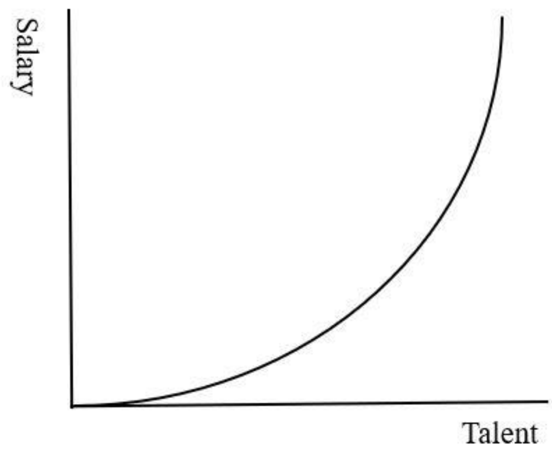

Figure 2.3. Convex Relationship between Talent and Salary.

The second superstar theory, by Adler (1985), posits a different way of explaining the rationale behind high salaries for superstars. The theory of Adler (1985) is in line with that of Rosen (1981) in that large economies of scale are feasible in sports due to the development of technology and irrelevance between the cost of production (i.e., the game) and the number of spectators. However, it holds that player's popularity from the media coverage and network effects are the driving force for the salary differences, even when superstars are not talented. Adler (1985, 2006) follows the theory of consumption capital (Stigler & Becker, 1977), where consumption capital refers to the previously accumulated capital stocks that affect the current consumption. In this model, sports fans accumulate knowledge on certain players (e.g., superstars) and discuss players' performance. This discussion increases

fans' enjoyment while they interact with other sports fans (i.e., positive network externalities). Adler's (1985) model therefore suggests that positive network externalities and media coverage enable sports fans to consume "superstar" products because the more the fans know about the players, the more they enjoy and accumulate positive network externalities.

Superstar-related literature. Numerous studies have used superstar theories (Adler, 1985; Rosen, 1981) to examine the effect of superstar status on players' salaries in various sports settings. While most previous studies agree on using traditional performance factors (e.g., goals and assists) as proxies for talent (in Rosen's sense), several types of media coverage and network effects have been used to measure "popularity" (in Adler's sense), including press releases (Franck & Nüesch, 2008, 2012; Lehmann & Schulze, 2008; Treme & Allen, 2011), Google hits (Garcia-Del-Barrio & Pujol, 2007), Facebook fans (Prinz et al., 2012), and All-Star votes (Berri & Schmidt, 2006; Berri et al., 2004; Brandes et al., 2008; Hausman & Leonard, 1997). For this reason, previous literature has not reached a consensus on the superstar effect, leaving room for further investigation of this issue.

Treme and Allen (2011) used data from the 2001-2006 National Football League seasons to investigate whether talent and popularity can explain salary differences among wide receivers. Using performance variables (e.g., the number of college touchdowns) as an indicator of talent and media exposure (e.g., the amount of media exposure in major U.S. newspapers) as an indicator of popularity, the authors found evidence of superstar effects of popularity but not talent. They noted that popularity from media exposure translates into higher salaries to NFL players, while both media exposure (i.e., popularity measure) and college performance (i.e., talent measure) are important determinants of wide receivers in the first year. However, as

the study included only wide receivers for a limited number of seasons, it cannot be generalized to other sports leagues.

Within the soccer literature, Lucifora and Simmons (2003) conducted the first empirical study on the superstar effect in professional sports. They included a superstar variable measured by goals and assists while controlling for players' experience, reputation, and team quality. Using 533 soccer players who played during the 1995-1996 season in the ISLs (i.e., Serie A and Serie B), the authors found evidence for the superstar effect, as defined by Rosen's (1981) theory. They found that strike rates and assists were significant factors in explaining high salaries for forwards, while midfielders with more goals enjoyed a superstar premium. This study, however, is limited to testing Rosen's (1981) superstar theory and does not consider Adler's (1985) theory.

Garcia-Del-Barrio and Pujol (2007) examined the effect of both talent and popularity to explain the variance in players' market value in the SSL. They used a traditional performance variable measured by press releases (e.g., Puntos Marca and Liga Fantastica) for the talent index and a Google hits variable for the popularity index. Defining superstars as "those players with the highest Internet exposure as measured by Google variable" (p. 63), the authors found evidence of the positive effect of talent and popularity on players' market value during the 2001-2002 season, supporting both Rosen's (1981) and Adler's (1985) theories.

Lehmann and Schulze (2008) tested superstar theory in the GSL (Bundesliga) using 651 players from the 1998-2000 seasons. They employed OLS and quantile regression, using three measures for players' talent (i.e., goals, assists, and tackles) and media exposure (i.e., number of hits in the "Kicker" sports magazine) to measure players' popularity. The authors failed to find evidence of the superstar effect by

performance or popularity; that is, neither talent nor popularity demonstrates the proportional variance in players' salaries. They explained that the salary differential can be attributed to different performance and popularity but did not describe why Rosen's (1981) and Adler's (1985) theories are not supported in the Bundesliga.

Using the 2001-2006 seasons, Franck and Nüesch (2012) also tested the Bundesliga to examine whether players' talent or popularity leads to a large differential in wages between regular players and superstars. Using the popularity variables measured by the number of annual exposures in newspaper and magazines and talent variables measured by on-pitch success (e.g., goals, assist, shots, saves, and cards), they verified both Adler's and Rosen's superstar effect within the Bundesliga context. More specifically, they found that, in the 95% quantile, superstars' salaries increased by 4.5% (€0.25 million; 0.045×5.5 million) with an additional goal and 11.9% (€0.25 million; 0.119×5.5 million) with an additional media exposure. By contrast, the RPs' salaries increased by only 4% (€0.06 million; 0.04×1.5 million). This implies that superstars experience a higher level of salary increase than RPs resulting from their performance statistics. The findings of Franck and Nüesch's study are inconsistent with those of Lehmann and Schulze (2008), who did not find empirical evidence of superstar effect in the Bundesliga.

This discrepancy in the superstar effect on players' salaries in prior soccer literature indicates that its impact may change over time. In addition, the mixed evidence for superstar effects in European Soccer Leagues may be attributed to unclear measurements of superstars. Both Adler (1985) and Rosen (1981) developed a clear argument regarding superstar effects, but discussion of the degree to which talent or popularity can explain superstars' compensation has not yet been resolved (Kiefer, 2014).

Major League Soccer literature. In the superstar literature, it is still controversial as to which variable (talent or popularity) is more adequate in explaining superstars' salaries, because different definitions and measures of superstardom have been devised. In the National Basketball Association, for example, "superstar" refers to "a player who has made the All-Pro team five times, or if he has only played a few years, dominates his position" (Scott et al., 1985, p. 38), while Jane (2016) defined superstar as "a player who makes top performances or who gets a top salary" as a proxy of talent (in the Rosen sense) and "a player who is an All-Star player and the total votes received by the star player" as a proxy of popularity (in the Adler sense) (p. 397). Moreover, various measures of talent (e.g., goals per game ratio, goals, assists, tackles, and touchdowns) and popularity (e.g., media exposure, Google hits, Facebook fans, and All-Star votes) have been used to examine the effect of superstar status on compensation. Nevertheless, it is nearly impossible to use an objective measure of "superstar" and to quantify what determines superstar status (Krueger, 2005), resulting in mixed results as to its effect.

Unlike other professional sport leagues, where it is difficult to objectively define and measure superstar status, the DP rule, an exceptional feature of MLS, provides a less arbitrary definition (Jewell, 2017). As designated players are, in general, more talented and popular while positively influencing attendance (DeSchriver, 2007; Jane, 2016; Parrish, 2013), the DP rule provides MLS a legitimate reason for using designated player status (DPS) as a proxy for superstars (Coates et al., 2016; Jewell, 2017; Kuethe & Motamed, 2010).

In addition to the DP rule, the All-Star experience has also been used as a proxy for superstars in MLS (Kuethe & Motamed, 2010; Wooten, 2013) as well as other professional sports leagues (e.g., Berri & Schmidt, 2006; Berri et al., 2004;

Brown et al., 1991; Burdekin & Idson, 1991; Idson & Kahane, 2000). In MLS, for example, a total of 26 players are nominated as All-Star players during the midseason break through a combination of fan votes, coach and general manager votes, and media exposure (Kinkead, 2017). Although the All-Star experience may represent players' popularity, it does not fully capture the superstar effect (Kuethe & Motamed, 2010), which combines the effects of both popularity (Adler, 1985) and talent (Rosen, 1981). With this knowledge, previous literature has examined the superstar effect using DPS or both DPS and All-Star experience in the wage model.

Coates et al. (2016), for example, investigated how salary structure in MLS affects team production. Using DPS as a proxy for superstars, the authors found that team performance is negatively related to increases in salary inequality, as measured by the Gini coefficient. Jewell (2017) tested the effect of superstars on MLS attendance with data from the 2007-2012 seasons. He defined superstars as "the highest paid DPs" (p. 242) and used the term "marquee player" (referring to a player who makes more than $2 million in base salary) instead of "superstar" in order to capture both talent (Adler, 1985) and popularity (Rosen, 1981). He found that few marquee players attract MLS fan demand (i.e., attendance) and that the superstar effect diminishes over time. Two studies have examined the effect of superstar status (i.e., DPS) on players' compensation within MLS.

Kuethe and Motamed (2010) investigated salary determination with a focus on the effect of superstar status using 193 soccer players who played in the 2007 season and were on the 2008 season roster. They used two different measures of superstar status in MLS: participation in the All-Star games and DPS. During MLS's midseason break, a squad of 18 players is selected to compete with a European club based on media exposure and votes from fans, players, coaches and general managers. The

authors acknowledged, however, that the All-Star games variable can only capture the reputation effect (i.e., popularity) and not the superstar effect. For this reason, the interaction variables that can capture talent (i.e., performance) were included in order to fully understand whether players who participate in All-Star games are more talented and popular. DPS were considered a second proxy for the superstar. Using OLS and quantile regression, Kuethe and Motamed found empirical evidence of the superstar effect. The DPS and All-Star games variables were both shown to increase players' salaries for not only the league's average players but also the top 5% of earners, confirming superstar theory in MLS.

Wooten (2013) also tested salary determination to investigate whether superstar theory is supported in MLS, using four different categorical measures of the superstar effect: national team experience at the international level, All-Star games experience, starting line-up (best 11 members) list based on fan voting, and DPS. Using 838 players from the 2010-2012 seasons, the author found that, along with performance variables (e.g., goals and assists), superstar status is a significant determinant of players' salaries in MLS. The author further explained that performance statistics are the main determinants in the lower quantiles, while superstar effect plays a key role in determining players' compensation in the upper quantiles. This finding shows the importance of quantile regression, which may indicate that superstar effect may be different in different wage distributions.

While several measures (e.g., DPS and All-Star experience) have been used to define superstar status in MLS, scholars seem to have reached a consensus that DPS is a proxy for the superstar. For this reason, this dissertation also uses DPS as a proxy for superstar status. Consistent with the findings of the previous literature, it is

expected that designated players are more likely to earn higher compensation. This expectation leads to the second hypothesis:

H2 There is a positive relationship between superstar status (i.e., designated player status) and compensation.

Superstar and discrimination. Previous research has explored salary determination and discrimination from two different perspectives: by race or nationality (i.e., discrimination theory) and superstar salary (i.e., superstar theory). Again, there is limited research that investigates whether pay discrimination is also of significance to superstars, who are more talented (Rosen, 1981) and popular (Adler, 1985). Exploring the existence of salary discrimination among superstars is important because the DP rule was introduced to sign star players and promote the success of MLS by increasing attendance and revenue. If certain players are discriminated against in MLS, they are unlikely to choose to play in the league, but will instead play in ESLs, where financial rewards are guaranteed (Prockl & Frick, 2018b). The degree to which players' salaries are affected by their origin of birth should therefore be investigated.

Despite the importance of understanding pay discrimination in MLS, only one study has examined salary difference by origin of birth among superstars. Prockl and Frick (2018b) tested whether salary discrimination by origin of birth exists in MLS. Using performance data for the 2006-2015 seasons and salary data for the 2006-2016 seasons, they employed OLS, quantile regression, and fixed effect model. To better understand the existence of salary discrimination by origin of birth, the authors differentiated regular players and superstars (i.e., designated players) due to the heterogeneity in performance and players' characteristics between the two groups. They found evidence of salary discrimination among RPs: players from South America, Central America, and Western Europe were paid more and players from

Asia and Oceania were paid less than comparable domestic (i.e., North American) players. They also found pay discrimination among DPs: the highest-paid players from North America enjoyed a salary premium over similarly gifted DPs from South America, Western Europe, and the Caribbean. This evidence suggests salary discrimination by origin of birth among both RPs and superstars. The authors were cautious, however, about stating that local superstars are favored in MLS, because the main determinants of DP salaries in their simple model were club-specific effects (e.g., market size).

While Prockl and Frick (2018b) first attempted to differentiate regular players and designated players and investigate wage determination for each group, there are several reasons further investigation on salary discrimination among superstars is needed. First, OLS regression may not be appropriate to fully investigate the existence of salary discrimination among superstars. Prockl and Frick employed both OLS and quantile regression to estimate the effect of RPs' origin of birth on compensation, however, they did not use quantile regression to explore whether there is salary discrimination among superstars because of the limited observations of DPs. Unlike OLS, which reveals the relationship between mean dependent variable and independent variables, quantile regression could give more insights on whether there is other possible evidence of discrimination in different wage distributions (Lehmann & Schulze, 2008). As the MLS players' salaries are highly positively skewed (Kuethe & Motamed, 2010), it is necessary to employ quantile regression to better understand the existence of invisible pay discrimination among superstars across the distribution (Hamilton, 1997; Holmes, 2011; Keefer, 2013).

Second, the study of Prockl and Frick (2018b) did not include performance statistics (i.e., goals and assists) in the designated players model, making the result

less reliable. Players' performance statistics, within the salary determination literature, are important factors affecting compensation because talented players could contribute more to a team's success (i.e., winning). With this knowledge, researchers have inquired into the pay-performance relationship in MLS and showed a positive relationship between a player's performance and payroll (Celik & Ince-Yenilmez, 2017; Lee & Harris, 2012). As the omission of relevant variables could potentially bias the results (Clarke, 2005), I included players' performance statistics in the DPs model to estimate the existence of salary discrimination among superstars.

Third, they acknowledged that their sample size of 145 observations is very small, suggesting that further confirmation of salary discrimination among designated players is required. They found the initial evidence that North American superstars are paid more than comparable players from South America, Western Europe, and the Caribbean. However, this finding contrasts with previous MLS studies (e.g., Celik & Ince-Yenilmez, 2017; Kuethe & Motamed, 2010; Medcalfe & Smith, 2018), which found that local players (i.e., North American players), including both RPs and DPs, are paid less than players from other regions (e.g., South America and Europe). As this contradictory finding may be attributed to the small sample size, further study with a larger dataset is needed in order to derive more reliable results as the finding of Prockl and Frick (2018b) may be inconclusive. For this reason, this dissertation includes 293 observations of DPs, more than double the sample size used by Prockl and Frick (2018b).

Fourth, the main focus of their study was not the existence of salary discrimination among superstars. They focused on, instead, the effect of league regulation on MLS players' salaries; thus, the study was limited to indicating the possible evidence of salary discrimination among designated players (i.e., superstars)

in MLS. For this reason, there is a need to study the degree to which superstars' salaries are influenced by their origin of birth with a focus on discrimination context.

To date, no attempt has been made to use quantile regression to explore the degree to which superstars' compensation is affected by their origin of birth. Therefore, this dissertation is the first to employ quantile regression to uncover the evidence of salary discrimination among superstars in different salary distributions while comparing the results of both OLS and quantile regression analyses. In addition, this study endeavors to fill this gap in the literature on salary discrimination among superstars by focusing on discrimination theory and by examining whether players from certain regions are either favored or discriminated against in the MLS labor market with a larger dataset. Consistent with the findings of Prockl and Frick (2018b), the third hypothesis is as follows:

H3 There is salary discrimination by players' origin of birth among superstars.

Human Capital Theory

Introduction

Understanding the role of human capital in wage determination literature has been an important issue because each person has different level of human capital. For this reason, previous studies have examined the effect of various human capital factors on employee compensation (Shamki & Shehemi, 2019). These factors include education (Aydinli, Oral, & Oral, 2019; Caruth & John, 2008; Liu & Zhang, 2008; Morikawa, 2016), age and experience (Agarwal, 1981; Bhattarai, 2017; Medoff & Abraham, 1980), and gender (Ohlott, Ruderman, & McCauley, 1994; Ufuophu-Biri & Iwu, 2014).

Professional athletes, of course, have various types of human capital, and these factors vary by players. According to human capital theory (HCT), there are wage

differentials between players with different levels of human capital. Relatively little attention, however, has been paid to wage determination in the professional sports labor market using human capital factors. For this reason, this study included human capital factors as determinants that may affect both regular and superstar players' compensation. The purpose of this section is thus to use HCT to explain the degree to which compensation of an athlete is determined and to provide an economic model of the salary of an individual professional athlete. This section seeks to not only build on the literature on human capital but also attempts to provide comprehensive theoretical frameworks for salary determination by examining the importance of human capital in professional sports.

Theoretical Framework

HCT was developed in the 1950s by Theodore Schultz and Gary Becker, two academics at the Chicago School of Economics (Blaug, 1992). The term "human capital" derives from the neo-classical economic model, which assumes that individuals attempt to maximize their economic interests (Tan, 2014). Accordingly, HCT suggests that individuals invest in human capital through education and training to optimize future economic returns from the workplace. An individual gains human capital (e.g., skills and knowledge) through formal education, on-the-job experience, and vocational training. The increased knowledge and skills improve an individual's productivity and compensation (Tan, 2014). Blaug (1992) has stated that investment is not only "for the sake of present enjoyments but for the sake of pecuniary and non-pecuniary returns in the future" (p. 207). This reasoning suggests that investment in education and training is positively correlated with future earnings. Thus, the concept of workers investing in marketable skills has been key to labor economics (Acemoglu & Autor, 2011).

Human capital has been described as “productive wealth embodied in labor, skills and knowledge” (OECD, 2001), whether innate or acquired, that contributes to economic productivity (Garibaldi, 2006). HCT posits that individual compensation is influenced by a person’s level of human capital factors, such as education, experience, skills, and abilities (Becker, 1964; Mincer, 1974). The theory also suggests that an individual’s wage is positively influenced by education; education can therefore be seen an economic investment. As Marshall (1920) stated, human capital is “the most valuable of all capital is that invested in human beings” (p. 564).

HCT indicates that level of human capital directly correlates with a worker’s compensation (Becker, 1964; Mincer, 1974). Within business and economics contexts, scholars have explored the relationship between human capital and compensation and suggested that there is a positive relationship between remuneration and human capital factors such as experience and age (Bhattarai, 2017; Boudarbat, Lemieux, & Riddell, 2006; Danity, Cheng, & Moore, 2005; Morikawa, 2016), education (Addabbo & Favaro, 2011; Yang & Mayston, 2012), and skills (Chen, Ge, Lai, & Wan, 2013; Di Paolo & Tansel, 2015; Ginsburgh, Melitz, & Toubal, 2017). Although an individual’s human capital can be measured by various factors such as natural ability, innate and acquired skills, age and experience, talent, inventiveness, and innate and acquired skills (Kucharcikova, 2011), I will focus on four factors that can be applied to the professional sports labor market: experience, age, skills (or innate abilities), and physical attributes.

Compensation and experience. Experience can be measured as employment length in years or tenure in the position (Wright, 1990). According to HCT, more experience (i.e., more years of employment) increases individuals’ compensation, because experience reflects more accumulation of useful human capital (Grant,

Leadley, & Zygmont, 2013). Individuals are more likely to work better by doing, even failing from time to time, accumulating know-how in their occupation over time. Intuitively, more experienced employees are more productive and can contribute more to the corporation than employees who are less experienced. Experienced individuals will therefore have a higher MRP than inexperienced individuals and are thus expected to receive higher compensation.

A positive relationship between experience measured by employment length and tenure status and compensation has been found in a variety of settings, including university presidents (Banker, Plehn-Dujowich, & Xian, 2010; Medoff & Abraham, 1980, 1981; Pfeffer & Ross, 1988), CEOs (Agarwal, 1981; Brockman, Lee, & Salas, 2016; Custodio, Ferreira, & Matos, 2013), engineers (Aydinli et al., 2019), and general workers (Bhattarai, 2017). In a study of over 600 presidents in higher education, for example, Pfeffer and Ross (1988) demonstrated that the experience variable, measured by employees' tenure in the position, had a positive effect on the compensation of university presidents. They also indicated that this result is intuitive given that university presidents accumulate skills required for holding their specific position over the course of their careers.

The effect of experience on salary is not limited to the executive leader; it also applies to general workers. Aydinli et al. (2019) examined the compensation of engineers in Turkey and found that engineers with 11-20 years' experience earn 22.29 and 3.66 times the salary of engineers with 0-2 years and 6-10 years of experience, respectively. They also noted, however, that more experience does not always guarantee a higher level of compensation in that some experienced workers make a great deal of money in high positions while others continue to work in low-profile positions such as building inspectors. By using self-organizing maps to visualize the

relationship between the data, their results imply that employees' compensation would increase with experience up to a certain point.

The effect of individuals' experience on salaries also has been investigated within the sports labor market and found to be positively associated with players' salaries in professional sports settings such as the ESLs (Hubl & Swieter, 2002; Lucifora & Simmons, 2003), NFL (Berri, Humphreys, & Simmons, 2013; Leeds & Kowalewski, 2001), NBA (Wallace, 1988), MLB (Blass, 1992; Raimondo, 1983; Stone & Pantuosco, 2008), NHL (Jones et al., 1999; Marchand, Smeeding, & Torrey, 2006; Richardson, 2000), and MLS (Celik & Ince-Yenilmez, 2017; Kuethe & Motamed, 2010; Prockl & Frick, 2018b; Reilly & Witt, 2007). Wallace (1988), for example, examined salary determinations for the 1984-1985 National Basketball Association season using performance, race, position, and human capital as the specific variables of interest. The author found that years of experience in the NBA was the human capital variable (other than players' original draft positions and All-Rookie Team selection in the first year) that had the largest impact on players' compensation, indicating that experience is a key factor in explaining NBA players' salaries.

Stone and Pantuosco (2008) estimated the impact of experience on compensation in MLB and specifically focused on whether salary productivity elasticities for performance factors (e.g., slugging average, player durability, and player consistency) have soared over time. They found that player salaries increase with experience and that baseball team owners place more value on player productivity over time. The authors also noted several possible explanations for the positive relationship between experience and salary: 1) a player's productivity may be intensified by additional years in the league with accumulated know-how, and 2)

regardless of their performance statistics, players become more popular as their names are more recognizable to sports fans. The significance of human capital was further supported by Kuethe and Motamed (2010), who confirmed that experience has a positive effect on players' salaries in MLS. They found that players' salaries increase by 19%-33% with each additional year of MLS experience.

Findings from the previous literature demonstrate that a player with a greater level of experience is expected to have higher productivity and is hence seen as deserving higher compensation. As HCT posits, individuals who have made investments in work experience earn a wage premium in MLS. This leads to the following hypothesis:

H4 A player's salary is positively associated with his experience.

Compensation and age. Age is another component of human capital. HCT suggests that a worker's age, like experience, is positively associated with compensation (Becker, 1964). This is because there is a seniority effect: a worker's compensation increases for each year a worker remains in the occupation (Ransom, 1993). This increase, however, does not last until an individual's retirement, in that his or her MPL decreases at a certain point. For this reason, previous studies have inquired into the effects of age on compensation (Bhattarai, 2017; Boudarbat et al., 2006) while including quadratic specification in terms of age to capture age and compensation's concave relationship (Bhattarai, 2017; Morikawa, 2016). These studies have found that there is a positive but decreasing (i.e., concave) relationship: wages mostly increase alongside age, but this increase tends to drop off after a certain age.

Morikawa (2016), for example, analyzed the wage structure in the public and private sectors of the Japanese labor market. The author addressed age's positive

impact on workers' compensation and its decreased impact after the age range of 50-55. The positive effect of age and the negative effect of squared term of age (i.e., concavity) was also estimated by Bhattarai (2017), who tested the determinants of wages and labor supply in the United Kingdom. Salaries were found to increase with age until 45, when they dropped off. The findings of the above literature imply that wages tend to increase with age up to a certain point, but this increase tends to drop off in the general labor market.

Within the sports literature, scholars have examined the concavity of age-earning profiles in sports and discovered a positive (negative) effect of age (squared term of age) on salary in various sports settings including the ESLs (Bryson et al., 2013; Lucifora & Simmons, 2003; Nüesch, 2009; Thrane, 2019), NBA (Lee, Leonard, & Jeon, 2009; Simmons & Berri, 2011), MLS (Prockl & Frick, 2018b), and NHL (Lambrinos & Ashman, 2007; Marchand et al., 2006). Simmons and Berri (2011) analyzed the relationship between the human capital factor of age and players' salaries in the 1990-2008 NBA seasons. They determined that NBA players experience a maximized level of salary at 26 years of age, verifying that age (squared term of age) had a positive (negative) effect on players' remuneration.

This finding is different from that of Berri and Schmidt (2010), who reported that players' performance statistics peaked at 24 years of age in the 1977-2008 seasons. Simmons and Berri (2011) provided a possible explanation for the difference in ages of peak performance: not only did they use the recent data set, but players' performance has improved over time due to the improvement of conditioning methods and player training. This may show that players' peak age of performance could be prolonged with technical support.

More recently, Thrane (2019) investigated which individual characteristics and performance factors influence player’s earnings in the Norwegian professional soccer league. The study included 240 players who played more than two games in 2014. In controlling for the concavity of age-earning profiles (salaries tend to rise at the beginning of the year and flatten out when players reach the age of the highest performance level), the author demonstrated that age has a positive impact on player salaries, while its squared term demonstrated a negative relationship with compensation. This implies that soccer players earn more money until they reach their top performance at a certain age and their salaries decrease.

Within MLS literature, however, the evidence of age-earnings profile is mixed. Reilly and Witt (2007) investigated the determinants of MLS players’ base salaries in the 2007 season. The OLS regression from their study indicated that, all else being equal, salaries increase by 5.9% as the players become older. Similarly, Celik and Ince-Yenilmez (2017) found that each year of age is equivalent to an increase by 5.7% of players’ salaries in the 2007-2016 MLS seasons. However, these two studies did not include the square term of age, which controls the concavity effect, and did not fully capture the concavity of age effect on salary.

Kuethe and Motamed (2010), however, found a contrasting relationship between compensation and age for players in MLS. Using the 2007 single season with a total of 193 observations, they revealed that age negatively affected players’ remuneration, indicating a convex relationship between the two variables. While the study included both the age variable and square term of age to control for the concavity effect, the result showed that age was negatively associated with compensation and square term of age was positively associated with salary. This peculiar relationship (i.e., convexity) may be attributed to certain aspects of MLS

structure. The author explained that MLS, a relatively less-established league for superstars, offers a lucrative salary to well-known players at the end of their careers. For this reason, superstars receive maximized compensation with higher age. In addition, MLS offers a large amount of money to young superstars to keep them playing in the domestic league before they realize their higher salary possibility in the international soccer markets (e.g., the European Soccer Leagues).

Prockl and Frick (2018b) recently tested whether age and square term of age are significantly associated with regular and superstars in MLS. They found that, for the regular players, the age variable shows an inverted u-shape, indicating that players' salaries increase up to a certain point, but then decrease. To be specific, they noted that RPs reach their peak in salaries at 33.6 years old. For the designated players, however, they failed to find the effect of age on players' compensation, indicating that age does not contribute to the determination of superstars' salaries. They did not, however, provide an explanation for why age is significant in the RP model and not significant in the DP model, leaving room for further investigation into this issue. The concavity of age effect on salary was further supported by Medcalfe and Smith (2018), who demonstrated evidence of a positive (negative) effect of age (squared term of age) on both base salary and guaranteed compensation in MLS. Using data from the 2007-2014 MLS seasons, they confirmed that there is a concave relationship between salary and players' age.

As the above examples showed, the evidence of the effect of age on players' compensation is somewhat mixed because Kuethe and Motamed (2010) found a negative (positive) effect of age (squared term of age) on MLS players' compensation. Although the finding of their study has interesting points, they analyzed wage determinants including age with a single year, which cannot be

generalized. For this reason, consistent with the findings of Medcalfe and Smith (2018) and Prockl and Frick (2018b) with a broader data set, it is expected that there is a positive but decreasing (i.e., concave) relationship between salary and age in MLS. This leads to the following hypothesis:

$H5_a$ A player's salary is positively associated with his age.

$H5_b$ A player's salary is negatively associated with his squared term of age.

Compensation and skills (innate or acquired). Skills, whether innate or acquired, are another component of human capital that contribute to an organization in a unique way (Bontis, Dragonetti, Jacobsen, & Roos, 1999). According to HCT, variation in worker compensation can be explained by the level of skill that a worker brings to the organization (Davenport & Prusak, 1998). These skills increase work productivity, thereby attracting higher salaries because an individual with skills has a higher MPL and contributes more to the organization (Tan, 2014).

Several studies have concentrated on the effect of individual skills on compensation (Chen et al., 2013; Di Paolo & Tansel, 2015; Ginsburgh et al., 2017). Di Paolo and Tansel (2015), for example, estimated the economic benefits of learning foreign languages in Turkey with a study of over 6,000 adult males in 2007. They found that there was an economic premium for learning English, Russian, French, and German. Their results indicated that there was a positive relationship between foreign language skills (i.e., acquired skills) and workers' compensation.

Also, relevant is a study that assessed the relationship between innate skills (e.g., the dominance of the left or right hand) and compensation (Denny & O'Sullivan, 2007; Ruebeck, Harrington, & Moffitt, 2007). Denny and O'Sullivan (2007) reported that left-handed men receive 5% higher salaries than right-handed men because they are believed to be more creative. Similarly, Ruebeck et al. (2007)

demonstrated that highly educated men who were also left-handed received higher salaries than highly educated right-handed men, supporting the positive relationship between innate skills and compensation. The above literature demonstrate that innate skills are important in explaining individual's compensation.

After a recent study found a "surprising absence of plasticity in foot use, given the importance of learning, experience, and culture in models of handedness and footedness" (Carey et al., 2009, p. 650), empirical research has examined the effect of innate skills (e.g., left-handedness for baseball and hockey, and being ambipedal for soccer) on compensation within professional sports leagues such as MLB (Krautmann, Gustafson, & Hadley, 2003), ESLs (Bryson et al., 2013), MLS (Prockl & Frick, 2018b), and NHL (Coates, 2017; Fenn, Gerdes, & Rothstein, 2019). Within MLB literature, Krautmann et al. (2003) examined 180 pitchers between 1990 and 1994 to test whether special talent (i.e., left-handedness) is, because of its scarcity, associated with a salary premium for baseball pitchers. The study assumed that left-handed pitchers would have an advantage over right-handed pitchers based on the former's scarcity in the market; it found that left-handed pitchers earn higher salaries, indicating the positive impact of scarce talent on players' salaries.

Frick and Simmons (2007) examined scarce soccer talent, specifically the performance of ambipedal players. They found that ambipedal players had a salary premium of more than 50% and that these premiums were similar across major European Soccer Leagues. Bryson et al. (2013) also examined scarce soccer talent, specifically the performance of ambipedal players. They investigated whether both-footed or left-footed players experience market preference over right-footed players in the five European leagues (i.e., EPL, GSL, ISL, SSL, and Ligue 1). After controlling for player performance measures, the study found that both ambipedal players and

left-footed players had a significant earnings premium of 17.1% and 12.0%, respectively. This is attributed to the proposition that both-footed players are more likely to make space and goals from various angles. In addition, they can play in various positions, giving them market preference from the perspective of owners in that they can be multi-purpose players for their coach's strategy.

Findings on scarce talent in professional sports suggest that scarce talent can play a significant role in determining players' compensation. Within the soccer context, it is expected that players who are both-footed are paid more than right-footed or left-footed players because of their innate abilities. This leads to the following hypothesis:

H6 A player's salary is positively associated with his innate skills or scarce talent.

Compensation and physical attributes (height). Physical attributes such as appearance (Becker & Tomes, 1986), height (Weil, 2007), and weight (Aizer & Cunha, 2012) are also forms of human capital (Schultz, 2002). Scholars have investigated how an individual's physical attributes affects workers' compensation (Frieze, Olson, & Good, 1990; Frieze, Olson, & Russell, 1991; Hamermesh & Biddle, 1994; Harris, Harris, & Bochner, 1982; Hatfield & Sprecher, 1986; Mirta, 2001). Hatfield and Sprecher (1986), for example, investigated whether workers' salaries are associated with appearance, height, weight, and other attributes in the U.S. labor market. Their study discovered that height can positively influence wages. Frieze et al. (1990) analyzed the effects of height and weight on the salaries of 1,000 MBA graduates and demonstrated that, while height had a positive effect on starting salaries, being overweight had a negative effect, implying that physical attributes may influence individuals' compensation.

Within the realm of the sports world, physical attributes such as height and weight can be helpful to enhance productivity and performance, given that taller and heavier players contribute more to teams in certain positions. In soccer, for instance, forward players who are taller than opponents' defenders are more likely to score header goals. Although several studies have examined the effect of height and weight on the compensation of professional athletes (Idson & Kahane, 2000; Lambrinos & Ashman, 2007; Marchand et al., 2006; Prockl & Frick, 2018b; Weimar & Wicker, 2017), researchers have not reached a consensus on such an effect, and whether these physical attributes generate higher salaries remains controversial. For example, height has either been positively associated with compensation (Bryson et al., 2013; Lambrinos & Ashman, 2007) or found to be not significant (Prockl & Frick, 2018b; Weimar & Wicker, 2017). Nevertheless, taller players are believed to contribute to a team's success, in general, because of their heading ability (Bryson et al., 2013). Therefore, it is expected that physical attributes affect workers' compensation, according to HCT. This leads to the following hypothesis:

H7 A player's salary is positively associated with his physical attributes (e.g., height).

Other Determinations of Salaries

Introduction

In addition to players' origin of birth, superstar status, and human capital factors (i.e., age, experience, footedness, and height), other determinants also affect players' salaries. These include factors such as performance, league appearance (e.g., career games played), and position. While these factors are not the main focus of this dissertation, I have included three other salary determinants in MLS.

Related Literature

Performance and compensation. First, players' performance statistics naturally influence compensation given that players can contribute more to teams based on their talents. For this reason, estimating the relationship between a player's performance and payroll (i.e., the pay-performance relationship) has received a great deal of attention in sports economics. Individual performance factors have been found to influence players' compensation in professional sports leagues such as the ESLs (Bryson et al., 2013; Frick, 2011; Garcia-Del-Barrio & Pujol, 2005; Lehmann & Schulze, 2008; Lucifora & Simmons, 2003; Thrane, 2019), NBA (Wallace, 1988), NFL (Berri et al., 2013), NHL (Idson & Kahane, 2000; Jones et al., 1999; Lambrinos & Ashman, 2007), MLS (Celik & Ince-Yenilmez, 2017; Lee & Harris, 2012; Prockl & Frick, 2018b), and professional baseball leagues including MLB, other Japanese baseball leagues, and Chinese baseball leagues (Chen, Chuang, Kuo, & Chen, 2018; Krautmann et al., 2003; Leeds, Sakata, & Allmen, 2012; Raimondo, 1983; Scully, 1974; Stone & Pantuosco, 2008).

Professional athletes that perform better as measured by performance statistics are expected to receive higher levels of compensation. These performance statistics vary by sport. For soccer, they can include goals and assists. For baseball, they can include batting averages, on-base percentage, slugging percentage, wins above replacement, innings pitched, earned run average, walks plus hits per inning pitched, and strikeouts-to-walk ratio. For basketball, they can include points, rebounds, and blocks. For hockey, they can include goals, points, and penalties. For football, they can include reception, rushing attempts, rushing yards, kick returns, and tackles.

Raimondo (1983) examined the effect of player performance factors on compensation. The author verified a positive relationship between a player's

performance and compensation and confirmed that average slugging performance (measured by total bases by at-bats) plays a key role in explaining outfielders' compensation, while batting average and the ratio of strikeouts to walks are important factors for infielders and pitchers, respectively. Frick (2011) found that the variance in player compensation can be explained by variance in performance in terms of goals scored. A similar result was found by Celik and Ince-Yenilmez (2017), who attempted to probe into the salary differences under the salary cap in MLS. They used 2006-2007 MLS data to suggest that the number of goals and assists significantly accounts for the variation in players' salaries. Accordingly, I anticipate that players with better performance statistics are more likely to receive a greater amount of money. This leads to the following hypothesis:

$H8_a$ A player's salary is positively associated with individual performance factors (i.e., the number of goals scored).

$H8_b$ A player's salary is positively associated with individual performance factors (i.e., the number of assists scored).

League appearance and compensation. Second, league appearances can also positively influence a player's compensation (Idson & Kahane, 2000; Jones et al., 1999; Prockl & Frick, 2018b). This is because players with more on-field experience are more likely to play better and be more capable of overcoming difficulties such as injuries. If they have spent more time on-field, they are expected to receive more money due to their level of experience.

League appearances—measured by number of games played as starters or substitutes instead of years of experience—have been found to be positively associated with players' compensation in sports leagues. Idson and Kahane (2000), for example, demonstrated a positive relationship between career games played and compensation in the NHL. This was further supported by Prockl and Frick (2018b),

who confirmed that career games have a significant impact on MLS players' salaries, while Kahn (1993) suggested a similar relationship in MLB context.

In the soccer context, where the number of substitutions is limited, the effect of games started is more significant than that of games substituted (Celik & Ince-Yenilmez, 2017). This is because starting members are usually considered to be players of higher quality. Reilly and Witt (2007) sought to differentiate between a player who played for 90 minutes and a player who played for one minute, testing the separate effects of games started and substituted in MLS. One additional game started yielded a salary premium of 1.3%, while the benchwarmers (i.e., substitutes) experienced an average salary markdown of 3%. This was further supported by Celik and Ince-Yenilmez (2017), who found that games started can have a positive impact on compensation, while games substituted can have a negative impact on compensation. Consistent with the findings of the previous literature, I expect within the soccer context that players who start more games on the field receive more money while players who start more games as benchwarmers receive less money. This leads to the following hypothesis:

$H9_a$ There is a positive relationship between a player's salary and the number of games played as a starting member.

$H9_b$ There is a negative relationship between a player's salary and the number of games played as a benchwarmer.

Position and compensation. Third, variation in player's compensation can be also explained by each player's position, as a player in a particular position may contribute more to the team than players in other positions. For example, linemen experience a salary premium in the NHL, because they shoulder the key roles of either passing or shooting for a goal (Marchand et al., 2006). Similarly, the soccer literature has found that position influences player compensation in the European

Soccer Leagues (Frick, 2006, 2011; Garcia-Del-Barrio & Pujol, 2005; Hubl, & Swieter, 2002; Torgler & Schmidt, 2007). Torgler and Schmidt (2007), for example, found that forwards, who are expected to score goals and win games, experience a salary premium over midfielders and defenders.

Similarly, Frick (2011) determined that goalkeepers receive lower salaries than forwards, midfielders, and defenders. Battre, Deutscher, and Frick (2009) analyzed salary determinations within ESLs market, specifically the Bundesliga. They relied on 6,147 observations with 1,993 players between the 1995-1996 and 2007-2008 seasons. The authors found that goalkeepers make far less money than forwards, midfielders, and defenders. I can therefore speculate that players with different positions are paid differently. This leads to the following hypothesis:

H10 A player's position influences his salary.

Summary

In this chapter, the theoretical background of salary discrimination among superstars as well as the contextual setting, MLS, were thoroughly discussed. Particularly, the main focus of this dissertation, discrimination theory, was explained. Two different types of discrimination (i.e., statistical discrimination and associational discrimination) were introduced and both causes and forms of discrimination were described. Although the focus of this dissertation is salary discrimination, other forms of discrimination were introduced. These include hiring discrimination, exit discrimination and restriction of position as well as other forms of discrimination such as lower bonuses, reduced endorsement income, lower speaking engagements, and exclusion from managerial positions after a career. I followed the line of the above literature by focusing on pay discrimination based on players' origin of birth.

In the next part, the effect of superstar status on players' compensation was discussed using the superstar theory developed by Adler (1985) and Rosen (1981). Unlike other professional sports leagues, where the definition of "superstar" is relatively arbitrary, MLS has the DP rule. Since DPS has been used as a proxy for superstars within the exclusive context of MLS, this study followed the line of previous MLS literature. In addition, I examined the degree to which RPs and DPs are discriminated against by origin of birth, combining discrimination theory and superstar theory in MLS context. This issue is especially important because the DP rule was introduced in order to allow superstars, who positively affect attendance and team revenue, to promote the success of the league.

In the final part, human capital factors and other salary relevant determinants were discussed. Individuals invest in various types of human capital to maximize future economic returns. Players are expected to receive higher salaries if they have a higher level of human capital factors through education and training. While there are various human capital factors, I focused on variables (i.e., experience, age, footedness, and height) that can be applied to the professional soccer labor market. In addition to human capital factors, three salary determinants in MLS were also explained: productivity (i.e., performance statistics), league appearances measured by games played, and individual players' positions.

Regardless of the importance of investigating the existence of salary discrimination among superstars, previous literature has only attempted to individually examine salary discrimination among players as a whole or the superstar effect. Therefore, there is a need to investigate whether superstars are discriminated against in MLS. In the next chapter, I will explain the variables used in this study and empirical estimation for the analysis.

CHAPTER III

METHODOLOGY

Introduction

The purpose of this dissertation is to explore the existence of salary discrimination and the degree to which superstars are discriminated against by their origin of birth. To help answer the research questions and relevant hypotheses, this chapter describes and explains the variables, hypotheses, and statistical methods used in this study. The first part addresses the variables of interest and the research hypotheses. The second part explains the time period and sources of the data. The third part demonstrates the theoretical and practical issues regarding the econometric analyses including empirical estimation employed in this study.

Variables and Hypotheses

In the previous chapter, I explained the theoretical background of salary discrimination among superstars. This part describes the variables of interest and related hypotheses that are tested. Table 3.1 and 3.2 show all the hypotheses and variables used in this study, respectively.

Dependent Variable

The dependent variable (DV) in this study is the individual player's salary. Individual salary data are readily available from MLSPA, unlike professional soccer leagues in Europe in which player salaries are mostly confidential, because MLSPA publishes the salaries of all players under contract on a regular basis. There are two types of player salary in MLS: base salary and guaranteed compensation. Previous

studies have analyzed a salary equation using 1) the player's base salary (Celik & Ince-Yenilmez, 2017; Lee & Harris, 2012; Prockl & Frick, 2018b; Reilly & Witt, 2007), 2) guaranteed compensation (Kuethe & Motamed, 2010; Wooten, 2013), which includes the player's base salary and all signing and guaranteed bonuses, and 3) both the player's base salary and guaranteed compensation (Medcalfe & Smith, 2018; Prockl & Frick, 2018a). To my best knowledge, it is not yet been tested which of the two aforementioned variables is more appropriate in explaining the relationship between performance and remuneration. The use of the DV, either base salary or guaranteed compensation, has been determined by researchers based on its intended meaning in the context of their studies. For this reason, I used both base salary and guaranteed compensation in two different models and tested which variable is more appropriate based on the model fit.

Independent Variables

Origin of birth. The first main variable of interest is the players' origin of birth. This variable is employed to investigate whether players from certain continents are favored or discriminated against in the MLS labor market. If there is salary discrimination by players' origin of birth, we could say that players are either favored or discriminated against based on their demographic characteristics. I utilized two different geographic criteria for grouping players' origin of birth. First, FIFA division of associations and confederations was used: Asian Football Confederation (AFC), Confederation of African Football (CAF), Confederation of North America, Central America and Caribbean Association Football (CONCACAF), South American Football Confederation (CONMEBOL), Union of European Football Associations (UEFA), and Oceania Football Confederation (OFC) (Fédération Internationale de Football Association, n.d.). Using FIFA categorization of associations and

confederations is a reasonable approach, given that FIFA is the governing body of international soccer. However, it may not be appropriate to classify Europe as a single continent where various countries with different soccer histories exist. Thus, some previous scholars have used a more detailed classification of European soccer associations (Celik & Ince-Yenilmez, 2017; Prockl & Frick, 2018b).

Second, players' origin of birth was grouped into eleven different regions according to the United Nations (UN) Statistics Division: Africa, Asia, the Caribbean, Central America, South America, North America, Northern Europe, Southern Europe, Eastern Europe, Western Europe, and Oceania. Under the UN Statistics Division structure, Europe is divided into four regions (i.e., Eastern, Western, Northern, and Southern), providing a more detailed geographical classification. This additional detail makes it possible to determine whether players from certain European regions are more favored than players from other regions. Consistent with the findings of the previous literature on the effect of origin of birth on both RPs' and DPs' compensation, it is expected that players' salaries vary by their origin of birth, indicating that non-favored group(s) of players earn less money than favored group(s).

The superstar player. The second main variable of interest is whether a player is a DP or RP. This variable is a dummy variable that is equal to one if a player has designated player status in the current season, and it is zero otherwise. As discussed in Chapter 2, MLS provides a less arbitrary definition of the superstar status (Jewell, 2017) due to the DP rule, which allows each team to sign up to three players outside of the team's salary cap. As DPs are positively related with fan demand and have been found to be a legitimate proxy of superstars in MLS (Coates et al., 2016; Jewell, 2017; Kuethe & Motamed, 2010), this study used DPS as a proxy of superstar

player. Consistent with the previous literature, it is anticipated that players with DPS earn more money than RPs.

Control Variables

In addition to players' origin of birth and superstar status, I examined two groups of factors affecting players' compensation in MLS. The first group consists of human capital factors such as players' experience, age, innate skills (i.e., footedness), and physical attributes (i.e., height); the second group comprises other factors including league appearances, performance statistics (i.e., goals and assists), and position. These variables were included in this dissertation because previous literature has found a significant relationship between these variables and salaries in MLS.

Experience. As one factor of human capital, experience, which can be measured as the number of years in employment, can play a role in explaining players' salaries. This is because players with a higher number of years in their occupation accumulate useful know-how over time. Such players are thus more likely to make greater contributions to their teams with this experience. Consequently, experienced individuals will earn more money than players with less experience because of their higher MRP. As such, it is expected that there is a positive relationship between players' experience and compensation.

Age. Similarly to the experience variable, differences in players' compensation can be explained by players' age according to HCT. The seniority effect suggests that players' salaries increase over time, given that salaries rarely decrease, all other things being equal. However, this increase is not everlasting because players' MRP decreases at a certain age. Therefore, compensation mostly increases in accordance with a player's age, but drops off after a player's peak age. Thus, I included the age variable and its squared term to capture the concavity of age-

earning profiles. It is expected that there is a concave (i.e., positive but decreasing) relationship between salaries and age.

Footedness. Players' skills, whether innate or acquired, also affect players' salaries given that the level of skill could contribute to the team in a unique way. For example, players with both-footedness have an advantage over players with right-footedness or left-footedness, since they are capable of playing various positions while creating space and goals from different angles (Bryson et al., 2013). In this case, coaches would favor both-footed players as they can operate in different positions depending on the team's strategy, resulting in higher salaries for these players. Based on this reasoning, it is anticipated that there is a positive relationship between players' skills (i.e., both-footedness) and compensation.

Height. Players' physical attributes such as height, another factor of human capital, can explain earning distribution. Players can contribute more to their team with their physical attributes, leading to higher MRP. For example, in soccer, the odds of scoring are higher if forward players are taller than the opponent's defender(s). In a similar way, defenders can defend more effectively if they are taller than the opponent's striker(s), while taller midfielders have an advantage when competing for aerial balls, especially against shorter opponents. Therefore, it is expected that taller players will receive higher compensation than shorter players.

League appearances (starters and substitutes). League appearances (i.e., measured by the number of games played as a starter) can positively influence a player's compensation because players with more on-field experience are more likely to perform better. In the soccer context, where the number of substitutions is limited, the effect of games started is more significant than that of games in which a player was substituted because starting members are usually considered to be players of

higher quality. For this reason, this study differentiates between the number of games started and games substituted. Consistent with the findings of the previous literature (Celik & Ince-Yenilmez, 2017), a positive relationship between the number of games started and the players' salaries is expected. Based on similar reasoning, the number of games substituted can also negatively influence a player's compensation.

League appearances (minutes). This variable represents the total minutes played in the previous season and captures the actual on-field involvement of individual players (i.e., measured by the number of minutes played). This variable was included because there is a difference between playing 90 minutes in a game and playing for only one minute as a substitute (Reilly & Witt, 2007). Therefore, it is expected that there is a positive relationship between actual on-field minutes and compensation.

Goals and assists. Individual performance factors (i.e., the number of goals and assists) also affect the player's salary given that players who perform at a high level consistently contribute more to the team. Broadly, professional athletes who perform better (i.e., as measured by performance statistics) are expected to earn higher salaries. Therefore, previous literature has included performance factors (either previous season statistics or career statistics). I used the previous season's performance factors (i.e., goals and assists) in this study due to data availability. Regarding MLS, it was difficult to find a source where players' career statistics are described for each year. However, this data limitation is not a problem for this study, as soccer players are paid based on their recent performance rather than their career performance (Battre et al., 2009). Therefore, it is expected that a player's salary is positively associated with the previous season's individual performance factors.

Position. The last control variable is a player's position, given that a player in a particular position may contribute more to the team than players in other positions. For example, in soccer, forwards who contribute more to their teams by scoring goals and winning games are generally expected to experience a salary premium over players in other positions. It is expected that a player's position influences an individual's salary.

As MLS position types are classified differently from other soccer leagues, this study used MLSPA position classification (i.e., goalkeeper, defender, midfielder, forward, defender-midfielder, midfielder-defender, midfielder-forward, and forward-midfielder) instead of the traditional soccer position types (i.e., goalkeeper, defender, midfielder, and forward). In addition, this study analyzed MLS salary models both including and excluding goalkeepers because goalkeepers' performance statistics are measured in a different way from those of outfielder players (Lucifora & Simmons, 2003; Medcalfe & Smith, 2018, Prockl & Frick, 2018b).

Table 3.1

Hypotheses

Hypothesis	Description
Hypothesis 1	There is salary discrimination by players' origin of birth in MLS.
Hypothesis 2	There is a positive relationship between superstar status (i.e., designated player status) and compensation.
Hypothesis 3	There is salary discrimination by players' origin of birth among superstars.
Hypothesis 4	A player's salary is positively associated with his experience.
Hypothesis 5_a	A player's salary is positively associated with his age.
Hypothesis 5_b	A player's salary is negatively associated with his squared term of age.
Hypothesis 6	A player's salary is positively associated with his innate skills or scarce talent.
Hypothesis 7	A player's salary is positively associated with his physical attributes.
Hypothesis 8_a	A player's salary is positively associated with individual performance factors (i.e., the number of goals scored).
Hypothesis 8_b	A player's salary is positively associated with individual performance factors (i.e., the number of assists scored).
Hypothesis 9_a	There is a positive relationship between a player's salary and the number of games played as a starting member.
Hypothesis 9_b	There is a negative relationship between a player's salary and the number of games played as a benchwarmer.
Hypothesis 10	A player's position influences his salary.

Table 3.2

Definition of Variables

Variables	Description
SALARY	A player's base salary
COMPENSATION	A player's guaranteed compensation
DPS	=1, if the player is designated player in the current season
ALLSTAR	=1, if the player participated in All-Star games in the previous season
STARTS	The number of games started in the previous season
SUBS	The number of games substituted in the previous season
MINS	The number of minutes played in the previous season
AGE	A Player's age in the current season
AGE^2	The squared term of age variable
EXP	The number of years of experience in professional soccer
HEIGHT	A Player's height
FOOT (LEFT)	= 1, if the player is left-footed
FOOT (RIGHT)	= 1, if the player is right-footed
FOOT (BOTH)	= 1, if the player is both-footed
FOOT (NOT DEFINED)	= 1, if the player's footedness is not defined
UN (ASIA)	= 1, if the player's origin of birth is Asia
UN (AFRICA)	= 1, if the player's origin of birth is Africa
UN (CARRIBEAN)	= 1, if the player's origin of birth is Caribbean
UN (CENTRAL AMERICA)	= 1, if the player's origin of birth is Central America
UN (NORTH AMERICA)	= 1, if the player's origin of birth is North America
UN (SOUTH AMERICA)	= 1, if the player's origin of birth is South America
UN (WESTERN EUROPE)	= 1, if the player's origin of birth is Western Europe
UN (EASTERN EUROPE)	= 1, if the player's origin of birth is Eastern Europe
UN (NORTHERN EUROPE)	= 1, if the player's origin of birth is Northern Europe
UN (SOURTHERN EUROPE)	= 1, if the player's origin of birth is Southern Europe
UN (OCEANIA)	= 1, if the player's origin of birth is Oceania
FIFA (AFC)	= 1, if the player's origin of birth is Asia
FIFA (CAF)	= 1, if the player's origin of birth is Africa
FIFA (CONCACAF)	= 1, if the player's origin of birth is North America and Central America and the Caribbean
FIFA (CONMEBOL)	= 1, if the player's origin of birth is South America
FIFA (UEFA)	= 1, if the player's origin of birth is Europe
FIFA (OFC)	= 1, if the player's origin of birth is Oceania

Notes: Dependent variable is a player's base salary and guaranteed compensation.

Table 3.2, continued

Definition of Variables

Variables	Description
GLS	The number of goals scored in the previous season
AST	The number of assists scored in the previous season
POS (GK)	= 1, if the player is a goalkeeper
POS (D)	= 1, if the player is a defender
POS (M)	= 1, if the player is a midfielder
POS (F)	= 1, if the player is a forward
POS (D-M)	= 1, if the player is a defender-midfielder
POS (M-D)	= 1, if the player is a midfielder-defender
POS (M-F)	= 1, if the player is a midfielder-forward
POS (F-M)	= 1, if the player is a forward-midfielder

Notes: As for the dummy variables (i.e., FOOT, ORIGIN, FIFA ORIGIN, and POS), FOOT (BOTH), UN (NORTH AMERICA), FIFA (CONCACAF), and POS (D) are taken as the reference categories. These variables are omitted when estimating empirical models.

Research Design

Data Description

While players' salaries remain confidential in most European professional sports leagues, MLSPA has published the salaries of all players (APs) under contract on a regular basis since 2007. This study collected players' salary data for the 2007-2019 seasons and the performance data for the 2006-2018 seasons, given that MLS teams use individual player performance statistics from the previous season (*t-1*), rather than performance statistics for the current season (*t*), to determine individual players' salaries (Celik & Ince-Yenilmez, 2017). For example, players' contracts for the 2019 season depend on their prior performances during the 2018 season.

As previously mentioned, previous studies have included performance statistics in the wage equation using one of the following factors: 1) average career statistics, 2) average statistics from the recent previous seasons (e.g., three seasons), and 3) the statistics from the previous season. This dissertation specifically used the

previous season's performance factors (i.e., goals and assists) and appearance factors (i.e., games started, games substituted, and minutes played) because the use of the first two factors is not appropriate in MLS for the following reasons.

First, the use of average career statistics may be reasonable because the managers are interested in players' long-term performance instead of the recent one (Brown et al., 1991). This can only be used when the data on players' career statistics are available and MLS, however, does not record players' performance statistics when they are out of the league. For this reason, it is difficult to calculate average career statistics as many MLS players have professional experience outside of MLS (Wooten, 2013). In addition, it is also possible that a player with great career statistics may not be successful as previously at the end of the career. Therefore, average career statistics are not considered. Second, average statistics from the recent previous seasons could be a better proxy than average career statistics as it mitigates the problem of possible performance fluctuation across the seasons (Hill, 2004). Similar to the above case, however, it is impossible to compute average statistics from the recent previous seasons given that the data on MLS players who came from outside of MLS are not available. For this reason, average statistics from the recent previous seasons are not used in this dissertation.

Some people may argue that the use of statistics from the previous season may pose a problem if a large number of players are under multi-year contracts (Christiano, 1986). This is because performance statistics in the first year of the multi-year contract would not influence players' salaries in the second and consecutive years, which is already signed (Holmes, 2011). MLS, however, shows a different story in players' contracts and I believe the use of previous season statistics is the best estimate of players' compensation based on the following reasons.

First, unlike European Soccer Leagues where the information on player contracts is publicly available, MLS contracts are almost unknown to the public (Citro, 2019). Although few players' contract information has been released (e.g., David Beckham), it is often difficult to find a reliable source on player’s contract option and duration, indicating that the public is not aware of whether players are working under multi-year or year-to-year agreements. Based on the individual salary data from MLSPA, however, my best speculation is that most of the contracts are signed year by year given that both players’ base salary and guaranteed compensation have frequently changed across the season.

Second, the new 2020 MLS CBA indicates that player contracts are guaranteed in the second year, which is new to MLS (Major League Soccer, 2020). This suggests enough evidence to assume that a large number of players have signed year-to-year contracts each season. Therefore, it seems reasonable to use previous season statistics in analyzing players’ compensation as this dissertation includes players’ salary data for the 2007-2019 seasons.

Third, a positive relationship between the performance statistics from the previous season (*t-1*) and salary in the current season (*t*) was found in various sports settings (Battre et al., 2009; Christiano, 1986; Yang & Lin, 2012) including MLS (Celik & Ince-Yenilmez, 2017; Kuethe & Motamed, 2010; Prockl & Frick, 2018b; Reilly & Witt, 2007; Wooten, 2013). This finding is not surprising given that the manager may adjust players’ compensation based on players’ performance contribution from the previous year (Wooten, 2013). Therefore, the use of previous season statistics seems to be the most reasonable option in MLS especially when the information on players’ contracts is confidential.

The data employed in the empirical analysis were collected from multiple sources. Data on the DV of players' salaries are available from MLSPA's official website (https://mlsplayers.org/resources/salary-guide). Data on the independent variables (IVs), a set of player performance statistics (i.e., goals, assists, games started, games substituted, and minutes played), were obtained from the official MLS website (https://www.mlssoccer.com/stats) and Sports Reference (https://fbref.com/en/). Information on individual player characteristics (i.e., origin of birth, designated player status, All-Star experience, footedness, age, height, and position) was collected from the official MLS website, Sports Reference, Transfermarkt (https://www.transfermarkt.com/), and other websites, where available.

A total of 6,979 observations were collected in the initial stage, as there are 371 players in 2007, 411 players in 2008, 388 players in 2009, 406 players in 2010, 517 players in 2011, 552 players in 2012, 574 players in 2013, 568 players in 2014, 570 players in 2015, 585 players in 2016, 654 players in 2017, 694 players in 2018, and 689 players in 2019 (Figure 3.1). However, some observations were eliminated for the following reason: many players join MLS teams every season, but the relevant data for the players who were transferred from teams outside of MLS were not available on the official MLS website. Therefore, this dissertation includes only those players who played in MLS season preceding the year from which their salary data was collected. Out of 6,979 total observations for the 2007-2019 seasons, the following numbers of players from this initial sample played in the previous MLS season: 217 players in 2007, 225 in 2008, 238 in 2009, 270 in 2010, 305 in 2011, 332 in 2012, 354 in 2013, 364 in 2014, 355 in 2015, 385 in 2016, 377 in 2017, 401 in 2018, and 457 in 2019 (Figure 3.2). Accordingly, this dissertation covers 4,280 observations (61.3%) for the empirical analysis.

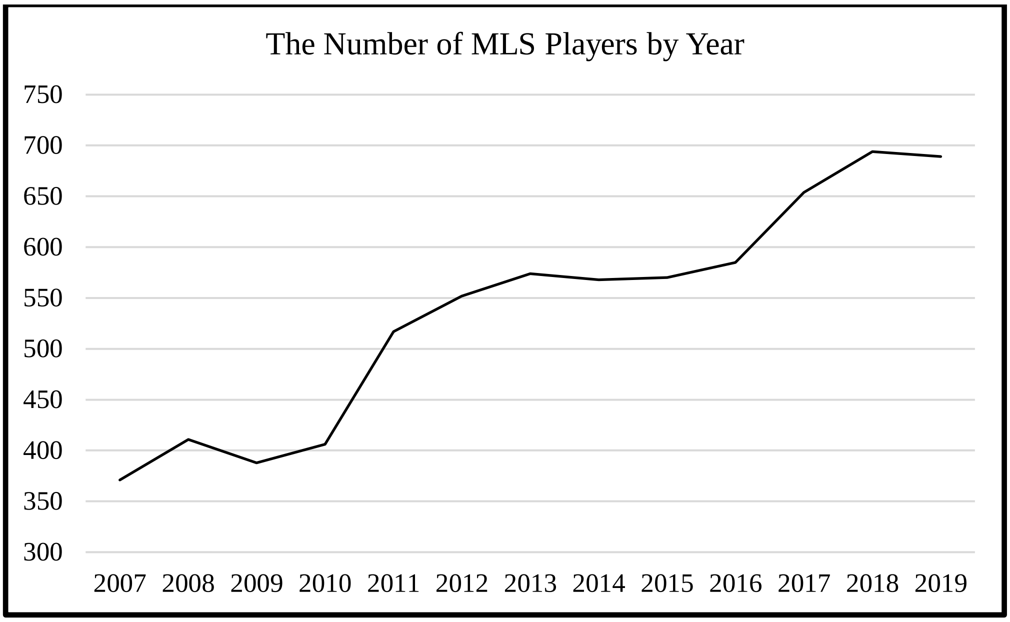

Figure 3.1. The Number of MLS Players by Year.

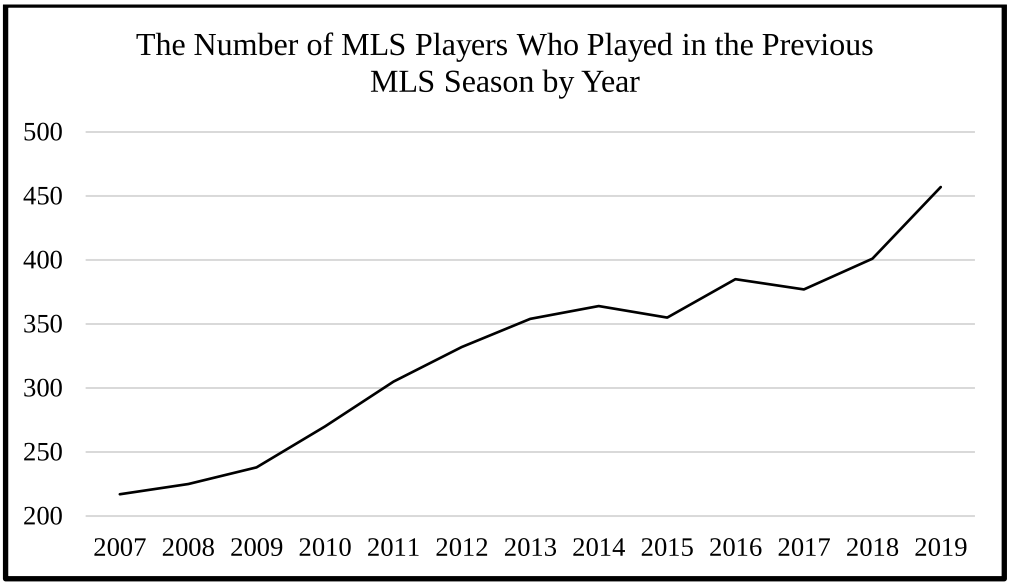

Figure 3.2. The Number of MLS Players Who Played in the Previous MLS Season.

Model Specification

In the previous part of this chapter, I explained the variables of interest, related hypotheses, and data period and collection procedure. In this part, I demonstrate the theoretical and practical issues of the study's econometric approach and empirical estimation, OLS regression and quantile regression, to answer the research questions and proposed hypotheses.

Theoretical and practical issues. This study uses multiple linear regressions, namely an OLS regression model and a quantile regression model, to answer the research questions and relevant hypotheses. Regression analysis, a popular technique for deriving statistical decisions, enables researchers to investigate the relationship between several IVs and one DV (Tabachnick & Fidell, 2013). This approach raises the question of what IVs should be included in the model to predict the DV. Broadly, a smaller number of IVs is desired because the goal of the model selection is to examine the fewest necessary IVs. Therefore, researchers should include those IVs that are significantly related to the DV but, at the same time, unrelated to other IVs. Since the decision of which variables to include can depend on the individual researcher, regression analyses require a careful and scientific approach (Tabachnick & Fidell, 2013).

In addition to theoretical issues, multiple regression should address practical issues such as the various assumptions that a regression should meet (Tabachnick & Fidell, 2013). In general, five assumptions should be met in a multiple linear regression model: normality, homoscedasticity, linearity, independence of error, and non-multicollinearity. First, the normality assumption states that the residuals are normally distributed, showing the shape of normal distribution. The normality assumption is especially important when testing with a small sample size (usually less than 200), although it is not required when the sample size is sufficiently large (usually more than 200), due to the Central Limit Theorem (Greene, 2002). Second, the homoscedasticity (i.e., equal variance) assumption suggests that each response is a realization from a distribution with the same variation for all responses. In other words, the variance of error terms should be similar (or the same) regardless of the value of the predictors (i.e., IVs). If the equal variance assumption is not met, the

confidence intervals and significance will not be reliable as they are biased. Third, the linearity assumption refers to the linear relationship between the outcome variable and predictor variables. This relationship can be determined from either the scatter plots or the residuals plots. Fourth, the independence of error assumption indicates that the errors in the model are uncorrelated with each other. The errors need to be randomly scattered while not influencing other values. The failure of this assumption results in an inappropriate prediction. The last assumption is non-multicollinearity. Multicollinearity indicates that two or more IVs are highly correlated with each other. In this case, the correlation coefficients of the predictors are not reliable because the size of the standard errors is inflated; thus, one of the approaches is that researchers delete some of the IVs, which are the least reliable.

Empirical estimation. As discussed above, this study utilizes both OLS regression and quantile regression to estimate the factors affecting players' salaries while uncovering the evidence of salary discrimination in MLS. The first regression is an OLS regression, which analyzes the effect of players' origin of birth on average MLS players. Three different models (one full model and two reduced models) were analyzed to answer the research questions. The first OLS model, the full model, which includes all MLS players in the sample (both RPs and DPs), was used to investigate whether there is any salary discrimination and any superstar effect.

$$\begin{aligned} ln(\text{SALARY}_{i,t}) = {} & \beta_0 + \beta_1(\text{GLS}_{i,t-1}) + \beta_2(\text{AST}_{i,t-1}) + \beta_3(\text{STARTS}_{i,t-1}) + \\ & \beta_4(\text{SUBS}_{i,t-1}) + \beta_5(\text{MINS}_{i,t-1}) + \beta_6(\text{DPS}_{i,t}) + \beta_7(\text{POS}_{i,t}) + \\ & \beta_8(\text{ORIGIN}_{i,t}) + \beta_9(\text{AGE}_{i,t}) + \beta_{10}(\text{AGE}^2{}_{i,t}) + \beta_{11}(\text{HEIGHT}_{i,t}) + \\ & \beta_{12}(\text{FOOT}_{i,t}) + \beta_{13}(\text{ALLSTAR}_{i,t-1}) + \beta_{14}(\text{Club}_i) + \beta_{15}(\text{Year}_i) + \varepsilon_{i,t} \\ & (i = \text{APs},\ t = \text{seasons}) \end{aligned} \tag{1}$$

In addition, two different reduced OLS models are used to differentiate between regular players and designated players in MLS, given the heterogeneity in performance and players' characteristics between these two groups (Prockl & Frick, 2018b). This approach allows this study to examine whether salary discrimination by origin of birth exists among RPs and DPs, respectively. Two different reduced models for RPs and DPs are respectively analyzed:

$$ln(\mathrm{SALARY}_{i,t}) = \beta_0 + \beta_1(\mathrm{GLS}_{i,t-1}) + \beta_2(\mathrm{AST}_{i,t-1}) + \beta_3(\mathrm{STARTS}_{i,t-1}) + \beta_4(\mathrm{SUBS}_{i,t-1}) + \beta_5(\mathrm{MINS}_{i,t-1}) + \beta_6(\mathrm{POS}_{i,t}) + \beta_7(\mathrm{ORIGIN}_{i,t}) + \beta_8(\mathrm{AGE}_{i,t}) + \beta_9(\mathrm{AGE}^2{}_{i,t}) + \beta_{10}(\mathrm{HEIGHT}_{i,t}) + \beta_{11}(\mathrm{FOOT}_{i,t}) + \beta_{12}(\mathrm{ALLSTAR}_{i,t-1}) + \beta_{13}(\mathrm{Club}_i) + \beta_{14}(\mathrm{Year}_i) + \varepsilon_{i,t} \quad (i = \mathrm{RPs},\ t = \mathrm{seasons}) \tag{2}$$

$$ln(\mathrm{SALARY}_{i,t}) = \beta_0 + \beta_1(\mathrm{GLS}_{i,t-1}) + \beta_2(\mathrm{AST}_{i,t-1}) + \beta_3(\mathrm{STARTS}_{i,t-1}) + \beta_4(\mathrm{SUBS}_{i,t-1}) + \beta_5(\mathrm{MINS}_{i,t-1}) + \beta_6(\mathrm{POS}_{i,t}) + \beta_7(\mathrm{ORIGIN}_{i,t}) + \beta_8(\mathrm{AGE}_{i,t}) + \beta_9(\mathrm{AGE}^2{}_{i,t}) + \beta_{10}(\mathrm{HEIGHT}_{i,t}) + \beta_{11}(\mathrm{FOOT}_{i,t}) + \beta_{12}(\mathrm{ALLSTAR}_{i,t-1}) + \beta_{13}(\mathrm{Club}_i) + \beta_{14}(\mathrm{Year}_i) + \varepsilon_{i,t} \quad (i = \mathrm{DPs},\ t = \mathrm{seasons}) \tag{3}$$

Unlike OLS regression on the mean response, which provides some information about the effect of players' origin of birth on compensation, the quantile regression offers a more detailed perspective on certain salary distributions. Quantile regression identifies the relationship between every quantile of DV and IVs while OLS identifies the relationship between mean DV and IVs (Leeds, 2014). In other words, quantile regression uncovers every possible relationship between DV and IVs in different wage distributions while OLS is limited to provide some information between mean DV and IVs.

It is worth noting a few differences in assumptions between OLS and quantile regression. Quantile regression, a method introduced by Koenker and Bassett (1978), is less restrictive in its assumptions that normality and homoscedasticity do not necessarily need to be met, whereas OLS is strict in its assumptions regarding outliers, normality, and equal variance (Petscher & Logan, 2014). The characteristics of quantile regressions are especially helpful to researchers in the sport industry because players' salaries are highly skewed to the right (Hamilton, 1997; Lucifora & Simmons, 2003). This method thus makes it possible to find the existence of salary discrimination among RPs and DPs in certain salary distributions, even if OLS regression may fail to find evidence of discrimination in wages. Although quantile regression can reveal interesting insights into whether there is an invisible market preference on players' origin of birth in certain distributions, it has been underemployed in sport economics (Leeds, 2014). Therefore, I employ quantile regression to investigate whether there is such salary discrimination among MLS players in certain salary distributions.

As with OLS regression, three different models (one full model and two reduced models) were analyzed to answer the research questions. The first quantile regression model, the full model, which includes all MLS players (both RPs and DPs), investigates whether there is any salary discrimination among APs in certain wage distributions.

$$\begin{aligned} Q^{\tau}(ln(\mathrm{SALARY}_{i,t})) = {} & \beta_0^{\tau} + \beta_1^{\tau}(\mathrm{GLS}_{i,t-1}) + \beta_2^{\tau}(\mathrm{AST}_{i,t-1}) + \beta_3^{\tau}(\mathrm{STARTS}_{i,t-1}) + \\ & \beta_4^{\tau}(\mathrm{SUBS}_{i,t-1}) + \beta_5^{\tau}(\mathrm{MINS}_{i,t-1}) + \beta_6^{\tau}(\mathrm{DPS}_{i,t}) + \beta_7^{\tau}(\mathrm{POS}_{i,t}) + \\ & \beta_8^{\tau}(\mathrm{ORIGIN}_{i,t}) + \beta_9^{\tau}(\mathrm{AGE}_{i,t}) + \beta_{10}^{\tau}(\mathrm{AGE}^2{}_{i,t}) + \beta_{11}^{\tau}(\mathrm{HEIGHT}_{i,t}) + \\ & \beta_{12}^{\tau}(\mathrm{FOOT}_{i,t}) + \beta_{13}^{\tau}(\mathrm{ALLSTAR}_{i,t-1}) + \beta_{14}^{\tau}(\mathrm{Club}_i) + \beta_{15}^{\tau}(\mathrm{Year}_i) + \\ & \varepsilon_{i,t}^{\tau} \ (i = \mathrm{APs},\ t = \mathrm{seasons}) \end{aligned} \tag{4}$$

Moreover, two different reduced quantile regression models were used to differentiate regular players and designated players. This approach allows this study to examine whether salary discrimination by origin of birth exists among RPs and DPs, respectively, in certain wage distributions. Therefore, two different reduced models for RPs and DPs were respectively analyzed:

$$Q^{\tau}(ln(\text{SALARY}_{i,t})) = \beta_0^{\tau} + \beta_1^{\tau}(\text{GLS}_{i,t-1}) + \beta_2^{\tau}(\text{AST}_{i,t-1}) + \beta_3^{\tau}(\text{STARTS}_{i,t-1}) + \beta_4^{\tau}(\text{SUBS}_{i,t-1}) + \beta_5^{\tau}(\text{MINS}_{i,t-1}) + \beta_6^{\tau}(\text{POS}_{i,t}) + \beta_7^{\tau}(\text{ORIGIN}_{i,t}) + \beta_8^{\tau}(\text{AGE}_{i,t}) + \beta_9^{\tau}(\text{AGE}^2{}_{i,t}) + \beta_{10}^{\tau}(\text{HEIGHT}_{i,t}) + \beta_{11}^{\tau}(\text{FOOT}_{i,t}) + \beta_{12}^{\tau}(\text{ALLSTAR}_{i,t-1}) + \beta_{13}^{\tau}(\text{Club}_i) + \beta_{14}^{\tau}(\text{Year}_i) + \varepsilon_{i,t}^{\tau} \quad (i = \text{RPs}, t = \text{seasons}) \tag{5}$$

$$Q^{\tau}(ln(\text{SALARY}_{i,t})) = \beta_0^{\tau} + \beta_1^{\tau}(\text{GLS}_{i,t-1}) + \beta_2^{\tau}(\text{AST}_{i,t-1}) + \beta_3^{\tau}(\text{STARTS}_{i,t-1}) + \beta_4^{\tau}(\text{SUBS}_{i,t-1}) + \beta_5^{\tau}(\text{MINS}_{i,t-1}) + \beta_6^{\tau}(\text{POS}_{i,t}) + \beta_7^{\tau}(\text{ORIGIN}_{i,t}) + \beta_8^{\tau}(\text{AGE}_{i,t}) + \beta_9^{\tau}(\text{AGE}^2{}_{i,t}) + \beta_{10}^{\tau}(\text{HEIGHT}_{i,t}) + \beta_{11}^{\tau}(\text{FOOT}_{i,t}) + \beta_{12}^{\tau}(\text{ALLSTAR}_{i,t-1}) + \beta_{13}^{\tau}(\text{Club}_i) + \beta_{14}^{\tau}(\text{Year}_i) + \varepsilon_{i,t}^{\tau} \quad (i = \text{DPs}, t = \text{seasons}) \tag{6}$$

Summary

In this chapter, I have explained the variables of interest, the proposed hypotheses, and the theoretical and practical issues of the study's econometric approach and empirical estimation to answer research questions and test research hypotheses. The first regression is an OLS regression, which is designed to investigate the existence of average salary discrimination among all players, regular players, and designated players, respectively. To better understand the possible market preference for certain players' origin of birth in specific salary distributions, the quantile regression is also employed. These two regressions using six models allow for the

uncovering of salary discrimination among MLS players. In the following chapter, I will explain the results from the empirical estimation.

CHAPTER IV

RESULTS

Introduction

In Chapter 3, I delineated variables, hypotheses, and empirical estimation in an attempt to better understand salary discrimination among superstars in MLS. This chapter is divided into three sections: descriptive statistics, preliminary analysis, and statistical results. The first part presents the summary statistics of the variables employed in this study, while the second part demonstrates the preliminary analysis through various assumption tests. The third part explains the process of model selection and statistical results for OLS estimation and quantile regression.

Descriptive Statistics

Before discussing preliminary analysis and statistical results, it is important to present the summary statistics of the relevant variables since they show the distribution of the data while addressing outliers and missing values (Libman, 2010). Descriptive statistics—including the mean, median, standard deviation, minimum, and maximum of all variables—were presented in Table 4.1. This study used 4,280 observations of MLS players (including both regular players and designated players) during the data period. One DV of this study, the players' base salaries (SALARY), demonstrated that the average salary for MLS players was $253,622, while the other DV, players' guaranteed compensation (COMPENSATION) showed that the mean of guaranteed compensation was $282,020—approximately $3,000 higher than that of

players' base salaries. The players' mean age (AGE) was 25.58, and MLS players stayed in professional soccer leagues for 5.48 years on average. The mean of players' height (HEIGHT) was 181cm, with a range from 158cm (Cristian Techera in Vancouver Whitecaps FC) to 201cm (Axel Sjöberg in Colorado Rapids).

Table 4.1

Descriptive Statistics: All Players (N=4,280)

Variable	Mean	Median	Ste. Dev.	Minimum	Maximum
SALARY	253,622.6	115,000	598,269.3	12,900	7,200,000
COMPENSATION	282,020.7	130,000	675,884.5	12,900	7,200,000
DPS	0.0685	0	0.2526	0	1
EXP	5.4846	5	3.8408	0	21
AGE	25.5883	25	4.2891	15	42
AGE^2	673.1537	625	226.6381	225	1,764
HEIGHT	181.0673	180	6.7442	158	201
STARTS	15.6129	15	10.3713	0	34
SUBS	3.4166	2	4.0143	0	28
MINS	1,399.956	1,396.5	899.8045	1	3,060
GLS	1.9467	1	3.3559	0	31
AST	1.4114	1	2.1415	0	16
ALLSTAR	0.0692	0	0.2538	0	1

Although the descriptive statistics of all MLS players were displayed in Table 4.1, it is of interest to determine whether there are any differences between regular players and designated players. Therefore, I used two different descriptive statistics to differentiate between the two groups (i.e., RPs and DPs) because of the heterogeneity in performance and players' characteristics (Prockl & Frick, 2018b). The descriptive statistics of RPs and DPs were presented in Table 4.2 and 4.3, respectively. The average base salary for designated players ($1,492,358) was approximately 9.2 times higher than that of regular players ($162,589.5), while the average guaranteed compensation for DPs was approximately 9.6 times higher than for RPs, indicating that the designated players experienced market preference in both base salary and guaranteed compensation. The DPs (28.1) were on average 2.7 years older than RPs

(25.4), as they had more career experience. In terms of performance statistics, the designated players showed better statistics in both goals and assists, indicating that they were more talented than regular players (Rosen, 1981). The league appearance variables (i.e., STARTS, SUBS, and MINS) indicated that the DPs were more likely to play a game as a starting member and spent more time on-field than the RPs. As for the All-Star experience (ALLSTAR), 30% of the DPs participated in All-Star games while only 5.22% of the RPs had All-Star game experience.

Table 4.2

Descriptive Statistics: Regular Players (N=3,987)

Variable	Mean	Median	Ste. Dev.	Minimum	Maximum
SALARY	162,589.5	105,000	255,506.2	12,900	6,660,000
COMPENSATION	177,642.9	120,333.3	282,591.7	12,900	7,167,500
EXP	5.2744	4	3.697	0	19
AGE	25.4046	25	4.2348	15	42
AGE^2	663.3213	625	222.7405	225	1,764
HEIGHT	181.2333	180	6.6528	158	201
STARTS	15.2328	15	10.3641	0	34
SUBS	3.4878	2	4.054	0	28
MINS	1,367.806	1,327	899.75	1	3,060
GLS	1.5964	0	2.7343	0	23
AST	1.233	0	1.8824	0	15
ALLSTAR	0.0522	0	0.2224	0	1

Table 4.3

Descriptive Statistics: Designated Players (N=293)

Variable	Mean	Median	Ste. Dev.	Minimum	Maximum
SALARY	1,492,358	800,000	1,643,488	50,000	7,200,000
COMPENSATION	1,702,342	813,333.3	1,852,348	56,250	7,200,000
EXP	8.3447	8	4.5594	1	21
AGE	28.0887	29	4.2466	18	40
AGE^2	806.9488	841	236.9965	324	1,600
HEIGHT	178.8055	179	7.5407	160	196
STARTS	20.785	23	9.0086	0	34
SUBS	2.4471	1	3.2847	0	17
MINS	1,837.437	2017	779.4886	88	3,039
GLS	6.7133	5	6.2048	0	31
AST	3.8396	3	3.5333	0	16
ALLSTAR	0.3003	0	0.4592	0	1

The distributions of individual players' characteristics (i.e., origin of birth, footedness, and position) for the regular players and designated players were reported in Table 4.4, 4.5, 4.6, and 4.7. Looking at Table 4.4, the distribution of MLS players' origin of birth by FIFA division showed the stark difference between the two groups; for example, more than half of the RPs (72.86%) came from CONCACAF (North America, Central America, and the Caribbean), while 95% of the DPs were relatively evenly distributed among CONCACAF (34.47%), CONMEBOL (36.18%), and UEFA (23.89%). It was also discerned that there were no DPs from OFC (Oceania).

Table 4.4

Distribution of Players' Origin of Birth by FIFA Division

Variable	RPs (#)	RPs (%)	DPs (#)	DPs (%)
FIFA (AFC)	24	0.6%	2	0.68%
FIFA (CAF)	266	1.66%	14	4.78%
FIFA (CONCACAF)	2,905	72.86%	101	34.47%
FIFA (CONMEBOL)	373	9.36%	106	36.18%
FIFA (UEFA)	17	0.43%	70	23.89%
FIFA (OFC)	402	10.08%	0	0%
Total	3,987	100%	293	100%

Table 4.5

Distribution of Players' Origin of Birth by UN Statistics Division

Variable	RPs (#)	RPs (%)	DPs (#)	DPs (%)
UN (ASIA)	27	0.68%	3	1.02%
UN (AFRICA)	266	6.67%	14	4.78%
UN (CARRIBEAN)	185	4.64%	7	2.39%
UN (CENTRAL AMERICA)	176	4.41%	34	11.6%
UN (NORTH AMERICA)	2,544	63.81%	60	20.48%
UN (SOUTH AMERICA)	373	9.36%	106	36.18%
UN (WESTERN EUROPE)	132	3.31%	19	6.48%
UN (EASTERN EUROPE)	21	0.53%	3	1.02%
UN (NORTHERN EUROPE)	180	4.51%	29	9.9%
UN (SOURTHERN EUROPE)	61	1.53%	16	5.46%
UN (OCEANIA)	22	0.55%	2	0.68%
Total	3,987	100%	293	100%

The distribution of MLS players' origin of birth by the UN Statistics Division was presented in Table 4.5. Similar to the distribution of MLS players' origin of birth by FIFA division, more than half of regular players were from North America (63.81%) followed by South America (9.36%) while the largest proportion of DPs were from South America (36.18%) followed by North America (20.48%). This indicates that MLS players were mostly from either North or South America.

The distribution of players' footedness (shown in Table 4.6) was largely right-footed for both regular players (68.12%) and designated players (69.97%). In addition, the sample had more both-footed DPs (12.29%) than both-footed RPs (4.97%). Information on the footedness of 307 RPs' observations (7.7%) was not available, whereas the data on DPs' footedness were widely available, except three players who are Luciano Emilio, Alvaro Fernandez, and Alberth Elis.

Table 4.6

Distribution of Players' Footedness

Variable	RPs (#)	RPs (%)	DPs (#)	DPs (%)
FOOT (BOTH)	198	4.97%	36	12.29%
FOOT (RIGHT)	2,716	68.12%	205	69.97%
FOOT (LEFT)	766	19.21%	46	15.7%
FOOT (NOT DEFINED)	307	7.7%	6	2.05%
Total	3,987	100%	293	100%

The distribution of players' positions was presented in Table 4.7. It showed that most of the regular players were defenders (31.4%) followed by midfielders (30.9%), forwards (18.38%), goalkeepers (9.81%), midfielder-forwards (4.11%), defender-midfielders (2.96%), and midfielder-defenders (1.35%). On the other hand, most of the DPs were midfielders (40.27%) followed by forwards (39.25%), midfielder-forwards (10.92%), defenders (5.46%), forward-midfielders (2.39%), and goalkeepers (1.02%).

Table 4.7

Distribution of Players' Position

Variable	RPs (#)	RPs (%)	DPs (#)	DPs (%)
POS (GK)	391	9.81%	3	1.02%
POS (D)	1,252	31.4%	16	5.46%
POS (M)	1,232	30.9%	118	40.27%
POS (F)	733	18.38%	115	39.25%
POS (D-M)	118	2.96%	1	0.34%
POS (M-D)	54	1.35%	1	0.34%
POS (M-F)	164	4.11%	32	10.92%
POS (F-M)	43	1.08%	7	2.39%
Total	3,987	100%	293	100%

Preliminary Analysis

Before conducting empirical estimation to understand the degree to which MLS players are discriminated against based on their demographic characteristics, it is important to check whether several assumptions (i.e., multicollinearity, normality,

homoscedasticity, linearity, and independence of error) for multiple linear regressions are met. Therefore, I checked the various assumptions.

First, I checked the assumption of non-multicollinearity using the correlation coefficients of the IVs and the variance inflation factor (VIF), which is a commonly used method to detect whether IVs are highly correlated (Greene, 2002). The correlation coefficients of the IVs and VIFs were presented in Table 4.8 and Table 4.9, respectively. Table 4.8 showed that STARTS and MINS were highly correlated ($r= 0.99$, $p<0.01$), and as were AGE and AGE^2 ($r=0.99$, $p<0.01$). This result is not unexpected, given that a player who began a game as a starting member is more likely to spend more time on the field. In addition, because they move together, the high correlation between age and squared term of age is intuitive.

A similar relationship was demonstrated in Table 4.9, which showed the VIFs for testing multicollinearity between the variables. The full model with all variables (Full Model) showed that the VIFs of AGE (102.746723), AGE^2 (104.368449), STARTS (167.320632), and MINS (159.416225) were above 10, a threshold for multicollinearity (O’Brien, 2007). For this reason, I removed the MINS variable in the second model (Reduced Model 1). The VIFs of AGE (102.413936) and AGE^2 (104.029527) were still above 10, however, resulting in the problem of multicollinearity. Although the multicollinearity from one variable and its squared term could be neglected and does not bias the estimates (Greene, 2002), in the third model (Reduced Model 2), I also removed the AGE^2 variable. The third model showed values of VIFs below 10 while meeting the assumption of non-multicollinearity. Nevertheless, since I was also interested in understanding both the positive effect of age (AGE) and the negative effect of squared term of age (AGE^2), I

separately analyzed the base model using AGE and the extended model using both AGE and AGE^2, holding constant the other variables.

Table 4.8

Correlation Matrix

	exp	age	age^2	height	starts	subs	mins	gls	ast	dps	allstar
exp	1	0.82 ***	0.82 ***	0.03 **	0.33 ***	-0.16 ***	0.32 ***	0.20 ***	0.19 ***	0.20 ***	0.20 ***
age	0.82 ***	1	0.99 ***	0.12 ***	0.35 ***	-0.19 ***	0.35 ***	0.15 ***	0.16 ***	0.16 ***	0.18 ***
age^2	0.82 ***	0.99 ***	1	0.11 ***	0.34 ***	-0.19 ***	0.34 ***	0.14 ***	0.15 ***	0.16 ***	0.18 ***
height	0.03 **	0.12 ***	0.11 ***	1	-0.01	-0.15 ***	-0.00	-0.10 ***	-0.25 ***	-0.09 ***	-0.00
starts	0.33 ***	0.35 ***	0.34 ***	-0.01	1	-0.31 ***	0.99 ***	0.36 ***	0.43 ***	0.14 ***	0.27 ***
subs	-0.16 **	-0.19 ***	-0.19 ***	-0.15	-0.31 ***	1	-0.27 ***	0.07 ***	0.03 **	-0.07 ***	-0.16 ***
mins	0.32 ***	0.35 ***	0.34 ***	-0.00	0.99 ***	-0.27 ***	1	0.36 ***	0.42 ***	0.13 ***	0.27 ***
gls	0.20 ***	0.15 ***	0.14 ***	-0.10 ***	0.36 ***	0.07 ***	0.36 ***	1	0.53 ***	0.39 ***	0.31 ***
ast	0.19 ***	0.16 ***	0.15 ***	-0.25 ***	0.43 ***	0.03 **	0.42 ***	0.53 ***	1	0.31 ***	0.26 ***
dps	0.20 ***	0.16 ***	0.16 ***	-0.09 ***	0.14 ***	-0.07 ***	0.13 ***	0.39 ***	0.31 ***	1	0.25 ***
allstar	0.20 ***	0.18 ***	0.18 ***	-0.00	0.27 ***	-0.16 ***	0.27 ***	0.31 ***	0.26 ***	0.25 ***	1

Notes: *p<0.1; **p<0.05; ***p<0.01

Table 4.9

Variance Inflation Factor

	Full Model	Reduced Model 1	Reduced Model 2
EXP	3.259298	3.258640	3.174156
AGE	102.746723	102.413936	3.229115
AGE^2	104.368449	104.029527	
HEIGHT	1.146175	1.129011	1.126376
STARTS	167.320632	1.637587	1.614504
SUBS	1.748041	1.237158	1.235787
MINS	159.416225		
GLS	1.675595	1.647448	1.647085
AST	1.694750	1.680917	1.678589
DPS	1.262663	1.260316	1.259864
ALLSTAR	1.223595	1.199713	1.196477

Notes: Reduced Model 1 omits MINS and Reduced Model 2 omits MINS and AGE^2.

Second, I checked the assumption of normality using histogram, boxplot, and the plots of the residuals. The histogram (Figure 4.1) and boxplot (Figure 4.2), which provide information about the dispersion of the data (Glass & Hopkins, 1996), showed that the residuals were not normally distributed. This can also be indicated by the normal probability plot. The observations lie well along the dotted line to meet the assumption of normality. The quantile-quantile plot (commonly known as the Q-Q plot) in Figure 4.3 showed that the observations did not lie well along the dotted line, showing evidence of non-normality. Although the above plots provided some information on normality, they were only snapshots giving a sense of how far the residuals were from normal distribution. Therefore, I conducted further statistical tests for normality. The results of the various normality tests—including the Shapiro-Wilk test ($W=0.574$, $p<0.01$), Anderson-Darling test ($A=382.46$, $p<0.01$), and Kolmogorov-Smirnov (i.e., Lilliefors) test ($D=0.226$, $p<0.01$)—rejected the null hypothesis of normality, suggesting that the assumption of normality was not met.

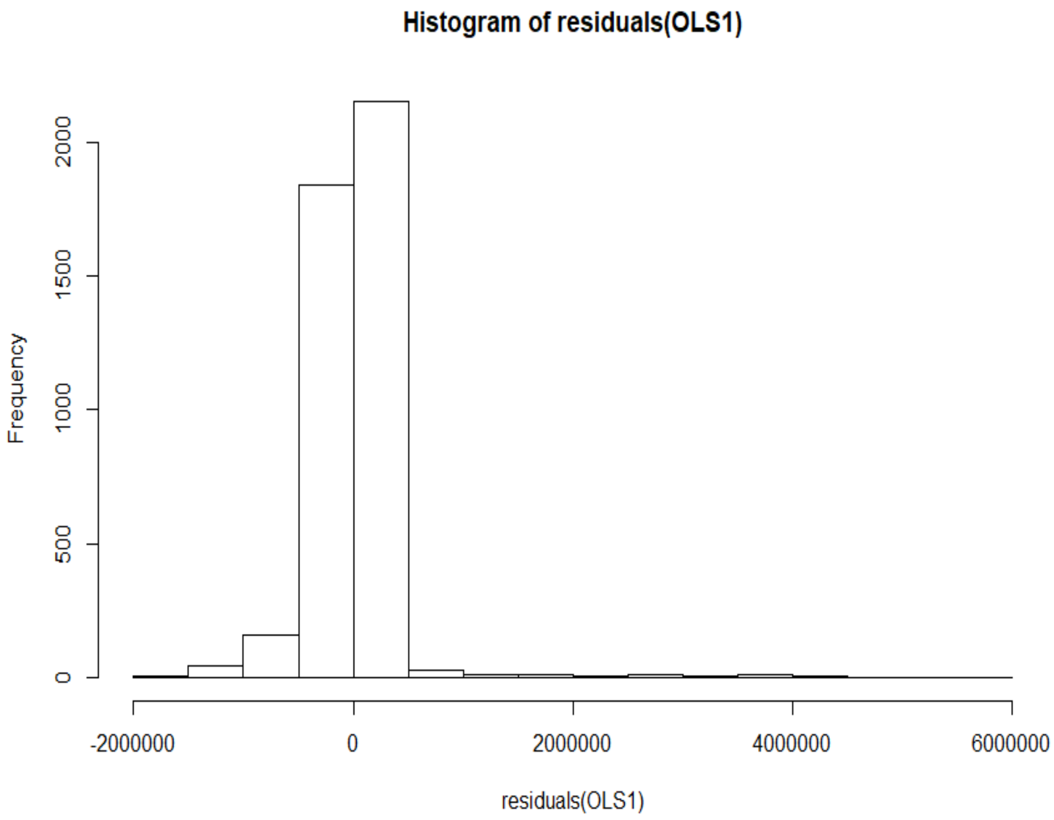

Figure 4.1. Normality Test Using Histogram of Residuals.

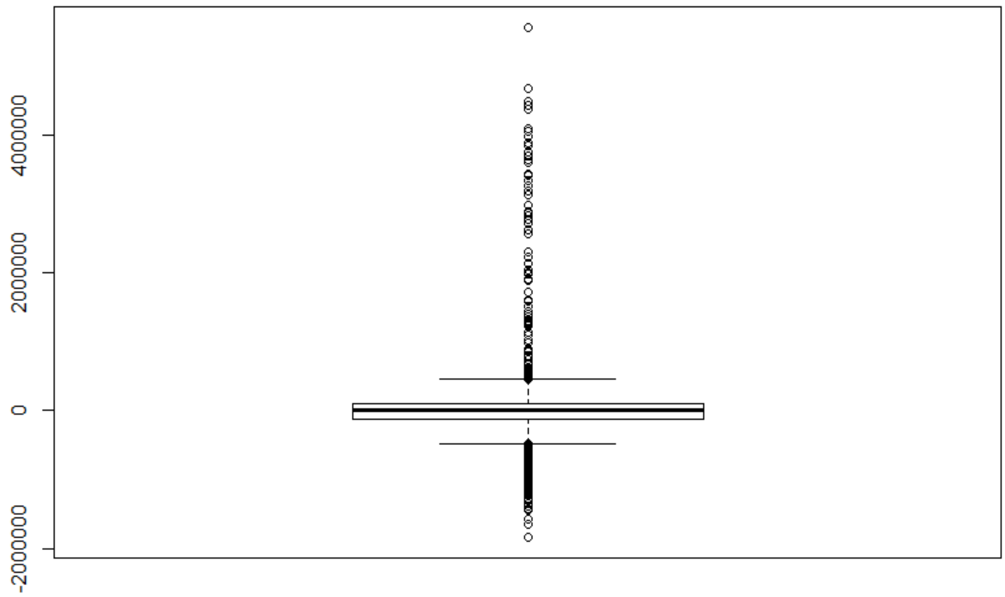

Figure 4.2. Normality Test Using Boxplot of Residuals.

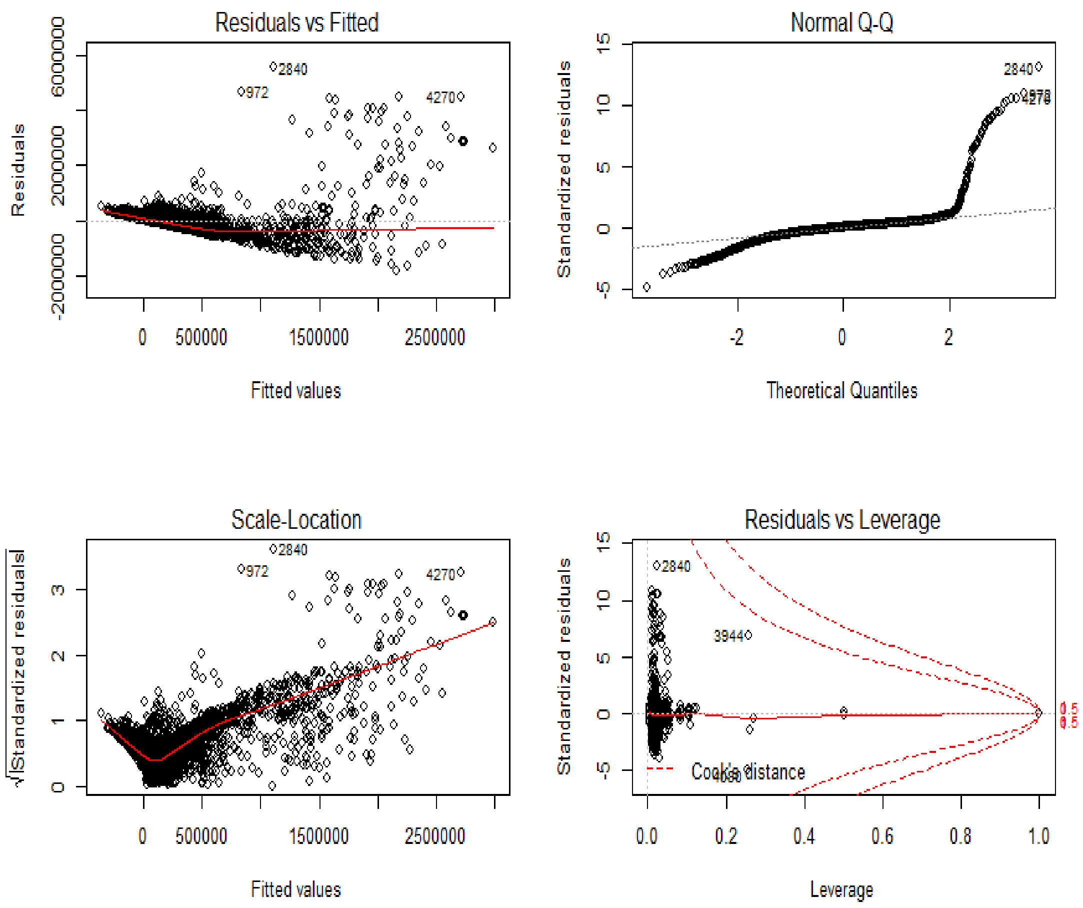

Figure 4.3. Assumption Test Using Various Plots of Residuals.

Third, using the plots of the residuals, I checked the assumption of homoscedasticity. The scale-location plot (bottom-left) shown in Figure 4.3 was particularly useful in checking the assumption of equal variance (i.e., homoscedasticity). It showed evidence of heteroscedasticity because the red line's trend had a negative and positive slope, rather than flat and horizontal with randomly and equally spread points. In addition, the results of the statistical tests—including the Non-Constant Variance Score test (x^2=0.226, $p<0.01$) and studentized Breusch-Pagan test (BP=946.76, $p<0.01$) —rejected the null hypothesis of equal variance, implying that the assumption of homoscedasticity was not met.

Fourth, I tested the assumption of linearity using the plots of the residuals. The residuals versus fitted plot (top-left) shown in Figure 4.3 was especially useful in checking the assumption of linearity. The residuals versus fitted plot showed no fitted pattern and the red line should be around zero to meet the assumption of linearity. However, residuals versus fitted plot (top-left) shown in Figure 4.3 seemed to demonstrate that the red line was not entirely flat. Lastly, I checked the assumption of independence of error. The result of the Durbin-Watson test (D-W=2.047, p=0.126) did not reject the null hypothesis of no correlation among residuals, indicating that the assumption of independence of error was met. Table 4.10 showed a summary of the results of the assumption tests.

Table 4.10

Results of the Assumption Tests

Assumption	Result
Normality	Not met
Homoscedasticity	Not met
Linearity	Not met
Independence of Error	Met

Notes: The assumption of non-multicollinearity was also checked.

Since the assumptions of normality, homoscedasticity, and linearity were not met, I decided to transform the DV (i.e., players' salaries) into various forms (i.e., Log transformation, Box-Cox transformation, and Square Root transformation). Log transformation of DV has been widely used in the sports economics literature, because it not only demonstrates direct elasticity estimates (Fort & Lee, 2006) but also enables researchers to consider heteroskedasticity from the large variance in players' salaries (Holmes, 2011). For this reason, I again checked the assumptions of normality, homoscedasticity, linearity, and independence of error using the natural logarithm of players' salaries.

First, I again checked the assumption of normality using various plots (i.e., histogram, boxplot, and the plots of the residuals). The log model of the histogram of residuals (Figure 4.4) and the boxplot of residuals (Figure 4.5) seemed to support evidence that the residuals were normally distributed. Moreover, the Q-Q plot (top-right in Figure 4.6) showed that the observations lied well along the dotted line, showing evidence of normality. Nevertheless, the above plots do not provide definite information on normality. Therefore, I conducted further normality tests; the results of the various tests—including the Shapiro-Wilk test ($W=0.983$, $p<0.01$), Anderson-Darling test ($A=11.707$, $p<0.01$), and Kolmogorov-Smirnov test ($D=0.035$, $p<0.01$)—again rejected the null hypothesis of normality, suggesting that the assumption of normality was not met, although the plots to some extent supported the evidence of normality.

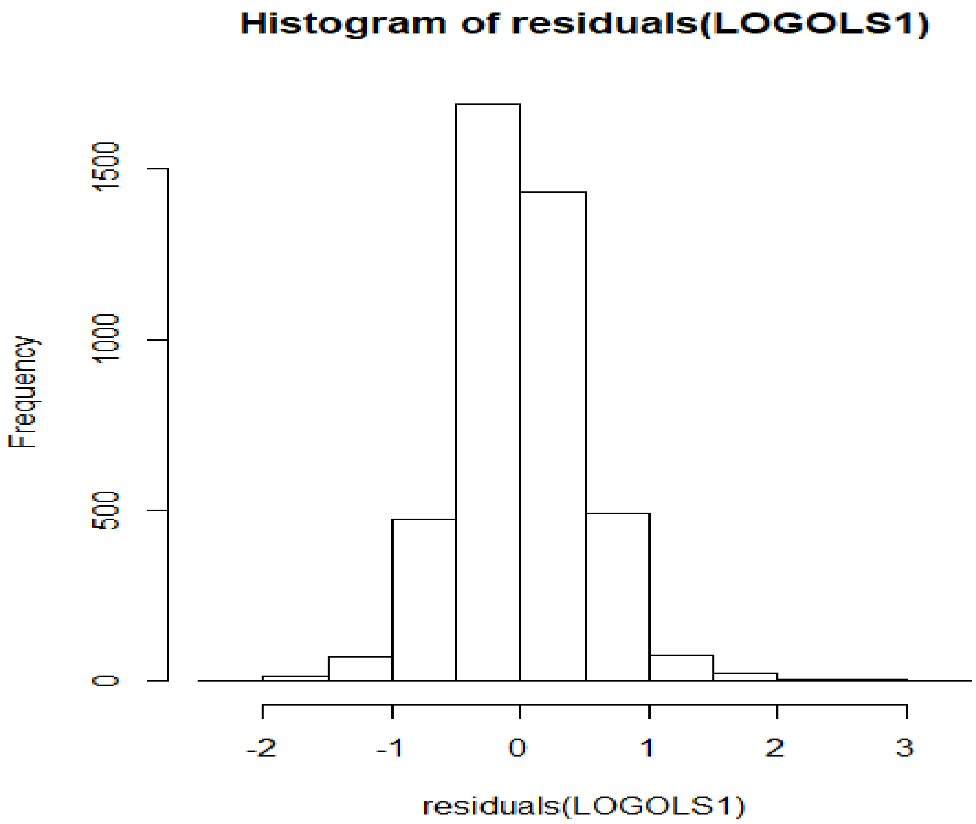

Figure 4.4. Normality Test Using Histogram of Residuals (Log Model).

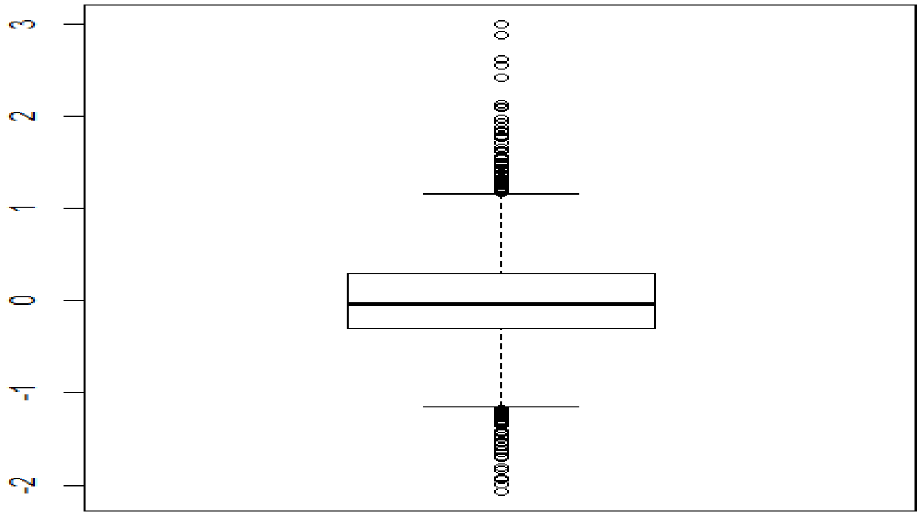

Figure 4.5. Normality Test Using Boxplot of Residuals (Log Model).

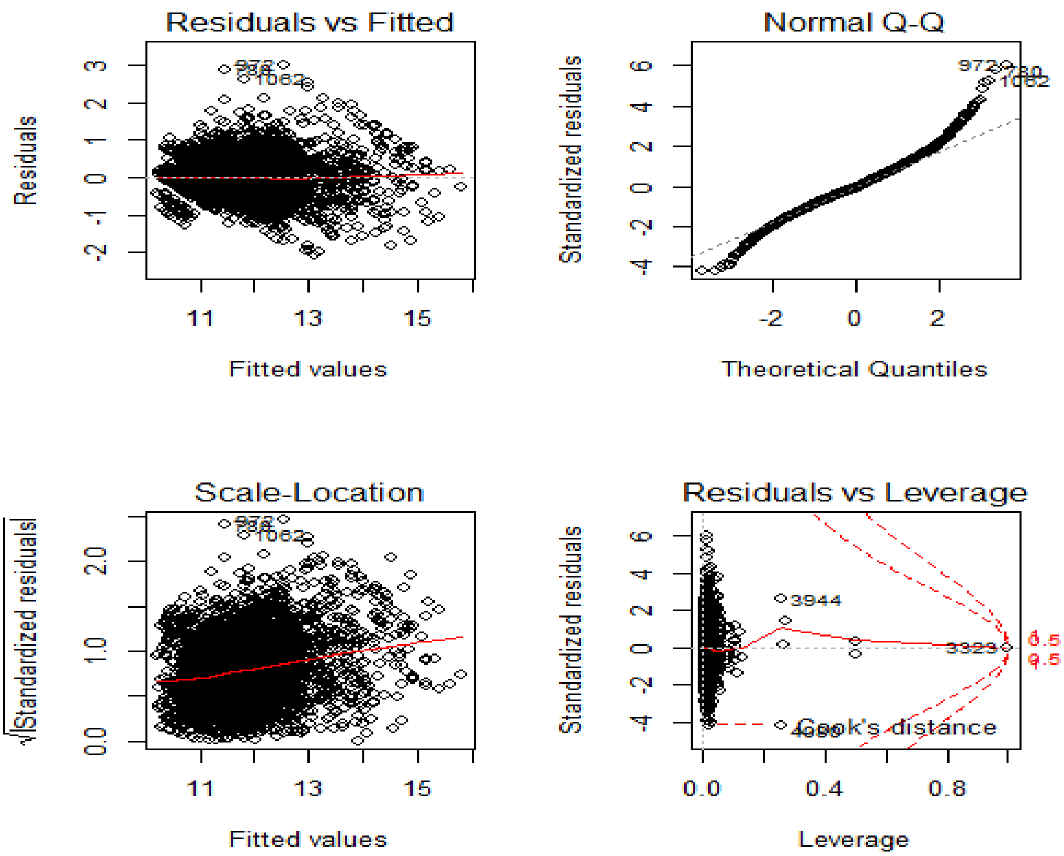

Figure 4.6. Assumption Test Using Various Plots of Residuals (Log Model).

Second, I checked the assumption of homoscedasticity using a scale-location plot (bottom-left in Figure 4.6). The plot showed evidence of heteroscedasticity because the red line had a certain upward trend, suggesting evidence of violation of the assumption of homoscedasticity. In addition, the results of the statistical tests—including the Non-Constant Variance Score test (x^2=429.23, p<0.01) and studentized Breusch-Pagan test (BP=424.71, p<0.01)—rejected the null hypothesis of equal variance, indicating that the assumption of homoscedasticity was not met. Third, I tested the assumption of linearity using the residuals versus fitted plot (top-left in Figure 4.3). This plot showed that the red line was flat and around zero with no certain pattern while meeting the assumption of linearity. Lastly, I checked the assumption of independence of error. The Durbin-Watson test (D-W=1.999, p=0.922) did not reject the null hypothesis, implying that the assumption of independence of error was met in the log model. Table 4.11 summarized of the results of the assumption tests of the log model.

Table 4.11

Results of the Assumption Tests (Log Model)

Assumption	Result
Normality	Not met
Homoscedasticity	Not met
Linearity	Met
Independence of Error	Met

Notes: The assumption of non-multicollinearity was checked in base model.

The results of the assumption test indicated that a few assumptions of multiple linear regression in both the base model and log model were not met. I therefore analyzed the data using two different approaches. I used OLS regression, despite the violation of a few assumptions in the log model. This is because it is often suggested that with a large enough sample size (N>30 or the number of observations

per variable>10) (Hogg, Tanis, & Zimmerman, 1977), assumption violation does not cause serious problems (Pallant, 2016), thus rarely impacting the results (Schmidt & Finan, 2018). In addition, OLS estimation has been widely used in estimating players' salaries (Kahn, 1991; Keefer, 2013) because it is the best linear unbiased estimator in linear regression (Bryson et al., 2013).

I also analyzed the data using quantile regression, which is more robust to the violation of normality and homoscedasticity assumptions (Koenker & Bassett, 1978) that were not met in the log model. For this reason, an extensive amount of research has adopted the quantile regression method (e.g., Berri & Simmons, 2009; Fort, Lee, & Oh, 2019; Hamilton, 1997; Holmes, 2011; Keefer, 2013; Leeds, 2014; Leeds & Kowalewski, 2001; Reilly & Witt, 2007; Treme & Allen, 2011; Vincent & Eastman, 2009) because players' salaries often have non-normal distribution (Berri et al., 2013). Therefore, I used the quantile regression for empirical estimation and compared it to OLS regression in order to better understand whether players' origin of birth impacted the salaries at any quantile of the salary distribution.

Statistical Results

This section explains the statistical results using both OLS and quantile regression to assess whether there is salary discrimination among each group (all players, regular players, and designated players). The first part explains the process of model selection and addresses the results of OLS regression using APs, RPs, and DPs. The second part shows the process of model selection and demonstrates the results of quantile regression using APs, RPs, and DPs.

Ordinary Least Squares Regression

I designed four different models in OLS regression to estimate the degree to which MLS players from certain regions are either favored or discriminated against

based on their origin of birth. As noted in Chapter 3, there are two types of salaries in MLS: base salary and guaranteed compensation. The use of DV has been arbitrarily determined by researchers based on its intended meaning of the context. For this reason, I used both base salary and guaranteed compensation in two different models. Similarly, previous scholars have used two geographic criteria, FIFA division and UN Statistics Division, for players' origin of birth. Therefore, I used both FIFA and UN Statistics Divisions in two different models. In sum, four different models (2x2) were employed using base salary, guaranteed compensation, FIFA division, and UN Statistics Division; I chose the best-fitted model for interpretation based on the model fit.

Ordinary least squares regression results of all players. The first OLS model included all MLS players (N=3,886) in the sample. I used this model to investigate whether there is salary discrimination among all players in MLS. I estimated the most appropriate model of APs by using the Bayesian information criterion (BIC) (Raftery, 1995) and the R-squared value. Table 4.12 demonstrated the OLS regression results using APs in MLS. The value of the BIC for Model 1 was the lowest (6209.894) followed by Model 2 (6270.873), Model 3 (6675.090), and Model 4 (6733.705). The value of R^2 and adjusted R^2 also showed a similar result: Model 1 has the highest value of R^2 (0.728) and adjusted R^2 (0.724) among the four models. Therefore, I chose to use the results of Model 1, the best-fitted model, for interpretation. This model includes the players' base salary as DV and the UN Statistics Division for grouping players' origin of birth.

The first main variable of interest in this dissertation, the player's origin of birth variable showed evidence of salary discrimination in MLS. The players from North America experienced wage discrimination compared to players from South

America ($\beta=0.359$, $p<0.01$), Central America ($\beta=0.347$, $p<0.01$), Western Europe ($\beta=0.340$, $p<0.01$), Eastern Europe ($\beta=0.397$, $p<0.01$), Northern Europe ($\beta=0.125$, $p<0.01$), Southern Europe ($\beta=0.496$, $p<0.01$), and Africa ($\beta=0.143$, $p<0.01$). I did not, however, find any significant difference in wages between players from North America and players from Asia, the Caribbean, and Oceania. In using the FIFA division in Model 2 and Model 4, I also found salary discrimination by players' origin of birth among all players: players from CONCACAF were paid less than the comparable players from CAF ($\beta=0.114$, $p<0.01$ in Model 2; $\beta=0.129$, $p<0.01$ in Model 4), CONMEBOL ($\beta=0.300$, $p<0.01$ in Model 2; $\beta=0.295$, $p<0.01$ in Model 4), and UEFA ($\beta=0.250$, $p<0.01$ in Model 2; $\beta=0.261$, $p<0.01$ in Model 4). Therefore, H1 was accepted.

The second main variable of interest, designated player status, was statistically significant at the 0.01 level in all models, supporting H2. When quantifying the correlation coefficient of 1.020 in Model 1, I found that designated players were paid on average 177.3% more than regular players. The All-Star games variable (ALLSTAR) was shown to increase players' salaries by 53%, which indicates that players who were voted as All-Star players in the previous season were given salary premiums in the current season.

I found various human capital factors to be significant in explaining players' salaries in MLS. First, the variable of scarce talent (i.e., footedness) showed that left-footed players and players whose footedness was not defined were paid about 10.1% and 17% less, respectively, than the both-footed players. There was no significant wage differential, however, between both-footed and right-footed players. The results therefore supported the hypothesis that scarce talent (i.e., both-footedness) was positively associated with players' salaries. Second, the age variable (AGE) was

found to be not significant in Model 1, although it was statistically significant at the 0.05 level in Model 2 and Model 3. Therefore, $H5_a$ was not accepted. Third, the player height variable (HEIGHT) was statistically significant in all models, showing that MLS players were paid 0.5% more with an increase in height of 1cm. For this reason, H7 was supported. Fourth, the experience variable (EXP) also indicated that players were paid 9.5% more with additional experience in professional soccer, supporting H4.

Other factors, including games started, games substituted, goals, and position were found to be statistically significant in Model 1. As hypothesized, the number of games started variable (STARTS) was positively associated with players' salaries, and the number of games substituted variable (SUBS) was negatively associated with players' salaries, supporting both $H9_a$ and $H9_b$. The results showed that one additional game started increased players' salaries by 1.7%, while one additional game substituted decreased players' salaries by 1.9%. The number of goals scored variable (GLS) was statistically significant at the 0.01 level supporting $H8_a$ while the number of assists scored variable (AST) was not statistically significant, not supporting $H8_b$. Lastly, the results confirmed that a player's position influenced his salary, supporting H10. For example, midfielders, midfielder-forwards, and forwards were paid about 8.4%, 24.6%, and 19% higher than defenders in MLS, respectively.

Table 4.12

Ordinary Least Squares Regression Results of All Players

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables of Interest	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	0.359***		0.358***	
	(0.029)		(0.031)	
UN (CENTRAL AMERICA)	0.347***		0.367***	
	(0.039)		(0.041)	
UN (WESTERN EUROPE)	0.340***		0.347***	
	(0.047)		(0.050)	
UN (EASTERN EUROPE)	0.397***		0.390***	
	(0.106)		(0.112)	
UN (NORTHERN EUROPE)	0.125***		0.138***	
	(0.063)		(0.042)	
UN (SOUTHERN EUROPE)	0.496***		0.533***	
	(0.063)		(0.067)	
UN (AFRICA)	0.143***		0.159***	
	(0.033)		(0.035)	
UN (ASIA)	0.167*		0.150	
	(0.095)		(0.101)	
UN (CARIBBEAN)	0.065		0.074*	
	(0.041)		(0.043)	
UN (OCEANIA)	0.094		0.062	
	(0.116)		(0.123)	
FIFA (AFC)		0.044		0.010
		(0.103)		(0.109)
FIFA (CAF)		0.114***		0.129***
		(0.033)		(0.035)
FIFA (CONMEBOL)		0.300***		0.295***
		(0.028)		(0.030)
FIFA (UEFA)		0.250***		0.261***
		(0.029)		(0.030)
FIFA (OFC)		-0.184		-0.210
		(0.145)		(0.154)
FOOT (LEFT)	-0.084**	-0.074*	-0.098**	-0.087**
	(0.039)	(0.039)	(0.041)	(0.042)
FOOT (RIGHT)	0.022	0.012	0.020	0.010
	(0.036)	(0.036)	(0.038)	(0.038)
FOOT (NOT DEFINED)	-0.165***	-0.180***	-0.186***	-0.201***
	(0.048)	(0.048)	(0.051)	(0.051)
POS (D-M)	0.039	0.043	0.044	0.049
	(0.050)	(0.050)	(0.053)	(0.053)
POS (F)	0.174***	0.189***	0.190***	0.205***
	(0.030)	(0.030)	(0.032)	(0.032)
POS (F-M)	0.086	0.064	0.091	0.068
	(0.077)	(0.077)	(0.081)	(0.082)

Table 4.12, continued

Ordinary Least Squares Regression Results of All Players

POS (M)	0.081***	0.086***	0.087***	0.092***
	(0.023)	(0.024)	(0.025)	(0.025)
POS (M-D)	-0.069	-0.048	-0.039	-0.016
	(0.072)	(0.073)	(0.076)	(0.077)
POS (M-F)	0.220***	0.221***	0.227***	0.227***
	(0.043)	(0.044)	(0.046)	(0.047)
EXP	0.091***	0.080***	0.091***	0.079***
	(0.004)	(0.004)	(0.005)	(0.004)
AGE	-0.002	0.007**	-0.010**	0.0002
	(0.004)	(0.004)	(0.004)	(0.004)
HEIGHT	0.005***	0.003**	0.005***	0.004**
	(0.001)	(0.001)	(0.002)	(0.002)
STARTS	0.017***	0.017***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.019***	-0.020***	-0.019***	-0.020***
	(0.002)	(0.002)	(0.003)	(0.003)
GLS	0.026***	0.027***	0.027***	0.027***
	(0.003)	(0.004)	(0.004)	(0.004)
AST	0.008	0.009*	0.011**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)
DPS	1.020***	1.057***	1.063***	1.102***
	(0.036)	(0.036)	(0.038)	(0.039)
ALLSTAR	0.424***	0.422***	0.437***	0.434***
	(0.037)	(0.037)	(0.039)	(0.039)
CONSTANT	-130.3***	-135.3***	-128.6***	-133.8***
	(5.262)	(5.296)	(5.587)	(5.621)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	3,886	3,886	3,886	3,886
BIC	6209.894	6270.873	6675.090	6733.705
R^2	0.728	0.721	0.704	0.697
Adjusted R^2	0.724	0.717	0.700	0.693
F Statistics	182.98***	193.99***	162.95***	172.70***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Ordinary least squares regression results of regular players. The second OLS model included regular MLS players (N=3,596) in the sample. This model was used in order to differentiate between regular players and designated players due to the heterogeneity in performance and players' characteristics among the two groups. I again chose the best-fitted model based on the BIC and the value of R-squared. The

value of the BIC for Model 1 was the lowest (5254.308) followed by Model 2 (5318.127), Model 3 (5779.521), and Model 4 (5838.745). In addition, the value of R^2 and adjusted R^2 were the highest in Model 1 (R^2=0.641; adjusted R^2=0.635). For this reason, I chose to interpret the results of Model 1 in Table 4.13, which was found to be the best-fitted model.

Player's origin of birth was statistically significant in explaining the variance of players' salaries among regular players. Similarly to the all players model, players from South America (β=0.422, $p<0.01$), Central America (β=0.343, $p<0.01$), Western Europe (β=0.308, $p<0.01$), Eastern Europe (β=0.425, $p<0.01$), Northern Europe (β=0.118, $p<0.01$), Southern Europe (β=0.545, $p<0.01$), and Africa (β=0.137, $p<0.01$) were paid more than the comparable players from North America. The salaries of players from Asia, the Caribbean, and Oceania, however, were not significantly different from those of the North American players. Using FIFA division, the evidence of salary discrimination was further supported in Model 2 and Model 4: players from CAF (β=0.113, $p<0.01$ in Model 2; β=0.124, $p<0.01$ in Model 4), CONMEBOL (β=0.376, $p<0.01$ in Model 2; β=0.365, $p<0.01$ in Model 4), and UEFA (β=0.246, $p<0.01$ in Model 2; β=0.260, $p<0.01$ in Model 4) were paid more than the North American players, all else being equal.

Human capital factors—including footedness, height, and experience—were found to be statistically significant. The footedness (FOOT) variable indicated that left-footed players were paid approximately 10.2% less than both-footed players while players whose footedness was not officially defined were paid 16.8% less than the comparable both-footed players. Players with both-footedness, however, did not receive a higher base salary than the players with right-footedness. Therefore, H6 was accepted. Players' height (HEIGHT) was positively associated with salaries in that

they were paid 0.4% more per 1cm height increase, supporting H7. The experience (EXP) variable showed that the RPs in MLS were paid about 8.3% more with an increase in professional soccer experience, supporting H4. The age variable (AGE), however, despite its significance in Model 2 at the 0.01 level, was not statistically significant in Model 1. Therefore, $H5_a$ was not accepted in the RPs model.

Other factors also affected the players' salaries. First, both the number of games started (STARTS) and the number of games substituted (SUBS) were statistically significant at the 0.01 level. For example, one additional game started was equivalent to an increase of base salary by 1.8% while one additional game substituted was equivalent to a decrease of salary by 1.8%, supporting both $H9_a$ and $H9_b$. Second, the number of goals scored (GLS) was positively associated with players' salaries; the number of assists scored (AST), however, was not associated with players' salaries. Therefore, $H8_a$ was accepted but not $H8_b$. Third, it was also confirmed that a player's position influenced his salary, supporting H10. MLS forwards, midfielders, and midfielder-forwards were paid about 15%, 5.9%, and 23.2% more, respectively, than defenders. Lastly, the All-Star variable (ALLSTAR) was shown to be positively associated with players' salaries in that players who participated in All-Star games earned approximately 46.5% more money than those who did not.

Table 4.13

Ordinary Least Squares Regression Results of Regular Players

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	0.422***		0.414***	
	(0.029)		(0.031)	
UN (CENTRAL AMERICA)	0.343***		0.369***	
	(0.039)		(0.042)	
UN (WESTERN EUROPE)	0.308***		0.318***	
	(0.047)		(0.050)	
UN (EASTERN EUROPE)	0.425***		0.422***	
	(0.105)		(0.113)	
UN (NORTHERN EUROPE)	0.118***		0.138***	
	(0.039)		(0.042)	
UN (SOUTHERN EUROPE)	0.545***		0.573***	
	(0.066)		(0.071)	
UN (AFRICA)	0.137***		0.151***	
	(0.032)		(0.034)	
UN (ASIA)	0.101		0.081	
	(0.093)		(0.100)	
UN (CARIBBEAN)	0.061		0.072*	
	(0.039)		(0.042)	
UN (OCEANIA)	-0.041		-0.068	
	(0.114)		(0.122)	
FIFA (AFC)		-0.058		-0.093
		(0.100)		(0.108)
FIFA (CAF)		0.113***		0.124***
		(0.032)		(0.034)
FIFA (CONMEBOL)		0.376***		0.365***
		(0.028)		(0.031)
FIFA (UEFA)		0.246***		0.260***
		(0.028)		(0.030)
FIFA (OFC)		-0.178		-0.202
		(0.136)		(0.146)
FOOT (LEFT)	-0.108***	-0.103***	-0.131***	-0.124***
	(0.039)	(0.039)	(0.042)	(0.042)
FOOT (RIGHT)	-0.006	-0.017	-0.014	-0.026
	(0.036)	(0.037)	(0.039)	(0.039)
FOOT (NOT DEFINED)	-0.184***	-0.200***	-0.213***	-0.228***
	(0.047)	(0.047)	(0.050)	(0.051)
POS (D-M)	0.036	0.040	0.041	0.045
	(0.047)	(0.047)	(0.509)	(0.051)
POS (F)	0.140***	0.149***	0.161***	0.171***
	(0.029)	(0.030)	(0.031)	(0.032)
POS (F-M)	0.044	0.030	0.058	0.043
	(0.077)	(0.078)	(0.083)	(0.084)

Table 4.13, continued

Ordinary Least Squares Regression Results of Regular Players

POS (M)	0.057**	0.063***	0.060**	0.067***
	(0.022)	(0.023)	(0.024)	(0.024)
POS (M-D)	-0.083	-0.063	-0.052	-0.030
	(0.068)	(0.068)	(0.073)	(0.074)
POS (M-F)	0.209***	0.208***	0.204***	0.203***
	(0.043)	(0.044)	(0.047)	(0.047)
EXP	0.080***	0.069***	0.081***	0.069***
	(0.004)	(0.004)	(0.005)	(0.004)
AGE	0.002	0.011***	-0.008*	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
HEIGHT	0.004**	0.002*	0.004**	0.003*
	(0.001)	(0.001)	(0.002)	(0.002)
STARTS	0.018***	0.017***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.018***	-0.019***	-0.017***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
GLS	0.039***	0.040***	0.038***	0.039***
	(0.004)	(0.004)	(0.004)	(0.004)
AST	0.006	0.007	0.009	0.010*
	(0.005)	(0.005)	(0.006)	(0.006)
ALLSTAR	0.382***	0.380***	0.383***	0.380***
	(0.039)	(0.040)	(0.042)	(0.043)
CONSTANT	-132.6***	-137.2***	-131.5***	-136.3***
	(5.020)	(5.060)	(5.401)	(5.439)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	3,596	3,596	3,596	3,596
BIC	5254.308	5318.127	5779.521	5838.745
R^2	0.641	0.630	0.599	0.588
Adjusted R^2	0.635	0.625	0.593	0.582
F Statistics	116.89***	123.21***	98.07***	103.27***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Ordinary least squares regression results of designated players. The third OLS model included designated MLS players (N=290) in the sample. This model was designed to assess whether there is evidence of salary discrimination among superstars (i.e., designated players). As shown in Table 4.14, I interpreted the results of Model 4: Although the values of R^2 (0.767) and adjusted R^2 (0.715) were the

highest in Model 3, the value of the BIC was the lowest in Model 4 (751.7122) followed by Model 2 (757.7122), Model 3 (763.0014), and Model 1 (771.3486).

The results concerning salary discrimination among designated players—the main interest of this dissertation—showed evidence of possible preference for players' origin of birth even among superstars in MLS. The analysis showed that players from CONMEBOL were paid about 22.9% less in guaranteed compensation than comparable players from CONCACAF. A similar result was found in Model 2, which showed that players from CONMEBOL were paid approximately 24.3% less than those from CONCACAF. Model 1 and Model 3 found that players from Asia (β=0.984, $p<0.05$ in Model 1; β=1.013, $p<0.01$ in Model 3) were preferred, while players from the Caribbean (β= -0.656, $p<0.05$ in Model 1; β= -0.630, $p<0.05$ in Model 3) were discriminated against in both base salary and guaranteed compensation compared to players from North America. Therefore, H3 was accepted.

One of the four human capital factors was significant in the designated players model. The experience (EXP) variable was statistically significant at the 0.01 level. It showed that DPs experienced an increase in compensation by 9.3% with additional experience in professional soccer, supporting H4. The age (AGE), height (HEIGHT), and footedness (FOOT) variables, however, were not associated with MLS players' salaries. Therefore, $H5_a$, H6, and H7 were not accepted.

As for the league appearance variables, both the number of games started (STARTS) and substituted (SUBS) were negative and significant at the 0.01 level. Players' salaries decreased by 2.2% with an increase in the number of games played and decreased by 6% with an increase in the number of games substituted. Therefore, $H9_a$ was not accepted, while $H9_b$ was accepted. Performance statistics variables (i.e., GLS and AST) did not affect DPs' salaries, not supporting H8. It was also found that

midfielder-forwards were paid 60.3% more than defenders, supporting H10. Lastly, there was a positive and significant relationship between DPs' salaries and the All-Star variable (ALLSTAR) at the 0.01 level. The DPs who were nominated as All-Star players last year were paid about 42.3% more than those who were not.

Table 4.14

Ordinary Least Squares Regression Results of Designated Players

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	-0.285*		-0.223	
	(0.166)		(0.164)	
UN (CENTRAL AMERICA)	0.048		0.099	
	(0.161)		(0.159)	
UN (WESTERN EUROPE)	-0.016		-0.010	
	(0.192)		(0.189)	
UN (EASTERN EUROPE)	0.513		0.598	
	(0.393)		(0.387)	
UN (NORTHERN EUROPE)	-0.262		-0.290*	
	(0.167)		(0.165)	
UN (SOUTHERN EUROPE)	-0.158		-0.105	
	(0.207)		(0.204)	
UN (AFRICA)	0.249		0.339	
	(0.231)		(0.228)	
UN (ASIA)	0.984**		1.013***	
	(0.389)		(0.384)	
UN (CARIBBEAN)	-0.656**		-0.630**	
	(0.301)		(0.297)	
UN (OCEANIA)	0.404		0.366	
	(0.463)		(0.456)	
FIFA (AFC)		0.520		0.471
		(0.466)		(0.462)
FIFA (CAF)		0.249		0.313
		(0.224)		(0.222)
FIFA (CONMEBOL)		-0.279**		-0.260**
		(0.131)		(0.130)
FIFA (UEFA)		-0.069		-0.082
		(0.120)		(0.118)
FOOT (LEFT)	-0.153	-0.127	-0.072	-0.043
	(0.167)	(0.168)	(0.164)	(0.167)
FOOT (RIGHT)	-0.093	-0.121	-0.090	-0.126
	(0.129)	(0.130)	(0.127)	(0.129)
FOOT (NOT DEFINED)	0.481	0.491	0.451	0.460
	(0.296)	(0.302)	(0.292)	(0.299)
POS (D-M)	-0.128	-0.224	-0.207	-0.329
	(0.676)	(0.687)	(0.667)	(0.680)
POS (F)	0.161	0.179	0.173	0.201
	(0.209)	(0.209)	(0.206)	(0.207)
POS (F-M)	-0.022	-0.105	0.037	-0.065
	(0.318)	(0.321)	(0.314)	(0.318)
POS (M)	0.178	0.158	0.201	0.186
	(0.194)	(0.194)	(0.191)	(0.192)

Table 4.14, continued

Ordinary Least Squares Regression Results of Designated Players

POS (M-D)	-0.227	-0.313	-0.289	-0.399
	(0.659)	(0.670)	(0.650)	(0.663)
POS (M-F)	0.323	0.387	0.400*	0.472**
	(0.237)	(0.238)	(0.234)	(0.236)
EXP	0.094***	0.095***	0.090***	0.089***
	(0.020)	(0.019)	(0.019)	(0.019)
AGE	0.033*	0.023	0.038**	0.029*
	(0.017)	(0.017)	(0.017)	(0.017)
HEIGHT	-0.008	-0.005	-0.003	-0.001
	(0.007)	(0.006)	(0.007)	(0.006)
STARTS	-0.014**	-0.018***	-0.019***	-0.022***
	(0.007)	(0.006)	(0.007)	(0.006)
SUBS	-0.054***	-0.057***	-0.059***	-0.062***
	(0.015)	(0.015)	(0.015)	(0.015)
GLS	0.005	0.007	0.009	0.010
	(0.010)	(0.010)	(0.010)	(0.010)
AST	-0.001	0.010	-0.0005	0.012
	(0.014)	(0.014)	(0.014)	(0.014)
ALLSTAR	0.317***	0.307***	0.365***	0.353***
	(0.102)	(0.102)	(0.100)	(0.101)
CONSTANT	-171.9***	-181.2***	-174.3***	-185.5***
	(35.672)	(36.144)	(35.162)	(35.783)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	290	290	290	290
BIC	771.3486	757.5422	763.0014	751.7122
R^2	0.758	0.740	0.767	0.748
Adjusted R^2	0.704	0.690	0.715	0.699
F Statistics	13.94***	14.69***	14.66***	15.28***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Ordinary least squares regression results including goalkeepers. As described in Chapter 3, previous scholars have analyzed the wage equation in MLS both including and excluding goalkeepers. The rationale for excluding goalkeepers from the sample is that the performance statistics of goalkeepers are not measured in the same way as for outfielder players such as defenders, midfielders, and forwards (Lucifora & Simmons, 2003; Medcalfe & Smith, 2018; Prockl & Frick, 2018b). For this reason, the base model excluded goalkeepers. It is possible, however, that salary

discrimination may function differently when goalkeepers are included. I therefore compared the models including goalkeepers and with the models excluding goalkeepers to assess any differences between them. Similarly to the previous OLS regression results excluding goalkeepers, the following section demonstrates the OLS regression results including goalkeepers.

As for the OLS regression results of all players including goalkeepers (N=4,280) in Table A-1, there was no stark difference between the models including and excluding goalkeepers, with the exception of the following results. First, unlike the models excluding goalkeepers in which players from South America, Central America, Western Europe, Northern Europe, Southern Europe, and Africa were paid higher than North American players, the models including goalkeepers showed that not only the above players but also players from the Caribbean were paid more (β=0.088, $p<0.05$) than players from North America. In other words, the Caribbean players were paid 9.2% more than the players from North America. Second, the position variable (POS) was statistically significant at the 0.01 level. The results showed that, all else being equal, goalkeepers (β= -0.094, $p<0.01$) were paid approximately 9% less than defenders.

Regarding the OLS regression results of regular players including goalkeepers (N=3,987) in Table A-2, the results were very similar to the above all players model. It was found that the Caribbean players were paid more (β=0.087, $p<0.05$) than players from North America by 9.1%. In addition, goalkeepers (β= -0.071, $p<0.05$) were paid approximately 6.9% less than defenders. In terms of the OLS regression results of designated players including goalkeepers (N=293) in Table A-3, there was no difference between the results of the DPs model including and excluding goalkeepers. This result is intuitive given that there were only three

designated goalkeepers in the sample, which could hardly affect the results. In sum, goalkeepers did not play a significant role in the DPs model.

Ordinary least squares regression results using both AGE and AGE^2. I excluded several variables from the empirical analysis because of multicollinearity between the variables, and one of which was the squared term of age (AGE^2). It is, of course, intuitive that there is strong collinearity between the variable and its squared term. For this reason, the base model excluded AGE^2, which may capture the concave relationship between age and salary (Bhattarai, 2017; Morikawa, 2016). This is because players' salaries tend to drop off after a certain age because of their decreased performance statistics, indicating a non-linear relationship between age and salary. With this knowledge, researchers have inquired into a positive (negative) effect of age (squared term of age) on salary (e.g., Bryson et al., 2013; Holmes, 2011; Kuethe & Motamed, 2010; Lucifora & Simmons, 2003; Medcalfe & Smith, 2018; Prockl & Frick, 2018b). The following section thus demonstrates the OLS regression results of all players, regular players, and designated players including both age (AGE) and the squared term of age (AGE^2) variable in the models, holding constant the other variables.

Regarding the OLS regression results of all players using both AGE and AGE^2 (N=3,886) in Table A-4, both AGE and AGE^2 were statistically significant at the 0.01 level, unlike the non-significance of AGE in the base model. This showed evidence of a positive effect of age on salary and a negative effect of the squared term of age on salary, supporting both $H5_a$ and $H5_b$. The results confirmed that MLS players earned more money as they grew older, but that this increase stopped after a certain age. The OLS regression results of regular players using both AGE and AGE^2 (N=3,596) was shown in Table A-5. Similar to the base model in Table 4.13, there was

no stark difference except for the significance of AGE (β=0.178, $p<0.01$) and AGE^2 (β= -0.003, $p<0.01$). The AGE variable indicated that RPs in MLS were paid a 18.6% higher salary per year up to a certain age. The positive (negative) relationship between players' age (squared term of age) supported both $H5_a$ and $H5_b$. As for the OLS regression results of designated players using both AGE and AGE^2 (N=290) in Table A-6, the AGE variable was statistically significant at the 0.05 level, however, AGE^2 was not statistically significant, although both AGE and variables AGE^2 were statistically significant at the 0.05 level in Model 1 and Model 2. In sum, $H5_a$ was accepted while $H5_b$ was not accepted in the DPs model.

Quantile Regression

In addition to OLS regression, I employed the quantile regression for the empirical estimation for the following two reasons. First, quantile regression is more robust to the violation of assumptions for the multiple linear regression in that normality and homoscedasticity assumptions do not need to be met, while for OLS regression, the assumptions of normality, equal variance, linearity, and independence of error should be met (Petscher & Logan, 2014). When conducting assumption tests, normality and homoscedasticity assumptions were not met even after the players' salaries were transformed into the form of a natural log. This result is not surprising because, as suggested by previous literature (e.g., Berri & Simmons, 2009; Hamilton, 1997), players' salaries were skewed to the right. For this reason, quantile regression is a useful alternative when the assumptions are not met (Leeds, 2014).

Second, the quantile regression could demonstrate a more detailed perspective on different salary distributions than OLS regression (Keefer, 2013). Unlike OLS estimation, which examines the relationship between mean DV and IVs, quantile regression investigates possible evidence of invisible market preference on

players' origin of birth at any salary distributions (Berri et al., 2013; Lucifora & Simmons, 2003). The player's origin of birth, for example, may affect the player's salary differently in the upper and lower quantiles. Therefore, quantile regression makes it possible to reveal the degree to which there is evidence of salary discrimination among various groups (i.e., APs, RPs, and DPs), even if wage discrimination may not be found in OLS regression using the conditional mean.

In the following section, I explained the results of quantile regression using APs, RPs, and DPs, respectively. Instead of determining the best-fitted model based on the model fit, the quantile regression was analyzed by using the model selected as the best-fitted model in OLS regression to compare the results of quantile regression to the results of OLS regression. I provided the results of quantile regression for APs, RPs, and DPs, respectively. In addition, I bootstrapped with 200 replications to secure the robustness of standard errors, since the data on DPs were collected from a small sample size (N=293) due to the short history of MLS (Petscher & Logan, 2014).

Quantile regression results of all players. Similarly to OLS regression, the first quantile regression model included all MLS players (N=3,886) in the sample to determine whether there is any invisible market preference for players' origin of birth at any particular salary distribution. I interpreted the quantile regression results of the all players model using SALARY and UN variables because Model 1 in OLS regression (which used SALARY and UN variables) was found to be the best-fitted model. The quantile regression result for APs was presented in Table 4.15.

The player's origin of birth variable showed evidence of salary discrimination among all players at all quantiles. Unlike in OLS regression in which players from South America, Central America, Western Europe, Eastern Europe, Northern Europe, Southern Europe, and Africa were paid higher than the North American players, the

extent to which a player's origin of birth affected his salary varied across the wage distribution. The result demonstrated that, except the non-significance of Western Europe players in the lowest salary distribution, players from South America, Central America, Western Europe, and Southern Europe experienced market preference in wages over North American players at all quantiles.

Notably, it was found that players from Eastern Europe, Northern Europe, Africa, and the Caribbean were paid more in the median and upper quantiles. At the 0.90 quantile, for example, players from South America ($\beta_{0.90}$=0.621, $p<0.01$), Central America ($\beta_{0.90}$=0.504, $p<0.01$), Western Europe ($\beta_{0.90}$=0.361, $p<0.01$), Eastern Europe ($\beta_{0.90}$=0.526, $p<0.05$), Northern Europe ($\beta_{0.90}$=0.243, $p<0.05$), Southern Europe ($\beta_{0.90}$=0.816, $p<0.01$), Africa ($\beta_{0.90}$=0.250, $p<0.01$), and the Caribbean ($\beta_{0.90}$=0.144, $p<0.05$) were all paid a premium of 86.1%, 65.5%, 43.5%, 69.2%, 27.5%, 126.1%, 28.4%, and 15.5% over North American players, respectively. The premium for the players from Asia and Oceania, however, was not significantly different from zero.

It was also apparent that there was stronger evidence of wage discrimination in the upper quantiles (i.e., 0.75 and 0.90) than in the middle (i.e., 0.50) and lower quantiles (i.e., 0.10 and 0.25), considering that eight out of ten groups were statistically significant at the 0.90 quantile, while only three out of ten groups were statistically significant at the 0.10 quantile. In addition, the magnitude of pay discrimination against player's origin of birth became larger from the 0.10 to 0.90 quantiles, indicating that origin of birth played a far more significant role in the upper percentiles. Therefore, H1 was accepted.

As for the other variables, there was no significant difference between the results of OLS regression and the quantile regression. Similarly as in OLS regression,

it was found that DPS, ALLSTAR, STARTS, SUBS, GLS, EXP, POS, and FOOT were statistically significant, supporting H2, H4, H7 $H8_a$, $H9_a$, $H9_b$, and H10. However, AGE was negative and significant ($\beta_{0.50}$= -0.010, $p<0.05$) only at the 0.50 percentile, showing little evidence to support $H5_a$. In addition, $H8_b$ was not supported due to its non-significance at all quantiles.

Table 4.15

Quantile Regression Results of All Players

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.174*** (0.038)	0.194*** (0.036)	0.379*** (0.045)	0.534*** (0.048)	0.621*** (0.057)
UN (CENTRAL AMERICA)	0.169** (0.066)	0.158*** (0.055)	0.406*** (0.063)	0.451*** (0.045)	0.504*** (0.088)
UN (WESTERN EUROPE)	0.122 (0.092)	0.222** (0.094)	0.440*** (0.058)	0.421*** (0.059)	0.361*** (0.087)
UN (EASTERN EUROPE)	-0.212 (0.262)	0.073 (0.202)	0.285 (0.266)	0.645*** (0.158)	0.526** (0.204)
UN (NORTHERN EUROPE)	0.023 (0.062)	0.042 (0.044)	0.084** (0.045)	0.158** (0.065)	0.243** (0.093)
UN (SOUTHERN EUROPE)	0.279*** (0.106)	0.318*** (0.114)	0.576*** (0.119)	0.649*** (0.132)	0.816*** (0.193)
UN (AFRICA)	0.020 (0.042)	0.078* (0.042)	0.102** (0.044)	0.217*** (0.052)	0.250*** (0.063)
UN (ASIA)	0.061 (0.130)	0.034 (0.099)	0.069 (0.075)	-0.046 (0.196)	0.473 (0.445)
UN (CARIBBEAN)	0.022 (0.060)	-0.010 (0.044)	0.052 (0.045)	0.129** (0.058)	0.144** (0.063)
UN (OCEANIA)	0.091 (0.127)	0.017 (0.096)	-0.040 (0.097)	-0.074 (0.291)	0.779 (0.557)
FOOT (LEFT)	-0.030 (0.054)	-0.017 (0.041)	-0.043 (0.048)	-0.147** (0.059)	-0.069 (0.083)
FOOT (RIGHT)	-0.030 (0.054)	0.031 (0.037)	0.055 (0.048)	0.017 (0.056)	0.082 (0.080)
FOOT (NOT DEFINED)	-0.167** (0.069)	-0.087* (0.050)	-0.111** (0.055)	-0.222*** (0.060)	-0.172* (0.100)
POS (D-M)	0.092 (0.065)	0.012 (0.040)	0.035 (0.049)	0.030 (0.054)	0.025 (0.080)
POS (F)	0.098** (0.045)	0.098*** (0.035)	0.129*** (0.036)	0.202*** (0.040)	0.210*** (0.057)
POS (F-M)	0.137 (0.105)	0.079 (0.084)	0.014 (0.058)	0.074 (0.094)	0.197 (0.174)
POS (M)	0.073** (0.034)	0.075*** (0.023)	0.050** (0.025)	0.089*** (0.031)	0.103** (0.041)
POS (M-D)	-0.061 (0.160)	0.026 (0.081)	-0.058 (0.063)	0.009 (0.077)	-0.001 (0.102)
POS (M-F)	0.096 (0.068)	0.142*** (0.046)	0.153*** (0.055)	0.230*** (0.057)	0.244*** (0.081)
EXP	0.060*** (0.007)	0.080*** (0.005)	0.104*** (0.006)	0.107*** (0.007)	0.114*** (0.009)
AGE	0.005 (0.006)	-0.002 (0.005)	-0.010** (0.005)	-0.004 (0.005)	-0.010 (0.008)

Table 4.15, continued

Quantile Regression Results of All Players

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
HEIGHT	0.005**	0.002	0.002	0.005**	0.001***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.019***	0.020***	0.015***	0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
SUBS	-0.010***	-0.012***	-0.015***	-0.019***	-0.022***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
GLS	0.025***	0.028***	0.032***	0.029***	0.032***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
AST	0.014*	0.006	0.005	0.007	0.013
	(0.007)	(0.007)	(0.006)	(0.007)	(0.010)
DPS	0.745***	0.905***	1.045***	1.075***	1.157***
	(0.095)	(0.081)	(0.061)	(0.063)	(0.136)
ALLSTAR	0.353***	0.381***	0.451***	0.514***	0.393***
	(0.073)	(0.074)	(0.045)	(0.049)	(0.088)
CONSTANT	-150.5***	-128.6***	-125.9***	-124.5***	-133.6***
	(8.566)	(6.100)	(5.749)	(6.276)	(10.283)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	3,886	3,886	3,886	3,886	3,886

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Quantile regression results of regular players. The second quantile regression model included regular MLS players (N=3,596) in the sample. This model was designed to investigate whether there is pay discrimination among regular players at certain salary distribution. Since the best-fitted model was Model 1 in OLS regression, I interpreted the quantile regression results of RPs using the SALARY and UN variables. The quantile regression result for RPs was shown in Table 4.16.

The player's origin of birth variable was statistically significant in the regular players model. In OLS regression, it was found that the RPs from North America were discriminated against compared to the comparable RPs from South America, Central America, Western Europe, Eastern Europe, Northern Europe, Southern Europe, and Africa. The quantile regression, however, provided more detailed information on

discrimination in different quantiles. Players from South America and Central America, for example, were paid more than North American players at all quantiles while players from Western Europe and Southern Europe enjoyed a salary premium over North American players for the 0.25, 0.50, 0.75, and 0.90 quantiles. In addition, the correlation coefficient mostly increased from 0.10 to 0.90, implying that the manifestation of discrimination was more evident in the upper quantiles. In other words, RPs' salaries were more likely to be determined by the player's origin of birth as they earn more money in MLS.

Eastern Europe and the Caribbean were positive and significant for the 0.75 and 0.90 quantiles while Africa was positive and significant for the 0.50, 0.75, and 0.90 quantiles. Players from Eastern Europe ($\beta_{0.90}$=0.655, p<0.01), the Caribbean ($\beta_{0.90}$=0.130, p<0.05), and Africa ($\beta_{0.90}$=0.260, p<0.01), for example, experienced salary premiums of 92.5%, 13.9%, and 29.7% at the 0.90 quantile. At all quantiles, however, there was no difference between the salaries of North American RPs and Asian and Oceanian RPs.

As for the other variables, the results were very similar to those of OLS regression. The statistical significance of POS, EXP, HEIGHT, STARTS, SUBS, GLS, and ALLSTAR supported the acceptance of H4, H7, $H8_a$, $H9_a$, $H9_b$, and H10. Regarding the players' footedness (FOOT) variable, it was found that both-footed players were only paid more than the players with no record of the preferred foot, but not, as found in OLS regression, the left-footed players. The AGE and AST were not significant at all quantiles; therefore, $H5_a$ and $H8_b$ were not accepted.

Table 4.16

Quantile Regression Results of Regular Players

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.193*** (0.041)	0.229*** (0.039)	0.438*** (0.042)	0.604*** (0.054)	0.641*** (0.052)
UN (CENTRAL AMERICA)	0.156** (0.067)	0.183*** (0.054)	0.417*** (0.063)	0.433*** (0.048)	0.440*** (0.083)
UN (WESTERN EUROPE)	0.060 (0.104)	0.225*** (0.079)	0.393*** (0.073)	0.441*** (0.067)	0.415*** (0.092)
UN (EASTERN EUROPE)	-0.204 (0.241)	0.073 (0.211)	0.354 (0.282)	0.672*** (0.192)	0.655*** (0.238)
UN (NORTHERN EUROPE)	0.012 (0.059)	0.047 (0.052)	0.081* (0.048)	0.179** (0.079)	0.275*** (0.084)
UN (SOUTHERN EUROPE)	0.163 (0.106)	0.312*** (0.118)	0.602*** (0.123)	0.688*** (0.129)	0.920*** (0.230)
UN (AFRICA)	0.026 (0.044)	0.057 (0.041)	0.101*** (0.040)	0.227*** (0.048)	0.260*** (0.075)
UN (ASIA)	-0.046 (0.139)	-0.013 (0.104)	0.037 (0.083)	-0.094 (0.231)	0.518 (0.547)
UN (CARIBBEAN)	0.004 (0.049)	-0.004 (0.038)	0.057 (0.045)	0.141** (0.058)	0.130** (0.062)
UN (OCEANIA)	-0.072 (0.112)	0.027 (0.096)	-0.023 (0.074)	-0.242 (0.113)	-0.260 (0.533)
FOOT (LEFT)	-0.076* (0.043)	-0.046 (0.046)	-0.055 (0.047)	-0.102 (0.066)	-0.099 (0.078)
FOOT (RIGHT)	-0.065 (0.040)	0.014 (0.043)	0.052 (0.046)	0.048 (0.058)	0.010 (0.076)
FOOT (NOT DEFINED)	-0.194*** (0.066)	-0.112** (0.054)	-0.117** (0.053)	-0.196*** (0.069)	-0.235*** (0.089)
POS (D-M)	0.077 (0.071)	0.015 (0.046)	0.012 (0.049)	0.005 (0.057)	0.029 (0.085)
POS (F)	0.097** (0.039)	0.089** (0.033)	0.108*** (0.034)	0.155*** (0.042)	0.183*** (0.059)
POS (F-M)	0.111 (0.145)	0.026 (0.084)	0.035 (0.068)	0.063 (0.129)	0.137 (0.163)
POS (M)	0.079** (0.030)	0.071*** (0.024)	0.044* (0.022)	0.060* (0.033)	0.101** (0.043)
POS (M-D)	-0.093 (0.137)	0.011 (0.088)	-0.060 (0.059)	-0.053 (0.092)	-0.003 (0.119)
POS (M-F)	0.096 (0.068)	0.104** (0.041)	0.156** (0.063)	0.256*** (0.064)	0.268*** (0.091)
EXP	0.054*** (0.007)	0.074*** (0.006)	0.092*** (0.006)	0.098*** (0.006)	0.103*** (0.010)
AGE	0.008 (0.006)	0.000 (0.005)	-0.005 (0.005)	-0.002 (0.005)	-0.007 (0.008)

Table 4.16, continued

Quantile Regression Results of Regular Players

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
HEIGHT	0.003	0.001	0.001	0.005**	0.009***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.019***	0.020***	0.017***	0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
SUBS	-0.012***	-0.013***	-0.014***	-0.018***	-0.020***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
GLS	0.028***	0.032***	0.037***	0.034***	0.037***
	(0.007)	(0.005)	(0.005)	(0.006)	(0.009)
AST	0.015*	0.007	0.003	0.011	0.013
	(0.009)	(0.007)	(0.006)	(0.007)	(0.010)
ALLSTAR	0.302***	0.413***	0.427***	0.448***	0.375***
	(0.073)	(0.084)	(0.053)	(0.052)	(0.086)
CONSTANT	-152.3***	-129.6***	-128.3***	-122.2***	132.9***
	(9.042)	(5.631)	(6.887)	(7.225)	(10.007)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	3,596	3,596	3,596	3,596	3,596

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Quantile regression results of designated players. The third quantile regression model included designated MLS players (N=290) in order to examine the effect of players' origin of birth across the distribution of designated players' salaries. As the best-fitted model was Model 4 in OLS regression for DPs, I interpreted the quantile regression results of designated players using COMPENSATION and FIFA variables. I also, however, considered the quantile regression result of DPs using the COMPENSATION and UN variables to investigate whether the manifestation of salary discrimination may work differently when using the UN to group players' origin of birth. The quantile regression results of DPs using the FIFA division and UN Statistics Division were reported in Table 4.17 and 4.18, respectively.

Using the FIFA division (Table 4.17), the AFC was positive and significant for the 0.10 quantile while the CONMEBOL was negative and significant for the 0.10

and 0.25 quantiles, supporting H3. Specifically, players from AFC ($\beta_{0.10}$=1.256, $p<0.05$) were paid a salary premium of 251.1% for the 0.10 quantile while players from CNONMEBOL were paid less by 40.2% ($\beta_{0.10}$= -0.514, $p<0.05$) at the 0.10 quantile and 33.4% ($\beta_{0.10}$= -0.406, $p<0.05$) at the 0.25 quantile. Using the UN Statistics Division (Table 4.18), it was found that players from South America, Central America, and the Caribbean were discriminated against in the lower quantiles while the players from Eastern Europe were paid more in the upper quantiles. In addition, Asian players experienced a salary premium over North American players at all quantiles, supporting H3.

Only one human capital factor was found to be significant in the designated players model. EXP was positive and significant at the 0.01 level at all quantiles. The result showed that DPs experienced a salary increase by 8.4%-10.4% with additional experience, supporting H4. FOOT, AGE, and HEIGHT, however, were not associated with DPs' salaries, and $H5_a$, H6, and H7 were not accepted. It was also found that the POS variable was positive and significant for the 0.25 quantile in both the FIFA and UN models. For example, a midfielder-forward was paid about 124.6% ($\beta_{0.25}$=0.809, $p<0.05$) more than a designated defender in the FIFA model and 109.8% ($\beta_{0.25}$=0.741, $p<0.05$) more than a designated defender in the UN model, supporting H10. Both STARTS and SUBS were negative and significant; thus, $H9_a$ was not accepted and $H9_b$ was accepted. Performance statistics (i.e., GLS and AST) were not associated with DPs' salaries, not supporting $H8_a$ and $H8_b$. Lastly, the ALLSTAR variable was positive and significant at the 0.01 level for the 0.25, 0.50, and 0.75 quantiles.

Table 4.17

Quantile Regression Results of Designated Players (FIFA)

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
FIFA (AFC)	1.256**	1.059*	0.734	0.436	-0.076
	(0.555)	(0.581)	(0.523)	(0.533)	(0.517)
FIFA (CAF)	0.321	0.462*	0.261	0.053	-0.093
	(0.316)	(0.250)	(0.249)	(0.338)	(0.423)
FIFA	-0.514**	-0.406**	-0.182	-0.104	-0.215
(CONMEBOL)	(0.252)	(0.188)	(0.160)	(0.222)	(0.253)
FIFA (UEFA)	-0.208	-0.153	0.024	0.078	0.018
	(0.217)	(0.173)	(0.193)	(0.179)	(0.230)
FOOT (LEFT)	-0.048	0.188	0.142	-0.181	0.038
	(0.260)	(0.239)	(0.257)	(0.332)	(0.353)
FOOT (RIGHT)	0.021	0.109	-0.069	-0.326	-0.146
	(0.222)	(0.208)	(0.228)	(0.321)	(0.298)
FOOT (NOT	0.267	0.460	0.318	0.586	0.423
DEFINED)	(0.442)	(0.494)	(0.639)	(0.884)	(0.857)
POS (D-M)	0.341	0.157	-0.104	-0.788	-1.337*
	(0.376)	(0.322)	(0.401)	(0.561)	(0.703)
POS (F)	0.230	0.293	0.298	0.387	0.035
	(0.356)	(0.306)	(0.236)	(0.335)	(0.452)
POS (F-M)	0.041	0.094	0.222	0.137	0.023
	(0.455)	(0.3650	(0.385)	(0.496)	(0.692)
POS (M)	0.374	0.294	0.191	0.371	-0.029
	(0.312)	(0.256)	(0.207)	(0.321)	(0.428)
POS (M-D)	0.222	0.027	-0.233	-0.806	-1.365*
	(0.323)	(0.251)	(0.377)	(0.541)	(0.712)
POS (M-F)	0.564	0.809**	0.455*	0.424	-0.005
	(0.364)	(0.312)	(0.271)	(0.388)	(0.502)
EXP	0.095***	0.086***	0.091***	0.081**	0.099***
	(0.030)	(0.024)	(0.023)	(0.030)	(0.036)
AGE	0.031	0.026	0.016	0.018	0.008
	(0.030)	(0.026)	(0.025)	(0.027)	(0.028)
HEIGHT	-0.012	-0.010	-0.001	0.017	0.007
	(0.010)	(0.009)	(0.011)	(0.010)	(0.011)
STARTS	-0.021**	-0.013	-0.009	-0.025***	-0.015
	(0.010)	(0.009)	(0.009)	(0.008)	(0.011)
SUBS	-0.076***	-0.061***	-0.049***	-0.055***	-0.032
	(0.028)	(0.023)	(0.019)	(0.017)	(0.023)
GLS	0.020	0.017	0.006	0.013	0.010
	(0.013)	(0.015)	(0.012)	(0.015)	(0.015)
AST	-0.002	-0.019	-0.002	0.045*	0.017
	(0.023)	(0.022)	(0.023)	(0.024)	(0.022)
ALLSTAR	0.179	0.337**	0.401***	0.351***	0.129
	(0.138)	(0.131)	(0.133)	(0.132)	(0.135)

Notes: Dependent variable is natural log of guaranteed compensation.

Table 4.17, continued

Quantile Regression Results of Designated Players (FIFA)

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
CONSTANT	-243.7*** (80.588)	-205.0*** (65.313)	-169.1*** (57.171)	-198.7*** (61.672)	-52.3 (84.228)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	290	290	290	290	290

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table 4.18

Quantile Regression Results of Designated Players (UN)

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	-0.671*** (0.246)	-0.548** (0.243)	-0.364 (0.290)	0.146 (0.288)	0.085 (0.322)
UN (CENTRAL AMERICA)	-0.488** (0.246)	-0.274 (0.221)	-0.124 (0.229)	0.378 (0.240)	0.278 (0.300)
UN (WESTERN EUROPE)	-0.499 (0.403)	-0.596 (0.484)	0.093 (0.417)	0.445 (0.372)	0.202 (0.418)
UN (EASTERN EUROPE)	-0.223 (0.621)	0.417 (0.587)	0.489 (0.630)	1.590** (0.701)	1.583** (0.720)
UN (NORTHERN EUROPE)	-0.428* (0.243)	-0.213 (0.227)	-0.332 (0.202)	-0.011 (0.265)	0.174 (0.312)
UN (SOUTHERN EUROPE)	-0.312 (0.315)	-0.007 (0.286)	-0.057 (0.267)	-0.053 (0.301)	-0.159 (0.298)
UN (AFRICA)	0.160 (0.350)	0.372 (0.301)	0.145 (0.318)	0.082 (0.410)	0.279 (0.435)
UN (ASIA)	1.281*** (0.415)	0.837** (0.392)	0.956*** (0.353)	1.166*** (0.384)	0.970** (0.501)
UN (CARIBBEAN)	-1.975** (0.980)	-0.805 (0.825)	-0.482 (0.384)	-0.451 (0.423)	-0.650 (0.635)
UN (OCEANIA)	1.185** (0.521)	0.941* (0.536)	0.636 (0.567)	0.839* (0.512)	0.144 (0.507)
FOOT (LEFT)	-0.016 (0.286)	0.391 (0.293)	0.139 (0.252)	-0.393 (0.283)	-0.257 (0.298)
FOOT (RIGHT)	0.020 (0.221)	0.175 (0.230)	-0.056 (0.233)	-0.327 (0.242)	-0.243 (0.244)
FOOT (NOT DEFINED)	0.434 (0.497)	0.549 (0.423)	0.289 (0.658)	-0.105 (0.679)	0.411 (0.695)
POS (D-M)	0.018 (0.345)	-0.063 (0.359)	-0.337 (0.424)	-0.648 (0.435)	-0.658 (0.543)
POS (F)	0.302 (0.347)	0.241 (0.290)	0.206 (0.290)	-0.051 (0.355)	0.115 (0.456)
POS (F-M)	0.007 (0.445)	0.213 (0.401)	0.231 (0.395)	-0.138 (0.505)	-0.182 (0.527)
POS (M)	0.304 (0.326)	0.300 (0.259)	0.252 (0.242)	-0.054 (0.333)	0.107 (0.433)
POS (M-D)	-0.094 (0.286)	-0.176 (0.340)	-0.377 (0.405)	-0.711 (0.463)	-0.759 (0.523)
POS (M-F)	0.470 (0.372)	0.741** (0.332)	0.438 (0.299)	-0.159 (0.394)	-0.107 (0.467)
EXP	0.075** (0.031)	0.060* (0.030)	0.082*** (0.031)	0.063* (0.029)	0.112*** (0.037)
AGE	0.046* (0.026)	0.045 (0.029)	0.032 (0.027)	0.044* (0.023)	-0.015 (0.027)

Table 4.18, continued

Quantile Regression Results of Designated Players (UN)

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
HEIGHT	-0.008	-0.004	-0.002	0.017	0.006
	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)
STARTS	-0.023**	-0.015*	-0.011	-0.015*	-0.021**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
SUBS	-0.078***	-0.058**	-0.038*	-0.046**	-0.053**
	(0.023)	(0.023)	(0.020)	(0.020)	(0.022)
GLS	0.024*	0.017	0.011	0.013	0.016
	(0.014)	(0.014)	(0.012)	(0.013)	(0.015)
AST	-0.005	-0.009	0.004	0.025	0.031
	(0.020)	(0.021)	(0.024)	(0.024)	(0.024)
ALLSTAR	0.166	0.321**	0.382***	0.227*	0.204
	(0.141)	(0.144)	(0.122)	(0.131)	(0.137)
CONSTANT	-259.8***	-183.3***	-154.8**	-148.5**	-72.6
	(68.966)	(62.188)	(60.737)	(64.789)	(69.347)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	290	290	290	290	290

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Quantile regression results including goalkeepers. In OLS regression, I compared two models of including and excluding goalkeepers and explained the differences between the results. Similarly, I explained the models including goalkeepers, and compared them to the models excluding goalkeepers in the quantile regression. Similarly to the previous quantile regression results excluding goalkeepers, the following section demonstrated the quantile regression results including goalkeepers.

Regarding the quantile regression results of all players including goalkeepers (N=4,280) in Table A-7, only two of the findings were significantly different compared to the quantile regression results of APs excluding goalkeepers. First, unlike the quantile regression results of APs excluding goalkeepers in which players from South America, Central America, Western Europe, Eastern Europe, Northern

Europe, Southern Europe, Africa, and the Caribbean were paid more than North American players at different quantiles, players from Oceania were paid 5.4% ($\beta_{0.90}$= -0.055, p<0.01) more than comparable players from North America at the 0.50 quantile. Second, defender-midfielders were positive and significant at the 0.01 level for the 0.25 and 0.50 quantiles, while goalkeepers were negative and significant at the 0.05 level for the 0.90 quantile.

When it comes to the quantile regression results of regular players including goalkeepers (N=3,987) in Table A-8, there was no significant difference other than the significance of players' footedness for the 0.75 quantile. It was found that left-footed players were paid 11.4% ($\beta_{0.75}$= -0.121, p<0.05) less than both-footed players. As for the quantile regression results of designated players including goalkeepers (N=293) in Table A-9, CONMEBOL was statistically significant at the 0.05 level for the 0.10 and 0.25 quantiles. The players from CONMEBOL were paid 38.8% ($\beta_{0.10}$= -0.491, p<0.05) and 33.3% ($\beta_{0.25}$= -0.405, p<0.05) less than comparable North American players. In addition, MLS midfielder-defenders were paid 75.6% ($\beta_{0.90}$= -1.410, p<0.05) less than designated defenders.

Quantile regression results using both AGE and AGE^2. Due to the high correlation to the AGE variable, the AGE^2 variable was excluded from the base model (both OLS and quantile regression). I therefore estimated the quantile regression results including both age and squared term of age variables in the extended model, and compared them to the base model, which only included the age variable. Most of the results were very similar to the base model; the following section thus explains the differences between the base model and the extended model. As for the quantile regression results of APs using both AGE and AGE^2 (N=3,886) in Table A-10, it was found that players' salaries were associated with both AGE and AGE^2. In the base

model, AGE was not significant at all quantiles; both AGE and AGE^2, however, were statistically significant at the 0.01 level at all quantiles, supporting both $H5_a$ and $H5_b$ in the extended model. The evidence of salary discrimination for players from the Caribbean was also found only for the 0.75 quantile, unlike the base model in which players from the Caribbean were discriminated against at the 0.75 and 0.90 quantiles.

Regarding the quantile regression results of regular players using both AGE and AGE^2 (N=3,886) in Table A-11, both AGE and AGE^2 were statistically significant at either the 0.01 or 0.05 level, again supporting $H5_a$ and $H5_b$. Moreover, both-footed players were paid more than left-footed players for the 0.50 and 0.75 quantiles and players with no record of the preferred foot at all quantiles other than the 0.25 quantile. For the quantile regression results of DPs using both AGE and AGE^2 (N=290) in Table A-12, there were several differences with the results of the base model. First, unlike the base model in which the AFC and CONMEBOL were significant, in the extended model, AFC was positive and significant at the 0.05 level for the 0.10 and 0.25 quantile while CAF was also positive and significant for the 0.25 quantile. In other words, players from AFC enjoyed a premium of 322.1% ($\beta_{0.10}$=1.440, $p<0.05$) and 278.9% ($\beta_{0.25}$=1.332, $p<0.05$) for the 0.10 and 0.25 quantiles. Moreover, at the 0.25 quantile, the players from CAF were paid 102.8% ($\beta_{0.25}$=0.707, $p<0.01$) more than the players from CONCACAF. Second, the AGE variable was significant at the 0.05 level for the 0.10 and 0.25 quantiles and the AGE^2 variable was significant at the 0.10 quantile, supporting both $H5_a$ and $H5_b$.

Summary

In this chapter, I discussed the descriptive statistics, assumption tests, and statistical results of possible salary discrimination among all players, regular players, and designated players in MLS. This study used both OLS and quantile regression to

investigate whether wage discrimination is of importance to designated players. The first regression, OLS regression, found through base and extended model that, in most cases, North American players were paid less than comparable players from other regions, supporting salary discrimination based on players' demographic characteristics (i.e., origin of birth). The second regression was the quantile regression, which also showed evidence of possible invisible market preference for players' origin of birth under certain distributions. The results of the hypotheses were aggregated and presented in Table 4.19. In the following chapter, I will discuss the findings of the results and their contributions and implications, along with limitations of the study and directions for future research.

Table 4.19

Results of Hypotheses Tests

	OLS			QR		
Model	APs	RPs	DPs	APs	RPs	DPs
Hypothesis 1	O			O		
Hypothesis 2	O			O		
Hypothesis 3			O			O
Hypothesis 4	O	O	O	O	O	O
Hypothesis 5_a	X (O)	X (O)	X (O)	X (O)	X (O)	X (O)
Hypothesis 5_b	(O)	(O)	(X)	(O)	(O)	(O)
Hypothesis 6	O	O	X	O	O	X
Hypothesis 7	O	O	X	O	O	X
Hypothesis 8_a	O	O	X	O	O	X
Hypothesis 8_b	X	X	X	X	X	X
Hypothesis 9_a	O	O	X	O	O	X
Hypothesis 9_b	O	O	O	O	O	O
Hypothesis 10	O	O	O	O	O	O

Notes: QR represents the quantile regression. O=accepted, X=rejected. The letters in the parentheses are the results of AGE^2 models.

CHAPTER V

DISCUSSION

Introduction

The purpose of this study is to investigate the existence of salary discrimination, particularly whether salary discrimination exists for superstars in MLS. Using MLS players' salary data for the 2007-2019 seasons, the results from OLS and quantile regression revealed the possible evidence of pay discrimination among all players, regular players, and even designated players. In this chapter, I will discuss the findings that are relevant to the research questions and hypotheses. Following the discussion of the findings, I address the contributions, implications, limitations, and suggestions of this study. Lastly, I provide directions for future research and the conclusion of this dissertation.

Discussion of Findings

In this section, I discuss the results of OLS regression of equations (1), (2), and (3) and the quantile regression of equations (4), (5), and (6). The results of this dissertation showed that various factors (including players' origin of birth, designated player status, and human capital factors, as well as other factors such as league appearances and individual characteristics) were either positively or negatively associated with MLS players' salaries. In the following sections, I discussed in detail the issue of pay discrimination and various factors affecting players' salaries.

Discrimination

Regular players model (H1). I was interested in determining whether there is any evidence of salary discrimination in MLS by players' origin of birth. In particular, this part analyzed whether discrimination manifested in the form of salaries among regular players and all players. The issue of wage discrimination among designated players is separately discussed in section addressing the DPs model (H3). Consistent with previous literature showing that players in the professional soccer labor markets are either favored or discriminated against based on their origin of birth (e.g., Bryson et al., 2013; Frick, 2011), hypothesis 1 posited that there is salary discrimination by players' origin of birth in the MLS labor market. The results from both the APs model and RPs model demonstrated that players from South America, Central America, Western Europe, Eastern Europe, Northern Europe, Southern Europe, and Africa experienced market preference in wages over players from North America.

The salary premium for players from Europe and South America is unsurprising in the context of European Soccer Leagues and MLS. This is because both European and South American players are likely to positively influence teams' revenue (Kalter, 1999) while attracting more fans to the stadium (Wilson & Ying, 2003); they are therefore favored in the soccer labor markets due to their higher MRP (Frick, 2011). Pedace (2008), for example, found that South American players experienced a wage premium in the EPL. European players, meanwhile, are favored in MLS, because soccer's longstanding history in Europe means they tend to outperform players from other regions (Prockl & Frick, 2018b). With this knowledge, a vast range of literature has found evidence of salary premiums for European (Celik & Ince-Yenilmez, 2017; Kuethe & Motamed, 2010; Medcalfe & Smith, 2018; Prockl

& Frick, 2018b) and South American players (Kerr, 2019; Kuethe & Motamed, 2010; Prockl & Frick, 2018b) in MLS. In line with Becker's (1971) discrimination theory, MLS teams sign players from Europe and South America with a salary premium because of their higher MRP.

One interesting finding is that players from Africa and Central America were also favored in MLS over North American players. Contrary to previous findings that European and South American players earn higher salaries than comparable North American players, a consensus has not yet been reached to the existence of a possible salary premium for (or discrimination against) players from other regions (e.g., Africa, Asia, Central America, and Oceania). Kuethe and Motamed (2010), for example, found that North American players are favored in MLS compared to African players, while Prockl and Frick (2018b) showed that players from Africa and Central America earn more money than North American players. The finding of salary premiums for players from Africa and Central America in this dissertation could be explained by a recent finding of Medcalfe and Smith (2018). Examining the 2007-2014 MLS seasons, they found that one additional player from CONCACAF or CAF increased home attendance by 1.5% and 2.5%, respectively. They suggested that MLS teams may consider having more players from Central America and Africa on their rosters in order to maximize the gate revenue because of their ability to attract spectators to the stadium. Using the same reasoning that European and South American players are favored because of their higher MRP, it is possible to conclude that players from Africa and Central America may be favored in MLS because they contribute to attendance increase.

Designated players model (H3). The main research interest of this dissertation is to understand the degree to which superstars are also discriminated

against in the MLS labor market based on their origin of birth. Despite superstars' potential contribution to promoting the success of the league, very little research has been conducted to investigate whether superstars encounter the issue of discrimination in MLS. Accordingly, hypothesis 3 proposed that superstars (i.e., designated players) are discriminated against based on their origin of birth.

Using the FIFA division, the OLS regression results revealed that South American players are discriminated against compared to players from CONCACAF. Similarly, the quantile regression results showed that superstars from CONCACAF are discriminated against compared to superstars from AFC at the bottom 10% of wage distribution, while they experience market preference over South American superstars in the lower salary ranges.

The finding that superstars from South America are discriminated against in MLS is unexpected. This evidence contrasts with the previous literature, which showed that South American players are favored in MLS (Kerr, 2019; Kuethe & Motamed, 2010; Prockl & Frick, 2018b) because they are found to be positively associated with gate attendance and team revenue (Kalter, 1999; Wilson & Ying, 2003). This result may be attributed to the different roles that are expected for RPs and DPs. Unlike regular professional athletes—whose salaries are mostly determined by their performance statistics (Antonietti, 2006; Frick, 2006; Scully, 1974)—superstars' popularity is expected to boost MLS attendance (Bradbury, 2020). Considering that soccer has been less successful in North America because of its short history (Coates et al., 2016), as well as the fact the DP rule was introduced in 2007 to develop MLS teams (Bradbury, 2020), the franchise should consider how superstars could contribute to the team revenue as well as team performance.

One possible explanation of this reverse discrimination is that MLS teams may not, in fact, maximize gate attendance and team revenue with an additional superstar from South America. As described in Table 4.4, designated players from CONMEBOL comprise the largest portion of superstars. This indicates that South American superstars are less scarce than players from other regions in the MLS labor market. Given that consumers (i.e., fans) are more likely to consume a product when the product is less available (Verhallen & Robben, 1994), current MLS teams may not prefer superstars from South America who are in oversupply. As most of the superstars in MLS are South American, they can only bring a marginal financial effect to the franchises; thus, they are no longer favored in the market.

Evidence of this reverse discrimination was also found by Prockl and Frick, (2018b), in the only other study that has examined whether there is salary discrimination among designated players in MLS. They found that North American superstars are favored over superstars from South America, Western Europe, and the Caribbean. Although Prockl and Frick used the UN Statistics Division for their interpretation and this study used the FIFA division, the findings that superstars from South America are discriminated against are very similar. To better compare the results of this dissertation with those of Prockl and Frick, I also employed the quantile regression using the UN Statistics Division and found the possible evidence of wage discrimination against South American superstars. It can therefore be said that salary discount for South American superstars is evident in MLS.

Another interesting finding, according to the results from the quantile regression, is the salary premium for superstars from Asia. Asian superstars were favored at the bottom 10% of wage distribution. It is possible that Asian superstars have the potential to boost MLS attendance. This is because "players make more

money the greater the representation of their race in the local population" (Kahn, 1992, p. 307), and fans prefer to consume players of their own race, ethnicity, or nationality (Kahn, 1992; Kerr, 2019). Ruihley et al. (2017), for example, found that Korean (Asian) fans prefer to watch a game with Korean players. Similarly, Kerr (2019) showed that Hispanic players experience a salary premium in Los Angeles where Hispanics comprise of a large portion of the population. Consistent with the findings of these previous studies, Asian MLS superstars may have been paid higher wages for the possibility of increasing attendance. Similarly to the positive impact of Yao Ming, the Chinese National Basketball Association superstar, on Houston Rockets' attendance and revenue as well as the Chinese basketball market (Yang & Lin, 2012), it can be speculated that MLS teams could bring more fans to the stadium and further open up Asian market by bringing Asian superstars to MLS (Kaiser, 2015). Although the impact of Asian superstars on attendance and TV demand in MLS is thus far unknown, given that 5.6% of Asian composition in the U.S. population (Hoeffel, Rastogi, Kim, & Shahid, 2012), it is reasonable to assume that Asian superstars could positively impact MLS attendance and team revenue.

In addition, this preference can also be explained by the scarcity of Asian superstars in MLS. As presented in Table 4.4, there were only two observations of Asian superstars in the designated players model, consisting of 0.68% of superstars in MLS. The scarcity of Asian players (both RPs and DPs) may be attributed to the fact that 1) MLS has yet to make an effort to hire top talent from the Asian market (Booth, 2019) and 2) the Asian players prefer to play in ESLs over MLS because of their reputation and financial benefits (Duerden, 2016; Prockl & Frick, 2018b). Similar to the speculation that South American superstars are not favored because of their oversupply in the MLS labor market, it is possible that Asian superstars are favored

due to their scarcity. Since the salary premium for Asian superstars may not be conclusive because of the limited observations of Asian designated players in the sample, there is a need for further understanding of whether Asian superstars are favored in MLS because of their ability to attract fans and bring monetary benefits to the teams.

The Superstar Effect (H2).

Hypothesis 2 posited that players with superstar status (i.e., designated player status) earn higher salaries than the regular MLS players. Understanding the superstar effect in MLS is imperative because the league has adopted the DP rule to increase its prosperity (Bradbury, 2020). One common problem in estimating the superstar effect on salary is the arbitrary definition of “superstars” in professional sports leagues. Various measurements—including number of Facebook fans (Prinz et al., 2012), press releases (Treme & Allen, 2011), Google hits (Garcia-Del-Barrio & Pujol, 2007), and All-Star votes (Hausman & Leonard, 1997)—have been used to capture superstars’ popularity in different sports settings. This means that the definition of superstars has not been objective (Jewell, 2017). The DP rule in MLS, however, provides a relatively objective definition of superstars because DPs function as superstars via their talent and popularity in the MLS labor market (Coates et al., 2016; Jewell, 2017) while increasing gate attendance (Jewell, 2017; Parrish, 2013) and ticket sales (Lawson et al., 2008).

Using designated player status as a proxy for superstars in MLS, the results of both OLS and quantile regression showed that superstars experience a significant salary premium over players without DPS. This finding is consistent with the work of Kuethe and Motamed (2010), who found a positive relationship between designated player status and players’ salaries. The superstar effect therefore is supported in MLS.

One interesting finding is the magnitude of the superstar effect. I found that superstar status was the most significant determinant of MLS players' salaries, implying that players should consider becoming designated in order to boost their salaries, though difficult to control. Other factors, of course, also affected players' salaries; however, the effects of those factors were not as significant as that of acquiring DPS. In addition, I found that the superstar effect becomes more important in the upper quantile: the higher the salary distribution, the greater the superstar effect. In other words, the superstar effect was greater in the upper quantiles than in the lower ones. Considering its significance and increasing effect, superstar status appears to be the most important factor in becoming a high-profile player in MLS.

Similarly to the effect of designated player status on players' salaries, the All-Star game experience in the previous season increased players' salaries in the current season. As previously explained, a total of 26 players are awarded roster spots for an annual All-Star game based on votes from the fan, manager, and the league commissioner (Kinkead, 2017). Unlike the DPS, which is awarded by the league based on players' talent and popularity, fans could play a role in determining All-Star players while voting for their favorite players. Therefore, a salary premium for All-Star players is not surprising given that players with All-Star experience are favored by fans (i.e., higher MRP) and attract more fans to the stadium.

Human Capital Factors

Experience (H4). Hypothesis 4 proposed that there is a positive relationship between a player's salary and his experience. The empirical results of both OLS and quantile regression showed that a player's experience was indeed positively associated with both base salary and guaranteed compensation. Player experience was

positive and significant at the 0.01 level at all models, indicating that experience plays a significant role in increasing the salary of RPs as well as the DPs in MLS.

According to HCT, it is expected that more experienced players will contribute more to the team and be more productive than other players due to their accumulation of know-how through their professional soccer career experience (Grant et al., 2013). In addition, managers are likely to pay the experienced players more money since players become recognizable to sports fans with additional years in the league (Stone & Pantuosco, 2008). For this reason, it is intuitive that, with their higher MRP, experienced players who are known to sports fans earn more money.

The findings of this study were consistent with the work of previous MLS literature (e.g., Celik & Ince-Yenilmez, 2017; Kuethe & Motamed, 2010; Prockl & Frick, 2018b; Reilly & Witt, 2007), which found a positive effect of experience on salary. Kuethe and Motamed (2010), for example, showed that the salaries of MLS players increased by 19%-33% with additional years in the league. The results showing a positive relationship between a player’s salary and his experience level are therefore not surprising.

Age ($H5_a$ & $H5_b$). HCT indicates that a player’s compensation level should increase each year due to the seniority effect (Ransom, 1993). Players’ salaries, however, reach the highest point at a certain age and then decrease, because their performance capability (i.e., MPL) also decreases after their peak age of performance. NBA players, for example, reach a maximum level of compensation at 26 years of age (Simmons & Berri, 2011), while RPs in MLS reach a maximum level at 33.6 (Prockl & Frick, 2018b). For this reason, previous literature has inquired into the concavity of age-earning profiles in various sports settings.

In the current study, however, the inclusion of both age and squared term of age caused the problem of multicollinearity, which should be met for the multiple linear regression. Although the problem of multicollinearity is not an issue when using one variable and its squared term (Greene, 2002), I used only the age variable in the base model and both age and squared term of age in the extended model. To better understand the positive effect of age and the negative effect of squared term of age in MLS, hypotheses 5_a and 5_b postulated that, due to the concavity effect, an MLS player's salary is positively (negatively) associated with his age (squared term of age). Interestingly, the results showed that age was not significant in the base model, while both age and the squared term of age were significant in the extended model.

In the base model (in which the age variable was used for the empirical estimation), it was found that a player's age was not associated with his salary. This finding is not consistent with the work of Reilly and Witt (2007) and Celik and Ince-Yenilmez (2017), who included the player's age variable and found a positive effect of age in MLS. Reilly and Witt (2007) found that MLS players' salaries increased by 5.9% during the 2007 season, and Celik and Ince-Yenilmez (2017) found an increase in salary of 5.7% per year over the 2007-2016 seasons. The two studies above did not, however, consider the concavity of age effect on salary and did not include the squared term of age. In studying the concavity of age-earning profiles in the context of MLS, Medcalfe and Smith (2018) and Prockl and Frick (2018b) found that the wage equation with only the age variable may not fully capture whether players' salaries decrease after a certain age. In other words, given that a player's wage increases up to a certain age, it is natural that there is no significant relationship between the age and compensation in MLS. In sum, a player's age did not play a role in explaining compensation using both OLS and quantile regression.

By contrast, the extended model, in which both age and squared term of age were used, found concavity of in MLS—that is, there was a positive relationship between age and compensation, while there was a negative relationship between the squared term of age and compensation. This finding is not surprising given that a player's performance reaches the highest level at a certain age and then decreases after a player's peak age in performance statistics, resulting in a decreased MPL. The existing literature also shows evidence of a positive (negative) effect of age (squared term of age) on MLS players' salaries (Medcalfe & Smith, 2018; Prockl & Frick, 2018b), supporting the assertion that players' salaries increase up to a certain age. Despite Kuethe and Motamed's (2010) argument attributing the convexity of age (negative effect of age and positive effect of squared term of age) in MLS to soccer's newness in North America, it is more logical to believe that MLS functions similarly to other professional soccer leagues.

One interesting finding is that, in the OLS results of the designated players model, age was positive and significant, while the squared term of age was negative but not significant. This indicates that the salaries of MLS superstars increased each year, but this increase did not drop after a certain wage. One possible explanation for this non-significance of the squared term of age for DPs is that—unlike ordinary players, whose salaries are influenced by their performance statistics on the field (Antonietti, 2006; Frick, 2006; Scully, 1974)—there are various factors affecting designated players' salaries, such as their ability to attract fans to the stadium and impact on other teammates on and off the field. Since DPs in MLS have been found to positively increase attendance (Jane, 2016; Jewell, 2017; Parrish, 2013) and team revenue (DeSchriver, 2007; Lawson et al., 2008), their salaries may not decrease after their peak performance age because, from the manager's perspective, they may still

benefit teams with their high MRP. It is therefore logical to assume that for superstars, salaries do not tend to decrease even after a certain age because of their popularity.

Footedness (H6). Hypothesis 6 indicated that an individual player's innate skills or scarce talent (i.e., both-footedness) could play a role in explaining MLS players' compensation. HCT posits that individuals (i.e., players) with skills or scarce talent may contribute more to the organization and increase productivity, which leads to higher compensation because of higher MRP (Tan, 2014). In the sports context, players with both-footedness are more likely to earn higher salaries because of their scarce talent and ability to play in multiple positions upon team's strategic plans (Bryson et al., 2013). For this reason, this study examined the effect of both-footedness on compensation. The results of OLS and quantile regression showed that the deviation in MLS players' salaries can be explained by their innate skills.

The OLS regression found that due to their talent in scarcity, both-footed players enjoyed market preference over players with left-footedness and players with no record of preferred footedness. Among regular players, for example, both-footed players were paid more. This finding is not surprising, given that 1) both-footed players can use both their left and right feet and are thus considered superior to left-footed players, and 2) players with no record of preferred footedness are often the players with less career experience in the league who are generally less popular to sports fans. The premium for being ambipedal was previously described by Frick and Simmons (2007) and Bryson et al. (2013) in the context of ESLs and Prockl and Frick (2018b) in MLS, indicating an economic benefit of both-footedness across soccer leagues.

The OLS regression also showed that footedness affected regular players' salaries, but not designated players' salaries. As presented in Table 4.6, more than

half of the DPs were right-footed: there were 205 right-footed players (69.97%), 36 both-footed players (12.29%), 24 left-footed players (15.7%), and 6 players with no record (2.5%). Unlike the RPs, who with their both-footedness can contribute significantly more to the teams, there are many ways that superstars can contribute to the team other than their ability to use both feet. The quantile regression showed a similar result to OLS regression in that both-footed players were paid more than the left-footed players and players with no record among RPs, but not among the DPs. Designated players' footedness therefore hardly affects compensation as they are capable of affecting game outcomes with their higher productivity on the field.

Height (H7). Hypothesis 7 posited that MLS players' physical attributes, such as height, could positively affect compensation. This is because taller players are more likely to contribute more to sports clubs in that taller forwards can score header goals and taller defenders can effectively win the ball in the air against opposing players. For these reasons, physical attributes are considered a form of human capital (Schultz, 2002). However, previous studies have not always found players' height variable to be a significant determinant of players' salaries in professional soccer markets (e.g., Prockl & Frick, 2018b; Weimar & Wicker, 2017).

This study's OLS regression results revealed that height was positively associated with RPs' salaries. This finding is not consistent with that of Prockl and Frick (2018b), who recently showed no significant relationship between height and compensation in MLS: Using both OLS and quantile regression, they found that height did not play a role in explaining regular MLS players' salaries during the 2006-2016 seasons. A possible reason for this difference is the use of different performance statistics and league appearance variables. In addition, the OLS regression result in Prockl and Frick's study was not reliable; according to BIC results, the fixed effect

model was superior to the OLS, leaving room for further investigation into the effect of height on compensation in MLS. Consistent with the findings of Bryson et al. (2013), who argued for a positive effect of height on players' salaries because of their heading ability, there is evidence to propose that height is positively associated with MLS players. I also found that DPs' salaries were not affected by physical attributes (i.e., height). There are several short MLS players, for example, whose salaries are in the highest salary distribution. Considering that Moralez Maxi, who is 160cm tall, was paid $2,000,000 in 2019 and Martinez Josef, who is 170cm tall, was paid $3,000,000, DPs do not necessarily need to be tall as far as they are talented and popular.

Other Variables

Goals and assists ($H8_a$ & $H8_b$). The relationship between a player's performance statistics (e.g., the number of goals and assisted scored) and compensation has been widely studied in sports economics, since individual performance naturally influences a player's salary because of his contribution to the team (Scully, 1974). For this reason, hypotheses 8_a and 8_b proposed that a players' salary is positively associated with a player's performance factors. The results showed that the number of goals scored played a role in explaining MLS players' salaries while the number of assists scored was not associated with salary.

I found that the number of goals scored was an important factor in determining regular MLS players' salaries. According to the MRP theory, a player is expected to earn compensation based on individual's contribution to an organization (Scott et al., 1985). This finding is not surprising given that players who positively influenced the game outcome with a higher number of goals scored were paid a higher level of compensation (Celik & Ince-Yenilmez, 2017; Frick, 2011).

The number of goals scored did not, however, impact the salaries of designated players in MLS, indicating no significant relationship between goals and salary. Although DPs scored more goals on average (6.71 goals) than the RPs (1.59 goals) in the sample, there was no evidence that the number of goals scored affected salaries among DPs. Unlike regular MLS players, whose salaries are closely related to their contribution to the outcome of a game, designated players can contribute to the teams in various ways, not only the number of goals scored. Similarly to the finding that superstars' salaries did not decrease after their age of peak performance due to their potential contribution to increasing the attendance and gate revenue, it can be speculated that there are other features that managers value in DPs and expect them to bring to the teams. Therefore, performance factors do not play a significant role (or only play a marginal role) in affecting individuals' compensation among superstar groups, where everyone is talented in scoring goals and assists.

Contrary to the effect of the number of goals scored on all players' and regular players' salaries, the number of assists scored was not significant. MLS players can contribute to their teams in various ways: scoring goals or assisting while helping other players to score goals. Although the number of assists scored is one factor of performance statistics, it may not be as important as the number of goals scored, since the players with a higher number of assists receive less credit than players with a high number of goals. This is in line with the current MLS award system, in which, the MLS Golden Boot is awarded to the highest regular-season scorer, but there is no award for the player with the highest number of regular-season assists. The number of assists scored may offer an idea of how players contribute to the team, but it does not necessarily affect MLS players' salaries.

League appearances ($H9_a$ & $H9_b$). Players with more experience measured by games played on the field are more likely to receive a higher salary (Grant et al., 2013). Particularly in the soccer context, the effect of the number of games started is different from the effect of the number of games substituted, because starting members are considered to be the best 11 players on the field (Celik & Ince-Yenilmez, 2017). For this reason, hypotheses 9_a and 9_b postulated that there is a positive (negative) relationship between a player's compensation and the number of games started (substituted). The results demonstrated that the number of games started (substituted) was positively (negatively) related to the RPs' salaries, but not the DPs' salaries.

For the regular players, the number of games started positively affected players' salaries while the number of games substituted negatively affected players' salaries. This indicates that RPs in MLS were paid higher compensation in the current season with each additional game played as a starting member in the previous season, while they received lower salaries with each additional game played as a benchwarmer in the previous season. Although it is difficult to assume that benchwarmers are inferior to the starting members, starting members are generally considered to be the key players. With this knowledge, players who played more games as starting members on the field received a higher salary the following year. Similarly, players who spent more time on the bench received a lower salary, as they are not the mainstays of the team. This finding is consistent with those of Reilly and Witt (2007) and Celik and Ince-Yenilmez (2017), who both found that the number of games started (substituted) yielded a wage premium (deduction) in MLS.

In contrast to the effect of league appearance on salary for regular players, the results showed that both the number of games started and substituted were negatively

associated with DPs' salaries. This finding is surprising, given that players who play more games as starting members are more likely to be paid higher compensation in general because of their importance and contribution to the team. One possible explanation for this is that the differentiation between starting members may work differently for DPs than for RPs. Although MLS superstars may significantly affect team performance with their talent, from the manager's perspective, they should not play all games as starting members because of the possibility of injury during the game. It is also important for the superstars to rest properly between and during the games in order to maximize their performance and satisfy home fans when they are on the field. Unlike the RPs, who have many substitutes, superstars' scarcity means that the manager should be more careful as to how many games they play. It is possible that valuable DPs would play an appropriate number of games as starting members instead of playing as many games as possible. An additional number of games started therefore does not increase DPs' salaries and may instead decrease compensation.

Position (H10). Hypothesis 10 posited that an MLS player's position could affect his salaries. The results showed that among regular players, midfielders, midfielder-forwards, and forwards were paid more than comparable defenders. Similarly to the proposition that NHL linemen earn more money because of their key role in scoring goals (Marchand et al., 2006), midfielders, midfielder-forwards, and forwards are also expected to experience a salary premium in MLS because they play a significant role in scoring goals and assists while directly affecting the game outcome.

Among designated players, it was found that midfielder-forwards experienced a salary premium over defenders. There are two possible reasons explaining this preference for midfielder-forwards in MLS. First, based on the manager's strategic

plans and the injury status of other players, players in the midfielder-forward position can play as both midfielders and forwards. This flexibility increases their value to the team. However, some may wonder why players in other dual positions (e.g., defender-midfielder and midfielder-defender) are not paid higher compensation. This leads to the second reason for the preference for midfielder-forwards: unlike the players in defender-midfielder or midfielder-defender positions, who are expected to pass the ball to the players in the front (e.g., midfielder, forward, and midfielder-forward), players in the midfielder-forward position have a higher chance of scoring goals and assists and may significantly affect the game outcome.

The above results were derived when goalkeepers were excluded from the sample; this is because the performance statistics of goalkeepers are measured in differently to those of defenders, midfielders, and forwards (Lucifora & Simmons, 2003; Medcalfe & Smith, 2018). Therefore, I analyzed the wage equation both including and excluding goalkeepers. When goalkeepers were included in the sample, it was found that among RPs, goalkeepers were paid lower compensation than comparable defenders, midfielders, midfielder-forwards, and forwards. This result is consistent with the findings of Frick (2011) and Battre et al. (2009), who uncovered that goalkeepers received lower compensation than players in other positions. Although the role of goalkeepers is as important as that of outfielder players, they are often considered to be less important than the outfielder players in winning games. Goalkeepers were not paid less than the players in other positions among DPs, however, because there was only one designated goalkeeper, Tim Howard, who is a national soccer hero in the U.S.

Contributions and Implications

The findings of this dissertation contribute to the existing labor economics and sport management literature in several ways, particularly in the areas of discrimination theory and superstar theory. First, this dissertation makes a theoretical contribution to the existing superstar literature by using designated player status as a proxy for superstar. Unlike in other professional sports, where the difficulty in objectively defining the term superstar can lead to mixed results as to the superstar effect on players' compensation, DPS can be used as an appropriate measurement for superstars (Coates et al., 2016) because of their talent (Rosen, 1981) and popularity (Adler, 1985). In using DPS as a proxy of superstars, I found that superstars earned a salary premium that was more than double that of the regular players, supporting the superstar effect in MLS (Jewell, 2017; Kuethe & Motamed, 2010). Given that the DP rule was introduced in order to attract more fans to the stadium and make MLS—a relatively new soccer league in North America—prosper, the results suggest that MLS could attract more superstars from across the world by advocating their potential financial benefits and promising them more compensation.

Second, this study also makes a theoretical contribution to the existing discrimination literature in sport management and economics by confirming prior evidence of salary discrimination in MLS. An extensive amount of previous research has examined the issue of discrimination in the economics and business domains (Schuman et al., 1997). Aligned with this research, most of the previous literature on sports discrimination has focused on American professional sports leagues (e.g., NFL, MLB, NBA, and NHL) or European Soccer Leagues (e.g., EPL, GSL, ISL, and SSL); due to its short history, however, very little research has been conducted on MLS (Coates et al., 2016). Consistent with the findings of the previous literature, I found

the possible evidence of salary discrimination in MLS: specifically, that local players (i.e., North American players) are less favored than players from Europe, Central America, South America, and Africa. Unlike previous studies, which used either a single season or fewer than 10 years with a limited dataset size, the findings of this dissertation could be reliable using a larger dataset of players' salaries for the 2007-2019 seasons. This study therefore builds on the existing discrimination literature by using a much larger dataset and showing the possible evidence of pay discrimination in MLS.

A Third theoretical implication of this dissertation lies in its combining of discrimination theory and superstar theory to examine the degree to which superstars encounter salary discrimination similar to that of regular players. Previous literature has either used discrimination theory to examine whether athletes are discriminated against or used superstar theory to determine if superstars are paid more as a result of their talent and popularity. The existence of wage discrimination for superstars in sports contexts was therefore unknown. Although Prockl and Frick (2018b) provided some evidence for discrimination among superstars (i.e., DPs), their limited sample size and the use of OLS regression did not fully capture the existence of pay discrimination. This dissertation is therefore the first attempt to use both OLS and quantile regression to determine the extent to which superstars' origin of birth affects their compensation in different wage distributions, thus providing the groundwork for future studies about discrimination among superstars. The results of OLS and quantile regression showed that based on their scarcity in the market, players from Asia are favored in MLS while players from South America are not. The results of the current research suggest that, all else being equal, MLS teams may be more likely to seek superstars from Asia than those from South America. This because Asian superstars

could attract more spectators to the team as sports fans are more likely to want to consume the product of Asian superstars because of their scarcity in the MLS labor market.

Fourth, this dissertation provides practical implications for MLS in terms of how they should operate. Despite MLS self-advertising as the most diverse professional league in North America based on players' birthplace (Major League Soccer, 2018), the results from this dissertation showed that MLS may be a discriminatory organization. As previously discussed, the DP rule was introduced in 2007 to help MLS to become a competitive worldwide professional soccer league while improving its prosperity and attracting more superstars (Bradbury, 2020). These talented and popular players, with their professional career experience in higher division leagues, were intended to increase attendance and team revenue for MLS franchises (Bradbury, 2020). Since the possible evidence of wage discrimination among superstars was found in MLS, the league could make efforts to become a non-discriminatory league and attract more superstars from around the world who would otherwise have played in ESLs. In this case, MLS could more effectively become a high-profile soccer league and achieve its attendance and revenue goals by advertising itself not only as the most diverse but also as non-discriminatory.

Limitations and Suggestions

This dissertation has several limitations. First, due to the arbitrary definition of superstars in the previous literature, the current study used designated player status as a proxy for superstars. In the European sports leagues, for example, different measurements—including goals, assists, media exposure, Google hits, Facebook fans, and All-Star experience—have been devised to analyze the superstar effect, resulting in mixed results. In MLS, several measurements such as DPS, All-Star experience,

national team experience, and starting line-up (best 11 members) have been used to analyze the superstar effect (Coates et al., 2016; Kuethe & Motamed, 2010; Wooten, 2013); however, previous literature has reached a consensus that DPS is an appropriate proxy of superstars in MLS. Although the DP rule provides MLS with a less arbitrary definition of a superstar because of players' talent and popularity (Coates et al., 2016), some people may argue that designated player status cannot be equivalent to superstar status. Nevertheless, in the absence of an objective definition of superstars, using DPS seems to be the most reasonable in MLS, though this is thus far unproven. For this reason, further research may consider using measurements other than DPS, if possible, in order to better examine the superstar effect in MLS.

Second, the sample size of 293 observations for superstars may not be large enough to be generalized compared to that of 3,987 observations for regular MLS players. For example, there were limited observations of superstars from Asia (N=3), Eastern Europe (N=3), Oceania (N=2), and the Caribbean (N=7) in the sample when considering the distribution of superstars' origin of birth by the UN Statistics Division. Previously, Prockl and Frick (2018b) tested salary discrimination among DPs and suggested further research into this issue because the sample size was very small with only 145 observations. For this reason, I included 293 observations of superstars, more than double the dataset employed by Prockl and Frick (2018b). Although some people may argue that the results are not conclusive because of the limited observations of DPs, this dissertation includes all possible available data about MLS players' salary and performance since its inaugural season. Therefore, the results from this dissertation can be regarded as more reliable, with a larger dataset that supported the findings of the previous literature. Future research could include

larger datasets over time, since MLS expansion is still ongoing, and teams will have more DPs on their rosters.

Third, the use of individual performance statistics, such as the number of goals and assists, as proxies for talent (in Rosen's sense) may not fully capture players' talent in a certain position. For example, the performance factors of goalkeepers are not measured in the same way as those of outfielder players, such as defenders, midfielders, and forwards (Lucifora & Simmons, 2003; Medcalfe & Smith, 2018, Prockl & Frick, 2018b). For this reason, MLS wage models, both including and excluding goalkeepers, were analyzed in this study. Similarly, defenders' performance statistics are measured differently from those of midfielders and forwards in that the primary role of defenders is to stop attacks from opponents, while forwards and midfielders are expected to contribute to the team by scoring goals and assists (Brownell, 2013). Although the number of goals and assists may be appropriate measurements of talent for forwards and midfielders, other measurement, such as clearances, blocks, and interceptions, are more important when measuring defenders' performance statistics (Lehmann & Schulze, 2008; Lucifora & Simmons, 2003). Future research can therefore differentiate players by position and analyze MLS wage models by group to correct for any possible positional bias in players' performance statistics.

Lastly, I used the previous season's performance statistics in the wage equation as a proxy for their talent in estimating how players' salaries are affected by the number of goals and assists scored in the previous season. There are other measurements for players' talent, of course, such as average career statistics and average statistics from the previous three to five seasons. Such statistics, however, cannot be used in MLS, where the information on players' contracts remains largely

confidential; it is thus impossible to know each player's contract duration and option. In addition, the recent MLS CBA implies that most MLS players are under yearly base contracts. Although performance factors from the previous season may not accurately capture a player's talent, they would be the most reasonable option in the current MLS system. Future research in this area may therefore derive more accurate results if the information on players' contracts becomes widely available to the public.

Directions for Future Research

In addition to my above suggestions regarding the limitations of this dissertation, future research could extend the current study in various ways. One suggestion is to investigate who is acting upon pay discrimination in MLS. The results of this dissertation showed the possible evidence of salary discrimination based on demographic characteristics (i.e., origin of birth) among both regular players and designated players. In particular, I found that Asian superstars experience salary premiums over North American superstars while South American superstars experience salary discounts compared to the North America superstars. According to Becker's (1971) discrimination theory, there are three possible sources of wage discrimination: employer, employee, and customer. In MLS, this means that the premium for Asian superstars and discount for South American superstars could be derived from the coach (manager), teammates, or fans. Unlike the European Soccer Leagues and traditional professional sports leagues in North America (i.e., NFL, NBA, MLB, and NHL), several studies of which showed evidence of one of the three above sources of discrimination (e.g., Burdekin & Idson, 1991; Kahn, 1991; Pedace, 2008), very little research has been conducted on MLS. Future research could therefore build on existing discrimination and superstar theory by investigating who is responsible for salary discrimination in MLS.

Another suggestion for future research is to examine the existence of pay discrimination among superstars in other professional sports leagues. No previous attempt has been made to investigate salary determinants for superstars in sports settings. Using both OLS and quantile regression, I found that in MLS, superstars' salaries are not determined in the same way as RPs' salaries. This implies that the wage equation for superstars in other professional sports may also be different from that of APs or RPs. While this dissertation focused on MLS, it would be interesting to uncover how superstars' salaries are affected by various factors (e.g., origin of birth) in European Soccer Leagues and traditional North American sports leagues. By doing so, future research could provide a new perspective, or more generalizable ideas, on 1) salary discrimination among superstars and 2) important salary determinants for superstars in a variety of sports leagues.

The other suggestion is to examine whether there are other forms of discrimination against minority players in MLS. While this dissertation focused on salary discrimination, which has been the most widely studied in academia (Kahn, 2000), there may be other forms of discrimination—including exit discrimination (Hoang & Rascher, 1999; Jiobu, 1988; Johnson & Marple, 1973), hiring discrimination (Brown et al., 1991; Grenier & Lavoie, 1988; Gwartney & Haworth, 1974; Hill & Spellman, 1984; Lavoie, Grenier, & Coulombe, 1987; Medoff, 1975; Scully, 1973, 1974), and positional segregation (Christiano, 1988; Curtis & Loy, 1978; Edwards, 1973; Johnson, 1988; Kahn, 1992; Kahn & Sherer, 1988; Lavoie et al., 1987; Loy & McElvogue, 1970; Medoff, 1986; Mogull, 1979; Pascal & Rapping, 1972; Smith & Seff, 1989; Yetman, 1987). Tests for such discrimination could provide a broader understanding of the manifestation of various forms of discrimination in MLS.

Conclusion

Discrimination has received a great deal of attention in the neo-classical era since Gary Becker's (1971) work, which provided the groundwork to examine various forms of discrimination. With this knowledge, a vast range of literature has been devoted to the exploration of salary discrimination in a variety of sports settings. Very little research, however, has been conducted to investigate whether superstars are also discriminated against based on their demographic characteristics. The issue of discrimination among superstars is of particular interest in MLS, because the DP rule was introduced for the prosperity of the league. To date, only one study by Prockl & Frick (2018b) has attempted to analyze this issue; it failed to provide reliable results, however, because of the study's limited sample size and its exclusion of relevant variables. This dissertation therefore endeavors to investigate whether there is any evidence of discrimination among superstars (i.e., designated players) in the MLS labor market, respectively, using an expansive dataset with a focus on discrimination theory and superstar theory.

The results of this dissertation uncovered that there is salary discrimination in MLS against players' origin of birth. For the regular players, it was found that the player's origin of birth played a role in explaining his level of compensation, which indicates pay discrimination. In addition, human capital factors such as experience, age, height, and footedness as well as other relevant factors including the number of games started and substituted, the number of goals scored, position, designated player status, and All-Star experience were significantly related to RPs' wages. Regarding the designated players (i.e., superstars), the possible evidence of salary discrimination was also revealed in that MLS superstars from Asia were favored while South American superstars were discriminated against. Human capital factors, however,

were not associated with superstars' salaries, with the exception of a positive effect of experience at all salary distributions. Other salary determinants, including the number of games started and substituted, position, and All-Star experience, were significant, while performance statistics (i.e., goals and assists) were not significant. I therefore concluded that both discrimination theory and the superstar effect were supported in MLS.

In closing, this dissertation contributes to the discrimination and superstar literature in sport management. To my best knowledge, the current study was the first to attempt to uncover salary discrimination in the sports setting, especially in MLS, using both OLS and quantile regression. With evidence of wage discrimination in MLS, this research provides implications for how MLS could operate to maximize gate attendance and team revenue and become a more high-profile and competitive professional soccer league. I hope that this study has laid the groundwork for future research that demonstrates further evidence of discrimination for superstars in various sports contexts.

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APPENDIX A

REGRESSION RESULTS TABLES

Table A-1

Ordinary Least Squares Regression Results of All Players Including Goalkeepers

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 1	Model 1	Model 1
UN (SOUTH AMERICA)	0.360***		0.361***	
	(0.028)		(0.030)	
UN (CENTRAL AMERICA)	0.348***		0.367***	
	(0.038)		(0.040)	
UN (WESTERN EUROPE)	0.329***		0.340***	
	(0.044)		(0.046)	
UN (EASTERN EUROPE)	0.400***		0.392***	
	(0.104)		(0.110)	
UN (NORTHERN EUROPE)	0.140***		0.154***	
	(0.037)		(0.040)	
UN (SOUTHERN EUROPE)	0.448***		0.475***	
	(0.059)		(0.063)	
UN (AFRICA)	0.147***		0.163***	
	(0.032)		(0.034)	
UN (ASIA)	0.166*		0.149	
	(0.093)		(0.099)	
UN (CARIBBEAN)	0.088**		0.101**	
	(0.039)		(0.041)	
UN (OCEANIA)	0.087		0.055	
	(0.104)		(0.110)	
FIFA (AFC)		0.048		0.014
		(0.101)		(0.107)
FIFA (CAF)		0.117***		0.131***
		(0.032)		(0.034)
FIFA (CONMEBOL)		0.301***		0.298***
		(0.028)		(0.029)
FIFA (UEFA)		0.247***		0.259***
		(0.027)		(0.028)
FIFA (OFC)		-0.135		-0.163
		(0.125)		(0.132)
FOOT (LEFT)	-0.085**	-0.074*	-0.099**	-0.086**
	(0.038)	(0.038)	(0.040)	(0.041)
FOOT (RIGHT)	0.018	0.011	0.017	0.010
	(0.035)	(0.036)	(0.037)	(0.038)
FOOT (NOT DEFINED)	-0.156***	-0.168***	-0.176***	-0.188***
	(0.045)	(0.045)	(0.048)	(0.048)
POS (D-M)	0.042	0.047	0.048	0.053
	(0.049)	(0.049)	(0.052)	(0.052)
POS (F)	0.172***	0.187***	0.189***	0.205***
	(0.029)	(0.029)	(0.031)	(0.031)
POS (F-M)	0.082	0.062	0.089	0.068
	(0.075)	(0.076)	(0.080)	(0.081)

Table A-1, continued

Ordinary Least Squares Regression Results of All Players Including Goalkeepers

POS (GK)	-0.094***	-0.114***	-0.091***	-0.112***
	(0.031)	(0.031)	(0.033)	(0.033)
POS (M)	0.078***	0.084***	0.084***	0.090***
	(0.023)	(0.023)	(0.024)	(0.024)
POS (M-D)	-0.073	-0.051	-0.043	-0.019
	(0.070)	(0.071)	(0.075)	(0.075)
POS (M-F)	0.217***	0.220***	0.224***	0.227***
	(0.043)	(0.043)	(0.045)	(0.046)
EXP	0.090***	0.079***	0.090***	0.079***
	(0.004)	(0.004)	(0.004)	(0.004)
AGE	-0.002	0.006*	-0.010***	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)
HEIGHT	0.004***	0.003**	0.005***	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
STARTS	0.017***	0.017***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.019***	-0.021***	-0.019***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
GLS	0.027***	0.027***	0.027***	0.027***
	(0.003)	(0.003)	(0.004)	(0.004)
AST	0.008*	0.009*	0.011**	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
DPS	1.033***	1.070***	1.078***	1.117***
	(0.035)	(0.036)	(0.037)	(0.038)
ALLSTAR	0.401***	0.397***	0.414***	0.410***
	(0.034)	(0.034)	(0.036)	(0.036)
CONSTANT	-128.2***	-132.6***	-126.3***	-130.9***
	(4.916)	(4.945)	(5.213)	(5.242)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	4,280	4,280	4,280	4,280
BIC	6679.508	6739.604	7181.556	7239.155
R^2	0.724	0.718	0.702	0.695
Adjusted R^2	0.721	0.714	0.697	0.691
F Statistics	191.33***	202.82***	171.09***	181.32***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-2

Ordinary Least Squares Regression Results of Regular Players Including Goalkeepers

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	0.426***		0.420***	
	(0.028)		(0.030)	
UN (CENTRAL AMERICA)	0.347***		0.372***	
	(0.038)		(0.041)	
UN (WESTERN EUROPE)	0.300***		0.315***	
	(0.043)		(0.046)	
UN (EASTERN EUROPE)	0.429***		0.425***	
	(0.104)		(0.111)	
UN (NORTHERN EUROPE)	0.136***		0.158***	
	(0.037)		(0.040)	
UN (SOUTHERN EUROPE)	0.477***		0.493***	
	(0.062)		(0.066)	
UN (AFRICA)	0.141***		0.156***	
	(0.031)		(0.033)	
UN (ASIA)	0.102		0.083	
	(0.092)		(0.099)	
UN (CARIBBEAN)	0.087**		0.102**	
	(0.037)		(0.040)	
UN (OCEANIA)	-0.028		-0.056	
	(0.102)		(0.109)	
FIFA (AFC)		-0.055		-0.088
		(0.098)		(0.106)
FIFA (CAF)		0.116***		0.127***
		(0.031)		(0.033)
FIFA (CONMEBOL)		0.379***		0.369***
		(0.028)		(0.030)
FIFA (UEFA)		0.243***		0.257***
		(0.026)		(0.028)
FIFA (OFC)		-0.135		-0.162
		(0.117)		(0.125)
FOOT (LEFT)	-0.110***	-0.102***	-0.134***	-0.124***
	(0.038)	(0.039)	(0.041)	(0.041)
FOOT (RIGHT)	-0.009	-0.018	-0.018	-0.026
	(0.036)	(0.036)	(0.038)	(0.039)
FOOT (NOT DEFINED)	-0.174***	-0.186***	-0.201***	-0.213***
	(0.044)	(0.045)	(0.047)	(0.048)
POS (D-M)	0.039	0.044	0.045	0.050
	(0.046)	(0.046)	(0.049)	(0.050)
POS (F)	0.138***	0.147***	0.159***	0.169***
	(0.028)	(0.029)	(0.030)	(0.031)

Table A-2, continued

Ordinary Least Squares Regression Results of Regular Players Including Goalkeepers

POS (F-M)	0.041	0.028	0.058	0.043
	(0.076)	(0.077)	(0.081)	(0.082)
POS (GK)	-0.071**	-0.090***	-0.065**	-0.082***
	(0.029)	(0.030)	(0.032)	(0.032)
POS (M)	0.054**	0.061***	0.057**	0.064***
	(0.022)	(0.022)	(0.024)	(0.024)
POS (M-D)	-0.088	-0.066	-0.056	-0.032
	(0.067)	(0.067)	(0.071)	(0.072)
POS (M-F)	0.205***	0.207***	0.201***	0.204***
	(0.043)	(0.043)	(0.046)	(0.046)
EXP	0.079***	0.068***	0.079***	0.068***
	(0.004)	(0.004)	(0.004)	(0.004)
AGE	0.001	0.010***	-0.008**	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
HEIGHT	0.003**	0.002*	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
STARTS	0.018***	0.018***	0.020***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.018***	-0.020***	-0.017***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
GLS	0.039***	0.040***	0.038***	0.040***
	(0.004)	(0.004)	(0.004)	(0.004)
AST	0.006	0.007	0.009	0.010*
	(0.005)	(0.005)	(0.006)	(0.006)
ALLSTAR	0.358***	0.355***	0.360***	0.357***
	(0.035)	(0.036)	(0.038)	(0.038)
CONSTANT	-130.4***	-134.3***	-128.9***	-133.1***
	(4.694)	(4.726)	(5.036)	(5.068)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	3,987	3,987	3,987	3,987
BIC	5696.688	5758.177	6258.665	6315.654
R^2	0.638	0.628	0.598	0.588
Adjusted R^2	0.633	0.624	0.592	0.583
F Statistics	123.58***	130.44***	104.46***	110.16***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-3

Ordinary Least Squares Regression Results of Designated Players Including Goalkeepers

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	-0.287*		-0.226	
	(0.165)		(0.163)	
UN (CENTRAL AMERICA)	0.046		0.097	
	(0.161)		(0.158)	
UN (WESTERN EUROPE)	-0.018		-0.013	
	(0.191)		(0.188)	
UN (EASTERN EUROPE)	0.510		0.595	
	(0.391)		(0.386)	
UN (NORTHERN EUROPE)	-0.264		-0.292*	
	(0.167)		(0.164)	
UN (SOUTHERN EUROPE)	-0.159		-0.107	
	(0.206)		(0.203)	
UN (AFRICA)	0.247		0.336	
	(0.230)		(0.227)	
UN (ASIA)	0.982**		1.010***	
	(0.388)		(0.382)	
UN (CARIBBEAN)	-0.653**		-0.628**	
	(0.300)		(0.296)	
UN (OCEANIA)	0.403		0.365	
	(0.461)		(0.454)	
FIFA (AFC)		0.520		0.470
		(0.465)		(0.460)
FIFA (CAF)		0.248		0.312
		(0.224)		(0.221)
FIFA (CONMEBOL)		-0.280**		-0.261**
		(0.131)		(0.129)
FIFA (UEFA)		-0.070		-0.084
		(0.119)		(0.118)
FOOT (LEFT)	-0.153	-0.127	-0.072	-0.043
	(0.166)	(0.168)	(0.164)	(0.166)
FOOT (RIGHT)	-0.093	-0.121	-0.090	-0.126
	(0.128)	(0.130)	(0.127)	(0.128)
FOOT (NOT DEFINED)	0.481	0.491	0.452	0.460
	(0.295)	(0.300)	(0.291)	(0.297)
POS (D-M)	-0.132	-0.226	-0.212	-0.331
	(0.674)	(0.684)	(0.664)	(0.678)
POS (F)	0.158	0.176	0.170	0.198
	(0.208)	(0.208)	(0.205)	(0.206)
POS (F-M)	-0.024	-0.107	0.034	-0.067
	(0.317)	(0.320)	(0.313)	(0.317)

Table A-3, continued

Ordinary Least Squares Regression Results of Designated Players Including Goalkeepers

POS (GK)	-0.541	-0.410	-0.362	-0.209
	(0.501)	(0.507)	(0.494)	(0.502)
POS (M)	0.177	0.156	0.200	0.184
	(0.193)	(0.193)	(0.190)	(0.191)
POS (M-D)	-0.231	-0.315	-0.293	-0.402
	(0.657)	(0.668)	(0.648)	(0.661)
POS (M-F)	0.322	0.385	0.399*	0.470**
	(0.237)	(0.237)	(0.233)	(0.235)
EXP	0.094***	0.095***	0.090***	0.089***
	(0.019)	(0.019)	(0.019)	(0.019)
AGE	0.033*	0.022	0.038**	0.029*
	(0.017)	(0.017)	(0.017)	(0.017)
HEIGHT	-0.008	-0.005	-0.003	-0.001
	(0.007)	(0.006)	(0.007)	(0.006)
STARTS	-0.015**	-0.018***	-0.019***	-0.023***
	(0.007)	(0.006)	(0.006)	(0.006)
SUBS	-0.054***	-0.057***	-0.059***	-0.062***
	(0.015)	(0.015)	(0.015)	(0.015)
GLS	0.006	0.007	0.009	0.010
	(0.010)	(0.010)	(0.010)	(0.010)
AST	-0.001	0.010	-0.001	0.012
	(0.014)	(0.014)	(0.014)	(0.014)
ALLSTAR	0.312***	0.302***	0.359***	0.347***
	(0.100)	(0.101)	(0.099)	(0.100)
CONSTANT	-170.3***	-180.6***	-173.7***	-185.0***
	(35.520)	(35.989)	(35.014)	(35.631)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	293	293	293	293
BIC	779.6487	765.9023	771.2427	760.0426
R^2	0.759	0.742	0.768	0.750
Adjusted R^2	0.705	0.691	0.716	0.700
F Statistics	13.89***	14.61***	14.63***	15.22***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-4

Ordinary Least Squares Regression Results of All Players Using both AGE and AGE^2

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	0.381***		0.373***	
	(0.029)		(0.031)	
UN (CENTRAL AMERICA)	0.375***		0.385***	
	(0.039)		(0.041)	
UN (WESTERN EUROPE)	0.339***		0.346***	
	(0.046)		(0.049)	
UN (EASTERN EUROPE)	0.383***		0.380***	
	(0.105)		(0.112)	
UN (NORTHERN EUROPE)	0.117***		0.132***	
	(0.039)		(0.042)	
UN (SOUTHERN EUROPE)	0.451***		0.541***	
	(0.062)		(0.067)	
UN (AFRICA)	0.153***		0.166***	
	(0.033)		(0.035)	
UN (ASIA)	0.190**		0.165*	
	(0.094)		(0.035)	
UN (CARIBBEAN)	0.074*		0.080*	
	(0.040)		(0.043)	
UN (OCEANIA)	0.099		0.066	
	(0.115)		(0.123)	
FIFA (AFC)		0.059		0.018
		(0.102)		(0.109)
FIFA (CAF)		0.121***		0.133***
		(0.033)		(0.035)
FIFA (CONMEBOL)		0.315***		0.304***
		(0.028)		(0.030)
FIFA (UEFA)		0.246***		0.259***
		(0.028)		(0.030)
FIFA (OFC)		-0.193		-0.216
		(0.144)		(0.154)
FOOT (LEFT)	-0.097**	-0.085**	-0.107***	-0.093**
	(0.039)	(0.039)	(0.041)	(0.042)
FOOT (RIGHT)	0.013	0.004	0.014	0.006
	(0.035)	(0.036)	(0.038)	(0.038)
FOOT (NOT DEFINED)	-0.166***	-0.182***	-0.187***	-0.203***
	(0.047)	(0.048)	(0.050)	(0.051)
POS (D-M)	0.032	0.037	0.039	0.045
	(0.049)	(0.050)	(0.053)	(0.053)
POS (F)	0.173***	0.189***	0.189***	0.206***
	(0.030)	(0.030)	(0.032)	(0.032)
POS (F-M)	0.081	0.058	0.088	0.064
	(0.076)	(0.077)	(0.081)	(0.082)

Table A-4, continued

Ordinary Least Squares Regression Results of All Players Using both AGE and AGE²

POS (M)	0.081***	0.086***	0.087***	0.092***
	(0.023)	(0.023)	(0.025)	(0.025)
POS (M-D)	-0.065	-0.042	-0.036	-0.013
	(0.071)	(0.072)	(0.076)	(0.077)
POS (M-F)	0.207***	0.209***	0.218***	0.220***
	(0.043)	(0.044)	(0.046)	(0.047)
EXP	0.100***	0.087***	0.097***	0.084***
	(0.004)	(0.004)	(0.005)	(0.005)
AGE	0.178***	0.167***	0.109***	0.098***
	(0.021)	(0.022)	(0.023)	(0.023)
AGE^2	-0.004***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
HEIGHT	0.004***	0.003**	0.005***	0.004**
	(0.001)	(0.001)	(0.002)	(0.002)
STARTS	0.015***	0.015***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.020***	-0.021***	-0.019***	-0.021***
	(0.002)	(0.002)	(0.003)	(0.003)
GLS	0.027***	0.027***	0.027***	0.027***
	(0.003)	(0.003)	(0.004)	(0.004)
AST	0.008*	0.009*	0.011**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)
DPS	1.018***	1.058***	1.062***	1.103***
	(0.003)	(0.036)	(0.038)	(0.039)
ALLSTAR	0.432***	0.428***	0.441***	0.438***
	(0.036)	(0.037)	(0.039)	(0.039)
CONSTANT	-131.5***	-136.7***	-129.4***	-134.6***
	(5.212)	(5.259)	(5.566)	(5.608)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	3,886	3,886	3,886	3,886
BIC	6145.287	6223.117	6655.085	6723.208
R^2	0.733	0.725	0.707	0.698
Adjusted R^2	0.729	0.721	0.702	0.694
F Statistics	184.39***	194.05***	161.71***	170.51***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-5

Ordinary Least Squares Regression Results of Regular Players Using both AGE and AGE²

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	0.443***		0.429***	
	(0.028)		(0.031)	
UN (CENTRAL AMERICA)	0.376***		0.391***	
	(0.039)		(0.042)	
UN (WESTERN EUROPE)	0.305***		0.317***	
	(0.046)		(0.050)	
UN (EASTERN EUROPE)	0.412***		0.414***	
	(0.104)		(0.113)	
UN (NORTHERN EUROPE)	0.105***		0.130***	
	(0.039)		(0.042)	
UN (SOUTHERN EUROPE)	0.551***		0.577***	
	(0.065)		(0.071)	
UN (AFRICA)	0.148***		0.158***	
	(0.031)		(0.034)	
UN (ASIA)	0.130		0.101	
	(0.092)		(0.100)	
UN (CARIBBEAN)	0.070*		0.078*	
	(0.038)		(0.041)	
UN (OCEANIA)	-0.040		-0.067	
	(0.113)		(0.122)	
FIFA (AFC)		-0.049		-0.087
		(0.099)		(0.107)
FIFA (CAF)		0.120***		0.129***
		(0.032)		(0.034)
FIFA (CONMEBOL)		0.390***		0.373***
		(0.028)		(0.031)
FIFA (UEFA)		0.239***		0.256***
		(0.028)		(0.030)
FIFA (OFC)		-0.182		-0.204
		(0.135)		(0.146)
FOOT (LEFT)	-0.111***	-0.113***	-0.133***	-0.125***
	(0.039)	(0.039)	(0.042)	(0.042)
FOOT (RIGHT)	-0.006	-0.017	-0.014	-0.026
	(0.036)	(0.036)	(0.039)	(0.039)
FOOT (NOT DEFINED)	-0.177***	-0.194***	-0.208***	-0.225***
	(0.046)	(0.047)	(0.050)	(0.051)
POS (D-M)	0.028	0.034	0.036	0.042
	(0.046)	(0.047)	(0.050)	(0.051)
POS (F)	0.140***	0.150***	0.160***	0.171***
	(0.029)	(0.029)	(0.031)	(0.032)

Table A-5, continued

Ordinary Least Squares Regression Results of Regular Players Using both AGE and AGE^2

POS (F-M)	0.042	0.027	0.057	0.042
	(0.076)	(0.077)	(0.082)	(0.084)
POS (M)	0.057**	0.063***	0.060**	0.067***
	(0.022)	(0.023)	(0.024)	(0.024)
POS (M-D)	-0.077	-0.056	-0.048	-0.026
	(0.067)	(0.068)	(0.072)	(0.073)
POS (M-F)	0.193***	0.194***	0.194***	0.195***
	(0.043)	(0.044)	(0.047)	(0.047)
EXP	0.089***	0.076***	0.087***	0.073***
	(0.004)	(0.004)	(0.005)	(0.005)
AGE	0.171***	0.157***	0.103***	0.089***
	(0.021)	(0.021)	(0.023)	(0.023)
AGE^2	-0.003***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
HEIGHT	0.003**	0.002	0.004**	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
STARTS	0.016***	0.016***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
SUBS	-0.019***	-0.020***	-0.018***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
GLS	0.039***	0.040***	0.038***	0.039***
	(0.004)	(0.004)	(0.004)	(0.004)
AST	0.006	0.007	0.009	0.010*
	(0.005)	(0.005)	(0.006)	(0.006)
ALLSTAR	0.381***	0.379***	0.382***	0.379***
	(0.039)	(0.039)	(0.042)	(0.042)
CONSTANT	-134.0***	-138.7***	-132.4***	-137.2***
	(4.977)	(5.031)	(5.386)	(5.434)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	3,596	3,596	3,596	3,596
BIC	5195.402	5277.983	5763.084	5832.363
R^2	0.647	0.635	0.602	0.590
Adjusted R^2	0.642	0.630	0.596	0.584
F Statistics	118.10***	123.31***	97.36***	101.87***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-6

Ordinary Least Squares Regression Results of Designated Players Using both AGE and AGE^2

Dependent Variable	ln(SALARY)		ln(COMPENSATION)	
Variables	UN	FIFA	UN	FIFA
Model	Model 1	Model 2	Model 3	Model 4
UN (SOUTH AMERICA)	-0.224		-0.176	
	(0.168)		(0.166)	
UN (CENTRAL AMERICA)	0.086		0.128	
	(0.161)		(0.159)	
UN (WESTERN EUROPE)	0.022		-0.019	
	(0.191)		(0.189)	
UN (EASTERN EUROPE)	0.549		0.626	
	(0.390)		(0.386)	
UN (NORTHERN EUROPE)	-0.227		-0.263	
	(0.167)		(0.165)	
UN (SOUTHERN EUROPE)	-0.121		-0.077	
	(0.206)		(0.204)	
UN (AFRICA)	0.254		0.342	
	(0.229)		(0.227)	
UN (ASIA)	0.951**		0.987**	
	(0.387)		(0.383)	
UN (CARIBBEAN)	-0.603**		-0.589**	
	(0.301)		(0.297)	
UN (OCEANIA)	0.509		0.447	
	(0.462)		(0.457)	
FIFA (AFC)		0.615		0.545
		(0.464)		(0.461)
FIFA (CAF)		0.234		0.301
		(0.223)		(0.221)
FIFA (CONMEBOL)		-0.240*		-0.229*
		(0.131)		(0.130)
FIFA (UEFA)		-0.052		-0.069
		(0.119)		(0.118)
FOOT (LEFT)	-0.256	-0.245	-0.151	-0.136
	(0.173)	(0.174)	(0.171)	(0.173)
FOOT (RIGHT)	-0.152	-0.193	-0.136	-0.183
	(0.131)	(0.133)	(0.130)	(0.132)
FOOT (NOT DEFINED)	0.387	0.384	0.379	0.376
	(0.298)	(0.302)	(0.294)	(0.301)
POS (D-M)	-0.161	-0.277	-0.233	-0.371
	(0.672)	(0.681)	(0.665)	(0.677)
POS (F)	0.163	0.191	0.175	0.211
	(0.208)	(0.207)	(0.205)	(0.206)
POS (F-M)	-0.062	-0.150	0.005	-0.101
	(0.317)	(0.319)	(0.313)	(0.317)

Table A-6, continued

Ordinary Least Squares Regression Results of Designated Players Using both AGE and AGE^2

POS (M)	0.159	0.144	0.186	0.176
	(0.192)	(0.192)	(0.190)	(0.191)
POS (M-D)	-0.208	-0.307	-0.274	-0.395
	(0.655)	(0.664)	(0.648)	(0.660)
POS (M-F)	0.278	0.341	0.365	0.436*
	(0.237)	(0.237)	(0.234)	(0.235)
EXP	0.098***	0.098***	0.093***	0.091***
	(0.020)	(0.019)	(0.019)	(0.019)
AGE	0.283**	0.310**	0.231*	0.256**
	(0.123)	(0.125)	(0.122)	(0.124)
AGE^2	-0.005**	-0.005**	-0.004	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
HEIGHT	-0.008	-0.005	-0.003	-0.001
	(0.007)	(0.006)	(0.007)	(0.006)
STARTS	-0.015**	-0.018***	-0.019***	-0.023***
	(0.007)	(0.006)	(0.006)	(0.006)
SUBS	-0.049***	-0.052***	-0.055***	-0.057***
	(0.015)	(0.015)	(0.015)	(0.015)
GLS	0.003	0.004	0.007	0.008
	(0.010)	(0.010)	(0.010)	(0.010)
AST	0.001	0.012	0.001	0.013
	(0.014)	(0.014)	(0.014)	(0.014)
ALLSTAR	0.346***	0.336***	0.387***	0.376***
	(0.102)	(0.102)	(0.101)	(0.102)
CONSTANT	-179.8***	-191.1***	-181.1***	-193.2***
	(35.699)	(36.068)	(35.311)	(35.851)
YEAR (Controlled)	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES
Observations	290	290	290	290
BIC	771.8990	756.8187	765.5585	753.3225
R^2	0.762	0.746	0.769	0.752
Adjusted R^2	0.708	0.696	0.717	0.702
F Statistics	13.95***	14.75***	14.53***	15.19***

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-7

Quantile Regression Results of All Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.165*** (0.034)	0.208*** (0.035)	0.378*** (0.041)	0.525*** (0.049)	0.632*** (0.055)
UN (CENTRAL AMERICA)	0.141** (0.066)	0.161*** (0.047)	0.388*** (0.063)	0.436*** (0.045)	0.513*** (0.092)
UN (WESTERN EUROPE)	0.158* (0.073)	0.245*** (0.080)	0.408*** (0.063)	0.420*** (0.067)	0.342*** (0.081)
UN (EASTERN EUROPE)	-0.223 (0.250)	0.100 (0.206)	0.382 (0.258)	0.650*** (0.190)	0.582*** (0.208)
UN (NORTHERN EUROPE)	0.009 (0.060)	0.070 (0.046)	0.115** (0.047)	0.181*** (0.061)	0.255*** (0.079)
UN (SOUTHERN EUROPE)	0.150* (0.090)	0.238** (0.100)	0.514*** (0.145)	0.639*** (0.120)	0.841*** (0.201)
UN (AFRICA)	-0.003 (0.040)	0.069* (0.041)	0.118*** (0.039)	0.224*** (0.049)	0.236*** (0.070)
UN (ASIA)	0.043 (0.120)	0.017 (0.102)	0.022* (0.080)	-0.045 (0.257)	0.491 (0.457)
UN (CARIBBEAN)	0.024 (0.060)	0.035 (0.042)	0.074 (0.044)	0.151*** (0.045)	0.161*** (0.060)
UN (OCEANIA)	-0.016 (0.094)	-0.021 (0.092)	-0.055*** (0.121)	0.113 (0.221)	-0.066 (0.500)
FOOT (LEFT)	-0.044 (0.052)	-0.046 (0.042)	-0.062 (0.048)	-0.146** (0.062)	-0.072 (0.089)
FOOT (RIGHT)	-0.039 (0.052)	0.000 (0.040)	0.033 (0.046)	0.010 (0.059)	0.069 (0.081)
FOOT (NOT DEFINED)	-0.149** (0.068)	-0.112** (0.046)	-0.130** (0.051)	-0.213*** (0.066)	-0.140 (0.091)
POS (D-M)	0.091 (0.065)	0.001*** (0.043)	0.055*** (0.053)	0.026 (0.053)	0.051 (0.086)
POS (F)	0.104** (0.039)	0.093 (0.033)	0.132 (0.036)	0.197*** (0.043)	0.194*** (0.056)
POS (F-M)	0.152* (0.094)	0.088 (0.078)	0.045 (0.062)	0.009 (0.098)	0.176 (0.175)
POS (GK)	0.041 (0.049)	-0.012 (0.030)	-0.042 (0.031)	-0.066* (0.037)	-0.106** (0.056)
POS (M)	0.071** (0.031)	0.065*** (0.025)	0.059** (0.026)	0.077** (0.030)	0.104** (0.040)
POS (M-D)	-0.028 (0.140)	0.016 (0.088)	-0.057 (0.058)	0.010 (0.084)	-0.003 (0.106)
POS (M-F)	0.113* (0.061)	0.134*** (0.048)	0.154** (0.059)	0.233*** (0.060)	0.240*** (0.082)
EXP	0.059*** (0.006)	0.078*** (0.006)	0.093*** (0.005)	0.102*** (0.006)	0.115*** (0.008)

Table A-7, continued

Quantile Regression Results of All Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
AGE	0.004	-0.003	-0.006	-0.001	-0.012*
	(0.006)	(0.005)	(0.004)	(0.005)	(0.007)
HEIGHT	0.004*	0.001	0.002	0.004*	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.018***	0.019***	0.017***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
SUBS	-0.010***	-0.014***	-0.016***	-0.018***	-0.021***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
GLS	0.024***	0.029***	0.035***	0.031***	0.031***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
AST	0.012	0.008	0.006	0.008	0.011
	(0.008)	(0.006)	(0.006)	(0.007)	(0.010)
DPS	0.768***	0.910***	1.078***	1.095***	1.207***
	(0.101)	(0.089)	(0.065)	(0.067)	(0.123)
ALLSTAR	0.365***	0.346***	0.424***	0.454***	0.395***
	(0.062)	(0.074)	(0.046)	(0.048)	(0.075)
CONSTANT	-146.4***	-126.5***	-122.6***	-118.5***	-130.1***
	(8.392)	(5.367)	(5.268)	(6.213)	(9.359)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	4,280	4,280	4,280	4,280	4,280

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-8

Quantile Regression Results of Regular Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.192*** (0.042)	0.239*** (0.042)	0.427*** (0.046)	0.594*** (0.050)	0.646*** (0.053)
UN (CENTRAL AMERICA)	0.151** (0.068)	0.207*** (0.060)	0.411*** (0.061)	0.434*** (0.055)	0.464*** (0.083)
UN (WESTERN EUROPE)	0.117 (0.101)	0.208*** (0.076)	0.344*** (0.070)	0.419*** (0.063)	0.346*** (0.092)
UN (EASTERN EUROPE)	-0.246 (0.260)	0.092 (0.188)	0.342 (0.285)	0.686*** (0.175)	0.690*** (0.234)
UN (NORTHERN EUROPE)	0.034 (0.059)	0.068 (0.048)	0.093* (0.047)	0.204*** (0.063)	0.278*** (0.079)
UN (SOUTHERN EUROPE)	0.122* (0.073)	0.219** (0.109)	0.512*** (0.140)	0.660*** (0.146)	0.940*** (0.211)
UN (AFRICA)	0.017 (0.043)	0.056 (0.041)	0.116*** (0.039)	0.244*** (0.052)	0.235*** (0.062)
UN (ASIA)	-0.040 (0.126)	0.001 (0.097)	0.013 (0.088)	-0.078 (0.166)	0.548 (0.521)
UN (CARIBBEAN)	0.020 (0.054)	0.029 (0.041)	0.068 (0.048)	0.194*** (0.053)	0.180*** (0.065)
UN (OCEANIA)	-0.029 (0.085)	-0.014 (0.083)	-0.075 (0.077)	-0.145 (0.171)	-0.212 (0.352)
FOOT (LEFT)	-0.081 (0.051)	-0.071 (0.044)	-0.057 (0.047)	-0.121** (0.060)	-0.087 (0.072)
FOOT (RIGHT)	-0.074 (0.045)	-0.001 (0.040)	0.045 (0.046)	0.026 (0.058)	0.019 (0.065)
FOOT (NOT DEFINED)	-0.191*** (0.068)	-0.120** (0.047)	-0.108** (0.052)	-0.202*** (0.067)	-0.204*** (0.074)
POS (D-M)	0.057 (0.063)	0.005 (0.046)	0.028 (0.049)	-0.003 (0.064)	0.041 (0.082)
POS (F)	0.096*** (0.037)	0.079** (0.034)	0.104*** (0.038)	0.138*** (0.044)	0.165*** (0.059)
POS (F-M)	0.133 (0.122)	0.027 (0.077)	0.045 (0.065)	0.050 (0.120)	0.141 (0.164)
POS (GK)	0.066 (0.047)	0.001 (0.030)	-0.047 (0.032)	-0.072* (0.038)	-0.061 (0.054)
POS (M)	0.077** (0.032)	0.062*** (0.022)	0.046* (0.026)	0.038 (0.033)	0.097** (0.041)
POS (M-D)	-0.125 (0.130)	0.009 (0.095)	-0.056 (0.059)	-0.029 (0.092)	0.007 (0.132)
POS (M-F)	0.086 (0.065)	0.103** (0.045)	0.164*** (0.063)	0.243*** (0.062)	0.263*** (0.081)
EXP	0.055*** (0.007)	0.072*** (0.005)	0.087*** (0.006)	0.096*** (0.006)	0.104*** (0.008)

Table A-8, continued

Quantile Regression Results of Regular Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
AGE	0.005	0.000	-0.003	-0.002	-0.011*
	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
HEIGHT	0.002	0.001	0.002	0.003	0.009***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.018***	0.020***	0.017***	0.015***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
SUBS	-0.011***	-0.014***	-0.015***	-0.017***	-0.019***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
GLS	0.028***	0.033***	0.039***	0.036***	0.039***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.009)
AST	0.011	0.010	0.006	0.009	0.007
	(0.008)	(0.006)	(0.007)	(0.008)	(0.011)
ALLSTAR	0.325***	0.348***	0.388***	0.398***	0.362***
	(0.069)	(0.073)	(0.056)	(0.049)	(0.072)
CONSTANT	-149.1***	-128.4***	-124.3***	-120.3***	-133.4***
	(8.248)	(5.504)	(5.800)	(6.602)	(8.908)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	3,987	3,987	3,987	3,987	3,987

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-9

Quantile Regression Results of Designated Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
FIFA (AFC)	1.267**	1.152**	0.241	0.420	-0.024
	(0.574)	(0.560)	(0.517)	(0.545)	(0.512)
FIFA (CAF)	0.394	0.492*	0.257	0.054	-0.058
	(0.367)	(0.260)	(0.274)	(0.316)	(0.420)
FIFA	-0.491**	-0.405**	-0.188	-0.109	-0.212
(CONMEBOL)	(0.262)	(0.204)	(0.213)	(0.216)	(0.269)
FIFA (UEFA)	-0.198	-0.145	0.026	0.076	0.056
	(0.236)	(0.203)	(0.206)	(0.209)	(0.231)
FOOT (LEFT)	-0.040	0.152	0.151	-0.165	-0.011
	(0.274)	(0.256)	(0.617)	(0.321)	(0.361)
FOOT (RIGHT)	0.007	0.095	-0.060	-0.315	-0.172
	(0.217)	(0.199)	(0.226)	(0.303)	(0.312)
FOOT (NOT	0.252	0.442	0.316	0.591	0.444
DEFINED)	(0.568)	(0.398)	(0.617)	(0.801)	(0.882)
POS (D-M)	0.370	0.260	-0.065	-0.904	-1.381*
	(0.364)	(0.300)	(0.442)	(0.558)	(0.705)
POS (F)	0.293	0.367	0.286	0.284	-0.045
	(0.357)	(0.314)	(0.289)	(0.323)	(0.467)
POS (F-M)	0.044	0.101	0.217	0.041	-0.052
	(0.474)	(0.394)	(0.384)	(0.496)	(0.650)
POS (GK)	0.143	0.187	-0.214	-0.007	-0.345
	(0.532)	(0.430)	(0.539)	(0.484)	(0.581)
POS (M)	0.413	0.336	0.182	0.262	-0.103
	(0.308)	(0.258)	(0.242)	(0.314)	(0.459)
POS (M-D)	0.235	0.089	-0.183	-0.923*	-1.410**
	(0.318)	(0.296)	(0.374)	(0.515)	(0.677)
POS (M-F)	0.584*	0.846***	0.458	0.312	-0.070
	(0.349)	(0.324)	(0.295)	(0.360)	(0.506)
EXP	0.094***	0.084***	0.091***	0.081***	0.095***
	(0.032)	(0.028)	(0.025)	(0.032)	(0.035)
AGE	0.033	0.027	0.016	0.017	0.009
	(0.033)	(0.030)	(0.026)	(0.027)	(0.026)
HEIGHT	-0.012	-0.009	-0.001	0.016	0.008
	(0.010)	(0.009)	(0.010)	(0.010)	(0.012)
STARTS	-0.021**	-0.011	-0.009	-0.025***	-0.017*
	(0.010)	(0.008)	(0.009)	(0.008)	(0.011)
SUBS	-0.078***	-0.066***	-0.049**	-0.054***	-0.035*
	(0.027)	(0.022)	(0.022)	(0.019)	(0.025)
GLS	0.019	0.013	0.007	0.012	0.011
	(0.015)	(0.013)	(0.013)	(0.015)	(0.015)
AST	-0.004	-0.015	-0.003	0.046*	0.019
	(0.024)	(0.020)	(0.021)	(0.021)	(0.025)

Table A-9, continued

Quantile Regression Results of Designated Players Including Goalkeepers

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
ALLSTAR	0.172 (0.150)	0.317** (0.130)	0.398*** (0.134)	0.351*** (0.135)	0.122 (0.140)
CONSTANT	-244.5*** (73.431)	-215.3*** (60.887)	-171.0*** (63.058)	-195.6*** (63.722)	-59.898 (78.846)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	293	293	293	293	293

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-10

Quantile Regression Results of All Players Using both AGE and AGE^2

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.209*** (0.044)	0.243*** (0.044)	0.398*** (0.045)	0.539*** (0.041)	0.605*** (0.059)
UN (CENTRAL AMERICA)	0.211*** (0.068)	0.203*** (0.056)	0.462*** (0.065)	0.440*** (0.047)	0.490*** (0.091)
UN (WESTERN EUROPE)	0.101 (0.089)	0.270*** (0.097)	0.471*** (0.067)	0.432*** (0.058)	0.407*** (0.095)
UN (EASTERN EUROPE)	-0.163 (0.237)	0.093 (0.187)	0.250 (0.241)	0.588*** (0.166)	0.500** (0.214)
UN (NORTHERN EUROPE)	0.003 (0.065)	0.041 (0.056)	0.084** (0.040)	0.157** (0.067)	0.228** (0.099)
UN (SOUTHERN EUROPE)	0.268** (0.108)	0.313*** (0.081)	0.597*** (0.111)	0.652*** (0.125)	0.832*** (0.214)
UN (AFRICA)	-0.004 (0.049)	0.082** (0.046)	0.143*** (0.040)	0.214*** (0.044)	0.228*** (0.065)
UN (ASIA)	-0.071 (0.117)	0.002 (0.120)	0.093 (0.097)	-0.015 (0.201)	0.545 (0.471)
UN (CARIBBEAN)	0.012 (0.060)	0.015 (0.040)	0.066 (0.049)	0.149** (0.059)	0.117* (0.069)
UN (OCEANIA)	0.072 (0.121)	0.007 (0.101)	-0.038 (0.115)	-0.185 (0.247)	0.046 (0.559)
FOOT (LEFT)	-0.023 (0.058)	-0.012 (0.044)	-0.053 (0.047)	-0.189*** (0.059)	-0.104 (0.084)
FOOT (RIGHT)	-0.021 (0.057)	0.050 (0.041)	0.044 (0.044)	-0.021 (0.054)	0.055 (0.081)
FOOT (NOT DEFINED)	-0.146* (0.074)	-0.072 (0.054)	-0.127** (0.051)	-0.251*** (0.065)	-0.218** (0.102)
POS (D-M)	0.061 (0.069)	0.006 (0.045)	0.054 (0.060)	0.035 (0.053)	0.004 (0.081)
POS (F)	0.110*** (0.040)	0.089*** (0.036)	0.130*** (0.036)	0.194*** (0.040)	0.201*** (0.060)
POS (F-M)	0.167* (0.100)	0.046 (0.082)	0.051 (0.075)	0.039 (0.076)	0.117 (0.197)
POS (M)	0.063** (0.034)	0.061** (0.028)	0.041* (0.023)	0.087*** (0.032)	0.111** (0.046)
POS (M-D)	-0.076 (0.145)	0.022 (0.098)	-0.084 (0.057)	0.008 (0.084)	-0.055 (0.108)
POS (M-F)	0.069 (0.066)	0.124** (0.056)	0.137** (0.054)	0.220*** (0.059)	0.246*** (0.076)
EXP	0.069*** (0.009)	0.088*** (0.006)	0.106*** (0.007)	0.111*** (0.007)	0.112*** (0.010)
AGE	0.119*** (0.044)	0.133*** (0.028)	0.154*** (0.029)	0.138*** (0.029)	0.123*** (0.043)

Table A-10, continued

Quantile Regression Results of All Players Using both AGE and AGE²

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
AGE^2	-0.002**	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HEIGHT	0.004**	0.001	0.002	0.003	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.018***	0.017***	0.014***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
SUBS	-0.011***	-0.014***	-0.017***	-0.021***	-0.021***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)
GLS	0.025***	0.030***	0.031***	0.033***	0.030***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.008)
AST	0.010	0.005	0.010	0.009	0.014
	(0.008)	(0.007)	(0.007)	(0.007)	(0.010)
DPS	0.727***	0.877***	1.041***	1.061***	1.206***
	(0.097)	(0.091)	(0.064)	(0.061)	(0.115)
ALLSTAR	0.377***	0.343***	0.442***	0.519***	0.421***
	(0.079)	(0.060)	(0.052)	(0.041)	(0.084)
CONSTANT	-151.3***	-128.5***	-129.6***	-124.8***	-129.1***
	(8.971)	(6.322)	(6.295)	(6.970)	(10.857)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	3,886	3,886	3,886	3,886	3,886

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-11

Quantile Regression Results of Regular Players Using both AGE and AGE²

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
UN (SOUTH AMERICA)	0.221*** (0.045)	0.279*** (0.036)	0.448*** (0.041)	0.606*** (0.052)	0.629*** (0.058)
UN (CENTRAL AMERICA)	0.183** (0.072)	0.244*** (0.059)	0.477*** (0.055)	0.416*** (0.050)	0.473*** (0.085)
UN (WESTERN EUROPE)	0.046 (0.098)	0.196** (0.093)	0.385*** (0.079)	0.425*** (0.064)	0.451*** (0.105)
UN (EASTERN EUROPE)	-0.187 (0.244)	0.100 (0.202)	0.383 (0.281)	0.672*** (0.193)	0.606*** (0.234)
UN (NORTHERN EUROPE)	0.020 (0.068)	0.038 (0.056)	0.069 (0.041)	0.155** (0.066)	0.286*** (0.093)
UN (SOUTHERN EUROPE)	0.213** (0.099)	0.299*** (0.112)	0.609*** (0.103)	0.761*** (0.122)	0.931*** (0.224)
UN (AFRICA)	0.001 (0.045)	0.081* (0.043)	0.136*** (0.040)	0.218*** (0.047)	0.244*** (0.068)
UN (ASIA)	-0.066 (0.132)	-0.017 (0.113)	0.051 (0.092)	-0.016 (0.225)	0.562 (0.552)
UN (CARIBBEAN)	0.000 (0.061)	0.021 (0.037)	0.086* (0.050)	0.130** (0.055)	0.111 (0.065)
UN (OCEANIA)	-0.077 (0.115)	0.029 (0.117)	-0.015 (0.094)	-0.188 (0.194)	-0.251 (0.458)
FOOT (LEFT)	-0.080 (0.053)	-0.028 (0.040)	-0.101** (0.048)	-0.136** (0.067)	-0.076 (0.070)
FOOT (RIGHT)	-0.069 (0.046)	0.042 (0.040)	0.001 (0.044)	0.017 (0.061)	0.033 (0.069)
FOOT (NOT DEFINED)	-0.195*** (0.067)	-0.072 (0.050)	-0.163*** (0.052)	-0.216*** (0.075)	-0.218*** (0.084)
POS (D-M)	0.073 (0.060)	0.007 (0.044)	0.033 (0.056)	0.022 (0.066)	-0.025 (0.088)
POS (F)	0.102** (0.041)	0.074** (0.033)	0.138*** (0.035)	0.161*** (0.041)	0.154** (0.057)
POS (F-M)	0.144 (0.122)	0.026 (0.081)	0.050 (0.073)	0.050 (0.101)	0.111 (0.190)
POS (M)	0.073** (0.030)	0.056** (0.025)	0.047** (0.025)	0.071** (0.033)	0.078* (0.043)
POS (M-D)	-0.097 (0.148)	0.014 (0.078)	-0.077 (0.051)	-0.027 (0.082)	-0.031 (0.139)
POS (M-F)	0.068 (0.060)	0.085* (0.047)	0.176*** (0.054)	0.234*** (0.062)	0.253*** (0.092)
EXP	0.059*** (0.008)	0.082*** (0.006)	0.101*** (0.006)	0.100*** (0.006)	0.102*** (0.010)
AGE	0.095*** (0.040)	0.122*** (0.032)	0.137*** (0.028)	0.142*** (0.033)	0.106** (0.044)

Table A-11, continued

Quantile Regression Results of Regular Players Using both AGE and AGE^2

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
AGE^2	-0.002**	-0.002***	-0.003***	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HEIGHT	0.003	0.001	0.002	0.004*	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
STARTS	0.018***	0.018***	0.019***	0.015***	0.011***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
SUBS	-0.013***	-0.013***	-0.016***	-0.022***	-0.021***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
GLS	0.030***	0.034***	0.035***	0.038***	0.040***
	(0.008)	(0.005)	(0.004)	(0.006)	(0.009)
AST	0.012	0.006	0.006	0.012	0.014
	(0.009)	(0.007)	(0.007)	(0.008)	(0.010)
ALLSTAR	0.334***	0.349***	0.401***	0.469***	0.385***
	(0.076)	(0.065)	(0.052	(0.056)	(0.087)
CONSTANT	-151.0***	-130.5***	-128.6***	-124.7***	-132.2***
	(8.604)	(5.770)	(6.063)	(8.054)	(9.886)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	3,596	3,596	3,596	3,596	3,596

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A-12

Quantile Regression Results of Designated Players Using both AGE and AGE^2

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
FIFA (AFC)	1.440**	1.322**	0.326	0.511	0.121
	(0.601)	(0.539)	(0.558)	(0.504)	(0.450)
FIFA (CAF)	0.565*	0.707***	0.257	0.042	-0.039
	(0.358)	(0.267)	(0.288)	(0.320)	(0.362)
FIFA	-0.383	-0.337	-0.154	0.013	-0.065
(CONMEBOL)	(0.236)	(0.222)	(0.198)	(0.253)	(0.241)
FIFA (UEFA)	-0.212	-0.045	-0.034	0.159	0.150
	(0.201)	(0.187)	(0.198)	(0.199)	(0.182)
FOOT (LEFT)	-0.135	-0.137	0.085	-0.376	-0.109
	(0.264)	(0.254)	(0.302)	(0.292)	(0.369)
FOOT (RIGHT)	-0.089	-0.027	-0.088	-0.377	-0.191
	(0.234)	(0.202)	(0.250)	(0.263)	(0.330)
FOOT (NOT	0.387	0.310	0.314	0.378	0.459
DEFINED)	(0.492)	(0.493)	(0.647)	(0.749)	(0.809)
POS (D-M)	0.071	0.149	-0.399	-0.768	-1.251**
	(0.344)	(0.337)	(0.400)	(0.575)	(0.612)
POS (F)	0.097	0.177	0.256	0.336	-0.006
	(0.344)	(0.293)	(0.244)	(0.292)	(0.396)
POS (F-M)	-0.111	-0.218	0.094	0.055	0.205
	(0.469)	(0.452)	(0.471)	(0.558)	(0.730)
POS (M)	0.172	0.149	0.068	0.202	-0.070
	(0.311)	(0.271)	(0.235)	(0.279)	(0.377)
POS (M-D)	0.097	0.075	-0.459	-0.808	-1.283**
	(0.294)	(0.322)	(0.366)	(0.539)	(0.616)
POS (M-F)	0.418	0.607*	0.342	0.294	-0.099
	(0.402)	(0.343)	(0.300)	(0.341)	(0.463)
EXP	0.091***	0.077***	0.103***	0.089***	0.108***
	(0.026)	(0.026)	(0.025)	(0.089)	(0.036)
AGE	0.485**	0.378**	0.217	0.396*	0.319
	(0.194)	(0.187)	(0.205)	(0.233)	(0.227)
AGE^2	-0.008**	-0.006*	-0.004	-0.007*	-0.006
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
HEIGHT	-0.018*	-0.010	-0.001	0.018*	0.012
	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)
STARTS	-0.018**	-0.011	-0.012	-0.023***	-0.022**
	(0.009)	(0.008)	(0.009)	(0.010)	(0.010)
SUBS	-0.051*	-0.053***	-0.045***	-0.060***	-0.048**
	(0.028)	(0.023)	(0.022)	(0.019)	(0.022)
GLS	0.025*	0.005	0.001	0.004	0.007
	(0.012)	(0.013)	(0.012)	(0.014)	(0.014)
AST	-0.019	-0.015	0.013	0.048*	0.023
	(0.024)	(0.021)	(0.026)	(0.023)	(0.021)

Table A-12, continued

Quantile Regression Results of Designated Players Using both AGE and AGE²

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
ALLSTAR	0.279*	0.402***	0.439***	0.322**	0.249*
	(0.141)	(0.142)	(0.123)	(0.135)	(0.138)
CONSTANT	-239.7***	-241.5***	-176.5***	-220.5***	-100.0
	(66.358)	(67.516)	(60.930)	(69.391)	(78.377)
YEAR (Controlled)	YES	YES	YES	YES	YES
CLUB (Controlled)	YES	YES	YES	YES	YES
Observations	290	290	290	290	290

Notes: Standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.