Department of Economics
Working Paper No. 247

Do individual salaries depend on the performance of the peers? Prototype heuristic and wage bargaining in the NBA

Harald Oberhofer
Marian Schwinner

May 2017

WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

Do individual salaries depend on the performance of the peers? Prototype heuristic and wage bargaining in the NBA*

Harald Oberhofer

Vienna University of Economics and Business
Austrian Institute of Economic Research
Harald.Oberhofer@wu.ac.at

Marian Schwinner

Stockholm School of Economics
40901@student.hhs.se

Abstract

This paper analyzes the link between relative market value of representative subsets of athletes in the National Basketball Association (NBA) and individual wages. NBA athletes are categorized with respect to multiple performance characteristics utilizing the k-means algorithm to cluster observations and a group's market value is calculated by averaging real annual salaries. Employing GMM estimation techniques to a dynamic wage equation, we find a statistically significant and positive effect of one-period lagged relative market value of an athlete's representative cluster on individual wages after controlling for past individual performance. This finding is consistent with the theory of prototype heuristic, introduced by Kahneman and Frederick (2002), that NBA teams' judgment about an athlete's future performance is based on a comparison of the player to a prototype group consisting of other but comparable athletes.

JEL classification: D82; J31; J44.

Keywords: Prototype heuristic; wage bargaining; NBA; Behavioral economics of organization;

*We are very grateful to Martina Björkman Nyqvist, Anna Dreber Almenberg, Maria Perrotta Berlin for helpful discussions and comments. This research was conducted during Marian Schwinner's visit as Junior Fellow at the Austrian Institute of Economic Research (WIFO). The hospitality of WIFO is gratefully acknowledged.

1 Introduction

One of the main results of agency theory is that properly designed contracts may align the interests of agents and the respective principal, if the contract provides incentives for the agent to choose the level of effort necessary to produce optimal output for the principal. The construction of such a contract is a rather easy computational task if the agent's actions are common knowledge to both parties. However, in most principal-agent settings it is either impossible or very costly for the principal to observe the agent's actions, which places special demand on the design of contracts. As proposed by Harris and Holmström (1982), past output may be taken as a proxy for the agent's willingness to show effort and her ability and, hence, form the foundation for contract negotiations. Here, the drawback is that output is often influenced by other factors outside of the agent's control and, thus, the principal has to decide on the appropriate compensation scheme under undesirable uncertainty.

The imperfect correlation of the agent's input and performance provides room for behavioral influences that are not considered in traditional agency theory. That is, the principal may be systematically biased in judging the cause of performance and, therefore, overestimate the importance of effort and ability. Thus, success is often wrongly attributed to internal factors of the agent. Bertrand and Mullainathan (2001), for example, show that the compensation of oil company executives is positively related to a raise in oil prices even though worldwide prices are set by global demand and the strategic behavior of the Organization of the Petroleum Exporting Countries (OPEC). Conversely, the executives' wage compensation is identified to be not affected by reductions in oil prices. Furthermore, wage preferences may depend on reference points such as past compensation. Camerer, Babcock, Loewenstein, and Thaler (1997) show that cab drivers adjust their daily labor supply according to an income target and Fehr and Goette (2007) find similar results in a field experiment with bicycle messengers.

This paper focuses on the principal's judgment of the agent's future performance and possible biases due to fundamental uncertainty regarding the output determining process. Tversky and Kahneman (1974) identified heuristics that may affect the principal's estimates of the ability and future effort of the agent according to the level of representativeness with respect to situations that come easily to mind. According to this theory, the principal may base her judgment about the value of the agent on past situations that serve as a comparison to current negotiations. As a consequence, the agreed compensation may depend on a set of available observations that show enough similarity. Consequently, we empirically test for the concept of *prototype heuristic* introduced by Kahneman and Frederick (2002), which states that judgments under uncertainty may be partly based on the principal's perception of the agent's prototype which can be operationalized as the average value of salient properties of a "homogeneous" set the agent belongs to.

This paper relies on a unique data-set for professional basketball players in the National Basketball Association (NBA) available for the years from 2009 to 2016. The labor market in the NBA provides an ideal environment to study behavioral effects in contract negotiations due to the availability of rich information on athlete performance, individual characteristics and compensation structures. Moreover, basketball is governed by a well defined set of rules and marginal contributions to team success (i.e., individual productivity) may be easily identified.

Athlete performance in the NBA is multi-dimensional and every player on the court needs to fulfill a certain role for the team to be successful. In the framework of this paper, we categorize athletes with respect to productivity dimensions in order to form representative sets of athlete roles. Based on this classification, average group-specific annual income is calculated which may be interpreted as the relative market value of a prototype. The main hypothesis to be tested is that wage bargaining in the NBA is governed by a prototype heuristic, such that past realized market values of the role of the athlete the teams are currently negotiating with affects offered wages.

The data provide broad support for this main hypothesis as one-period lagged role-specific market value does in fact positively affect individual salaries after controlling for individual performance. Given the visibility and competitiveness in professional sports, it is likely that NBA teams find it relatively easy to evaluate an athlete's ability and willingness to show effort by observing his on-court performance. However, individual wages are additionally affected by the past performance of the cluster the athlete is a member of, thus, clearly contradicting the main prediction from a simple principal-agent model that compensation is solely based on the agent's signaling of ability and effort.

In Section 2, we motivate the empirical work with a theoretical agency model and discuss implications of judgment bias regarding the principal's payment decision under uncertainty. Section 3 gives a brief background regarding the institutions governing individual contracts and market entry in the NBA and how athletes may be categorized by potential employers. Section 4 presents the utilized data, econometric methods and clustering techniques applied. Section 5 discusses the estimation results and provides a sensitivity analysis. Finally, Section 6 offers some concluding remarks.

2 Theoretical framework and relevant literature

A large body of theoretical literature on optimal contract theory discusses agency costs and the conceptional problem of moral hazard in contract negotiations.[1] This section presents a theoretical model of wage dynamics based on Harris and Holmström (1982) illustrating the principal's payment decision under uncertainty. In the NBA athletes are free to negotiate new contracts with any of the thirty teams. They are also allowed to negotiate contract extensions with current employers. Assuming that the athlete's effort is independent of the principal, all hypothetical future employers face the same judgment decision upon the athlete's ability that can only be estimated by observing the athlete's past performance. This process under imperfect information may be prone to heuristics and therefore dependent on additional factors that may influence the estimation process of an agent's ability.[2]

2.1 Principal-Agent model with asymmetric information

Let us consider a standard agency model in which an employee (agent) is compensated for costly effort by an employer (principal), whose success depends on the agent's effort and ability. The optimal contract maximizes the agent's utility from effort compensation while giving incentive to choose the level of effort that maximizes the principal's utility from production.

The moral hazard problem in a principal-agent setting arises when "full observation of actions is either impossible or prohibitively costly" (Holmström, 1979, p.74). As a consequence, both agent and principal

[1]See Holmström (1979), Grossman and Hart (1983) and Hart and Holmström (1986).

[2]A number of articles discuss the influence of judgment heuristics on market settings in other contexts. For example, Kliger and Kudryavtsev (2010) find that daily market returns affect investor's reaction to analyst recommendations, Barber and Odean (2008) discuss the effect of recent news on buy-decisions of investors and Lee, O'Brien, and Sivaramakrishnan (2008) find that analysts significantly overweight recent market developments regarding long-term forecasts.

are imperfectly informed about the agent's ability, which is only indirectly observed by production, i.e. the principal is not able to distinguish between true ability, effort and noise. Harris and Holmström (1982) proposed a model of wage dynamics in which both parties learn gradually about the agent's ability by observing output over time. Due to the imperfect correlation of production and ability, output can only serve as a proxy in a contract between the principal and the agent. Formally, an agent i with ability $\eta_{i,t}$ and effort $e_{i,t}$ in period t will produce an output

$$y_{i,t} = f(\eta_{i,t}, e_{i,t}, \epsilon_{i,t}), \tag{1}$$

where $\epsilon_{i,t}$ is an error term capturing the fact that output is driven by other factors than ability and effort. The time subscript on ability reflects a dynamic development of i's ability and assures that the agent's effort is not converging to 0 if analyzed in a career setting (Holmström, 1999).

Agent i has a Bernoulli utility function over effort, e_i and wage compensation, W,[3]

$$U_i(W_t, e_{i,t}), \tag{2}$$

which is assumed to be increasing in compensation, $\frac{\partial U_i}{\partial W_t} > 0$, and decreasing in effort, $\frac{\partial U_i}{\partial e_{i,t}} < 0$. The impact of present effort on future wages determines the agent's effort decision. Principal j's Bernoulli utility function over income is defined as

$$U_j(y_{i,t}, W_t), \tag{3}$$

which is assumed to be increasing in output, $\frac{\partial U_j}{\partial y_{i,t}} > 0$, and decreasing in compensation, $\frac{\partial U_j}{\partial W_t} < 0$.

The history of outputs up to period t, $y^{t-1} = (y_1, ..., y_{t-1})$, is assumed to be common knowledge and forms the basis for effort compensation. Further, given the agent exceeds her reservation utility $\bar{U}$, principal j faces the following infinite horizon[4] utility maximization problem:

$$\max_{\boldsymbol{W}} \mathbf{E}[\sum_{t=1}^{\infty} \beta^{1-t} \cdot U_j(y_{i,t}, W_t)|y^{t-1}], \tag{4}$$

subject to the constraints

$$\mathbf{E}[\sum_{t=1}^{\infty} \beta^{1-t} \cdot U_i(W_t, e_{i,t})|y^{t-1}] \geq \bar{U}, \tag{5}$$

$$\boldsymbol{e*} := \max_{\boldsymbol{e}} \mathbf{E}[\sum_{t=1}^{\infty} \beta^{1-t} \cdot U_i(W_t, e_{i,t})|y^{t-1}], \tag{6}$$

were $\boldsymbol{W} = (W_1, W_2, ...)$ denotes the principal's strategy function regarding paid compensation and $\boldsymbol{e} = (e_1, e_2, ...)$, the agent's strategy function regarding effort. $\beta < 1$ represents a discounting factor

[3]The subscript on effort compensation is dropped to emphasize that the wage payment depends on the agent's effort choice as on the principal's judgment decision.

[4]Following the literature on wage dynamics, an infinite horizon is chosen for simplicity. This also reflects that the agent's effort decision exceeds the duration of a contract since, assuming rationality, she is eager to provide signals to potential employers in the future.

which is assumed to be constant over time. At the optimal solution ($\boldsymbol{W}^*, \boldsymbol{e}^*$), the principal maximizes her lifetime utility with respect to production under the constraint that the agent's lifetime utility exceeds her reservation utility (participation constraint) and the agent maximizes her effort with respect to her decision rule (Spear and Srivastava, 1987).

2.2 Payment decision under uncertainty

Following Holmström (1999), the agent's wage in period t is based on the expected performance in period t conditional on the history of outputs up to that period $y^{t-1} = (y_1, ..., y_{t-1})$,

$$W_t = E[y_{i,t}|y^{t-1}] = E[\eta_{i,t}|y^{t-1}] + E[e_{i,t}|y^{t-1}] + E[\epsilon_t|y^{t-1}]. \tag{7}$$

Under the assumption of an independently distributed error term with mean 0, $E[\epsilon_t|y^{t-1}] = 0$, and given utility maximization of agent i, wage in period t solely depend on $E[\eta_{it}|y^{t-1}]$, the principal's perception of ability. Harris and Holmström (1982) assume the mean belief about ability to be normally distributed with mean m_t and variance $\sigma_{m,t}$, depending on a prior belief about ability $(m_1, \sigma_{m,1})$. The principal utilizes observations of past output to estimate the value of the agent. The estimate's accuracy increases with the number of periods output is observable. The market's learning process about the agent's ability is subject to the sequence $a_t = \eta_{i,t} + \epsilon_t = y_{i,t} - e^*_{i,t}$, assuming agent i always chooses the optimal effort level. Given the normality and independence of the error term, ϵ_t, and assuming that the dynamic evolution of ability follows a random walk, $\eta_{i,t+1} = \eta_{i,t} + \delta_t$ where $\delta_t \sim iid$, the market's learning process is well defined.[5] The variance of m_t decreases with time and converges to a steady state in which learning of output observations offsets the increased uncertainty of the dynamic development of ability (Holmström, 1999).

The principal's payment decision given by (7) is the main focus of this paper. The fact that performance is driven by other factors than the agent's input makes it difficult for the principal to accurately predict future performance. The uncertain nature of the agent's future productivity forces the principal to form believes regarding the likelihood of possible scenarios. There is a large body of literature discussing behavioral heuristics in such judgment decisions under uncertainty.[6] The moral hazard setting assumes the principal's decision on the appropriate wage to be made under imperfect information about the agent's ability and may therefore be prone to behavioral effects.

Tversky and Kahneman (1974) identified three key heuristics regarding judgments under uncertainty: representativeness (probabilities are estimated with respect to similarity to stereotypes), availability (probabilities are estimated with respect to information that comes more easily to mind) and adjustment/anchoring (estimates of probabilities are subject to a prior belief). Clearly, these three heuristics are not independent by definition. Information that come more easily to mind may be used to compare probabilities to and may further serve as a prior to adjust from. Hence, Kahneman and Frederick (2002) revised the theory of judgmental heuristics and introduced the concept of *attribute substitution* as the underlying process for cognitive shortcuts affecting judgments under uncertainty. The theory describes the substitution of the target attribute in question by a heuristic attribute, in case the for-

[5]See Holmström (1999) for an extensive discussion about the market's learning process when the agent's input factors are not directly observable.

[6]See Shiller (1999) for a literature review on cognitive heuristics in financial markets and Camerer and Malmendier (2012) for an extensive discussion of applications in industrial organization.

mer is relatively inaccessible. A typical example of attribute substitution is the task of categorical prediction reported in (Tversky and Kahneman, 1973). Experiment participants were asked to rank the likelihood that a fictive student has specialized in one of nine fields after being given a description of the student. The participants reported the same judgments of probability as a control group that ranked the nine fields via similarity to a typical student of the specialization even after discrediting the student's description.[7] Clearly, the participants substituted the target attribute (probability) for an easier available heuristic attribute (similarity).

2.3 Prototype heuristic in wage bargaining

Kahneman and Frederick (2002) discuss prototype heuristic as a generalization of representativeness heuristic and a common application of attribute substitution. The target attribute is (partly) substituted by similarity; the attribute in question is compared to a set of available observations of a set, given the set is homogeneous enough. "The prototype of a set is characterized by the average values of the salient properties of its members" (Kahneman, 2003, p. 1463). A variety of experiments provide evidence that the prototype heuristic influence willingness to pay decisions (Frederick and Fischhoff, 1998) and categorical prediction (Tversky and Kahneman, 1973) among other fields.[8]

In contract negotiations, principal j is faced with the judgment of agent i's ability under uncertainty, i.e. agent i's ability is unknown and may only be estimated by the observation of the output history. As a consequence, the principal may base her judgment partly on past events that show similarity to the negotiations which come more easily to mind and serve as a baseline to which the hypothetical outcome may be compared to. In other words, past negotiation outcomes may affect the principals' willingness to pay for agent i's services given that the agent's output history is observed.

The main challenge of this analysis is to establish a measurement of similarity utilized by the average principal in the NBA to compare athletes and to identify the prototype that may influence a team's judgment on athletes' ability. In general, we want to define similarity between two agents as the number of common neighbors they share in a n-dimensional space, where neighbors in this R^n are points located in a prespecified radius around the point in question. Based on this measure of similarity, one can identify k prototypes (i.e, clusters) in R^n so that the similarities in groups are high, while the similarity between groups are low (Jain, 2010).

The categorization in groups may be utilized by potential employers to compare athletes to each other and to further frame their judgment decisions of a specific athlete's ability on observations of similar athletes. Let c be the representative cluster of agent i, a subset of all available observations N, and y_c^{t-1} be the prototype production history for all members of $c \subseteq N$, i.e. the average performance of similar enough athletes.

Assuming prototype heuristic, wage in period t depends on the individual production history and additionally on the prototype history,

$$W_t = E[y_t | y^{t-1}, y_c^{t-1}]. \tag{8}$$

[7] This was done by telling the participants, all graduate students in psychology, that the description had been written while the student was in high school and on the basis of personality tests of dubious validity. The correlation coefficient of the mean judgment of the two groups is 0.98 Tversky and Kahneman (1973).

[8] See Kahneman and Frederick (2002) for an extensive discussion of empirical evidence for prototype heuristic.

If the prototype production history influences wage decisions, $E[y_t|y^{t-1}, y_c^{t-1}] \neq E[y_t|y^{t-1}]$. Hence, the principal's payment decision is influenced by the observation of y_c^{t-1} and may lead to a different wage paid for the agent's (expected) production. This effect may either be caused by the principal's perception of agent i's ability, $E[\eta_t|y^{t-1}, y_c^{t-1}]$, or through a difference in observed productivity, given that the agent is a member of cluster c, $E[\epsilon_t|y^{t-1}, y_c^{t-1}] \neq 0$.

More explicitly, this paper considers the average wage of the representative cluster c, that reflects the prototype production history. If NBA teams base their judgment about future performance of an athlete on the prototype of the representative cluster, the cluster's average wage observed in $t-1$ should still positively affect individual wages once controlling for the athlete's individual performance.

3 Institutional background: The National Basketball Association

The NBA is the men's professional basketball league in North America. 29 out of 30 teams are located in the USA and Toronto hosts the only team in Canada. Since 1967, the regular season is 82 games long, currently starts in the last week of October and ends in April of the following year. The league is divided in two conferences, the eastern conference and the western conference whose members are competing for eight playoff spots in each conference. However, each team plays at least two times against every other team in the NBA, independent of conference assignment. This paper studies the regular season performance of athletes. Although the championship is decided in the playoffs, regular season performance is important (i) for playoff performance due to seeding[9]and (ii) for the players since it serves as a signal to potential (future) employers.

Since 1970 labor issues in the NBA are governed by a legal contract, the Collective Bargaining Agreement (CBA), negotiated between the league and the National Basketball Player's Association (NBPA). The current CBA has been effective since December 8, 2011. The contract determines minimum and maximum salaries for individual athletes, the maximum team payroll (i.e, the salary cap) and rules regarding player signings, trades, etc. As this paper analyzes signed contracts before and after December 8, 2011, we also briefly discuss similarities and differences between the current CBA and the previous one, which has been effective from 2005 to 2011. In the CBA athletes playing their first seasons are referred to as *rookies* and athletes whose contracts are expired and are able to sign a new contract are referred to as *free agents*.

3.1 Salary cap

Total team payrolls are restricted by the salary cap defined in the CBA. The NBA collects total revenues and shares them equally among all teams in the hope to ensure competitiveness. Each year's salary cap depends on league-wide projected "basketball related income" (BRI) from last year.[10] According

[9] The NBA playoffs are organized as following: The best eight teams from each conference play three best-of-seven series where the winner advances to the next round. Playoff match-ups are organized such that the first seed (best record of the regular season) of each conference has, generally speaking, the easiest path to the conference finals in that the team plays against opponents with a worse regular season record compared to the second seed's opponents. Moreover, the team with the better regular season record is guaranteed to have at least as many home games than the opponent and four out of the maximum of seven games.

[10] BRI includes items such as broadcast rights, gate receipts, sponsorships, arena naming rights and parking revenues. See National Basketball Association (2011), Article VII(1)(a)

to the current CBA, total projected income is multiplied by 44.74% before subtracting projected player benefits and averaged with respect to the number of teams to calculate next year's salary cap. From the 2005/2006 season to the 2010/2011 season, the salary cap was based on 51% of projected basketball related income. While the salary cap restricts a team's payroll, the CBA contains exceptions which allow teams to sign athletes even though the cap is already exhausted or will be exceeded after the signing. These exceptions concern signings of a team's own free agents, replacement of players with a season-ending injury/illness and replacement for traded athletes (National Basketball Association, 2011, Article VII (6)).

While teams are able to spend more in salaries than the salary cap, teams that exceed a predetermined tax level (higher than the salary cap) are required to pay a tax to the NBA. The tax-rate depends on the incremental team salary above the tax level and if the team exceeded the tax level in three of the four previous seasons. The current tax starts at 150% (250% for "repeater") up to $4,999,999 additional spending exceeding the salary cap and increases in steps of $5 million. Before the 2013/2014 season, teams paid 100% tax rate on team salary above the tax level, (National Basketball Association, 2011, Article VII (12)(f)).

3.2 Market entry

Market entry in the NBA labor market is governed by a matching process, the NBA draft, which is held prior to the commencement of each NBA season, 10^{th} of July, on a date designated by the league's commissioner. The draft consists of two rounds with the number of selections being equal to the number of teams in the league in each round. The order of selection is determined by the win-loss record of the teams from the previous season[11] (National Basketball Association, 2011, Article X (3)).

No athlete is allowed to sign a contract in the NBA unless he has been eligible for selection in at least one NBA draft. Thus, the player has to be at least nineteen years of age during the calendar year the draft is held and at least one NBA season must have elapsed between his high school graduation and the draft in question. If the athlete did not graduate from high school, at least four calendar years must have elapsed since the graduation of his hypothetical graduation class. International athletes not graduating from an US high school have to be at least twenty-two years old or apply for "Early Entry" by expressing their desire to be selected in the draft in a writing received by the NBA at least sixty days prior to the draft. In order to be eligible for the NBA draft, international players have to be at least nineteen years old, (National Basketball Association, 2011, Article X (1)).

Once an athlete is selected by a team, a rookie scale contract may be negotiated. All rookie scale contracts with first round selections (currently selections one to thirty) include two guaranteed years with two separate one-year team options for season three and four. The agreed salaries are restricted for the full duration of the rookie contract and decreasing in the pick number. The first pick in 2015 received a first-year salary of $4,753,000 while the tenth pick received a first-year salary of $2,068,100 , (National Basketball Association, 2011, Article VIII (1)). Second round selections (currently selections thirty-one to sixty) do not have a salary scale like first round picks. They are free to negotiate any contract with the team that selected them. All undrafted athletes become unrestricted free agents and are allowed to negotiate contracts with any team in the NBA.

[11] The first draft-round is subject to a lottery process. The fourteen worst teams from the previous season obtain weighted chances to receive a certain selection number. For example, the worst team has a 25% chance to receive the first selection in next year's draft, while the 14th worst team has only a 0.5% chance.

3.3 Contract background

Once an athlete entered the NBA labor market, he is eligible to sign extensions or new contracts under certain time constraints.[12] Contract length is restricted to a maximum of five years under the current CBA. From the 2005/2006 season to the 2010/2011 season, a contract may have included an additional sixth year for *qualifying veteran free agents*.[13] Depending on the status of the current contract, an athlete may be able to negotiate a contract with any team in the NBA or to negotiate an offer sheet with any team which can be matched by the current employer. The latter situation is referred to as *restricted free agency* and is effective in the fourth year of a rookie scale contract if the team opted to keep the athlete under contract for the third and fourth season or for athletes who have been in the league three or fewer years, (National Basketball Association, 2011, Article XI (1)).

Additionally to restrictions on team payroll, athletes' individual salaries are governed by the CBA as well. Both, minimum and maximum salaries are based on the athlete's years of service in the league. In the 2015/2016 season, minimum salaries ranged from \$525,093 for athletes with zero years of experience up to \$1,499,490 for athletes with a minimum of ten years of experience in the NBA.[14]

Maximum limits on athletes' salaries are based on the salary cap and previous experience. For a player with up to six years of experience, the greater of 25% of the salary cap or 105% of the player's salary for the last year of the previous contract serves as the upper limit. For athletes between seven and nine years of experience, the greater of 30% of the salary cap or 105% of the player's salary for the last year of the previous contract serves as the upper limit, while a player with a minimum of ten years of experience may be eligible to receive a salary up to 35% of the salary cap or 105% of the player's salary for the last year of the previous contract. Additionally, the CBA 2011 introduced an exception regarding rookie contract extensions. If the athlete meets one of the following "30% Max Criteria" by the time of the contract extension, he is eligible to receive a salary between 25% and 30% of the salary cap: The player has been (i) named to the All-NBA first, second or third team (best fifteen athletes of the regular season voted by journalists) at least two times, (ii) voted an All-Star starter (five most popular athletes according to fan votes) at least two times, or (iii) named NBA MVP (most valuable player voted by journalists) at least once (National Basketball Association, 2011, Article II (7)).

3.4 Similarity of NBA athletes

The most obvious and simplest form of categorization in the NBA clusters athletes with respect to their official positions. The positions of the five athletes on the court are point guards (PG), shooting guards (SG), small forwards (SF), power forwards (PF) and centers (C) which are traditionally responsible for different tasks on the court. The point guard, for example, is the team's ball handler and play maker. He is responsible to lead the team on offense and put teammates in positions to succeed. However, the categorization in positions is very abstract and does not always necessarily reflect the contribution of an athlete.

[12]See National Basketball Association (2011), Article VII (7)

[13]The athlete must have played exclusively for one team for the last three seasons. However, if the player has been traded to another team during these three years, he still had the right to sign a contract of six years.

[14]See Table B1 in Appendix B for a detailed visualization of minimum and maximum salaries from the 2009/10 season to the 2015/16 season, (National Basketball Association, 2011, Article II (6)).

Take following example: Russell Westbrook and George Hill are two successful NBA athletes in our sample, both primarily playing on the PG position. Selected productivity measurements for the 2015/16 season, displayed in Table 1, show a tremendous difference in the role provided by these two PGs. The performance measures are "$3Par$", the share of three-point field goal attempts that are further away from the basket relative to overall field goal attempts; "$TRb\%$", the percentage of possessions after a missed field goal attempt that the player successfully obtained the ball; "$Ast\%$", the share of teammates' scoring possession the athlete assisted on; "$Usg\%$", the percentage of possessions used by the athlete while on the court[15]; "Pts/g", average points per game scored. While Russell Westbrook used a majority of team possessions himself (31.6% while he was on the court) and assisted on almost 50% of teammate's field goals, George Hill only used about 15.8% of team possessions but took almost 43% of his field goal attempts from three-point area, suggesting that he is more of a recipient of teammate's assists. The third player displayed in Table 1, Jared Dudley, had quite similar average statistics to George Hill and one may conclude that based on these characteristics, George Hill is *more similar* to Jared Dudley than to Russell Westbrook. However, while Weestbrook and Hill are categorized as PGs, Dudley plays a completely different position as PF, whose job description is traditionally very different from that of a PG. Such heterogeneity among members of positions is the reason why we apply different definitions of similarity among athletes for defining prototypes.

Table 1: point guard and power forward comparison: An example

	$3Par$	$TRb\%$	$Ast\%$	$Usg\%$	Pts/g
Russell Westbrook	0.236	0.124	0.496	0.316	23.475
George Hill	0.425	0.650	0.155	0.158	12.081
Jared Dudley	0.489	0.760	0.114	0.127	7.877

Notes: $3Par$ is the fraction of three-point field goals attempts of total field goal attempts ,$TRb\%$ is the percentage of successfully executed rebounds while on the court, $Ast\%$ is the percentage of assisted teammate's field goals while on the court, $Usg\%$ is the percentage of the team's possession ended by the player while on the court and Pts/g is the number of scored points per game.
Data are for the 2015/2016 regular season and obtained from http://www.basketball-reference.com on 30th of October, 2016.

Although the five basketball positions may not accurately describe the on-court role of athletes in the NBA, there are obvious heterogeneities between position averages. Moreover, NBA teams may be interested in the ability of an athlete to play at a certain position rather than his performance characteristics and, thus, explicitly consider the official position in their hiring decision. Table 2 displays position averages and standard deviations for the five performance measurements just discussed. The data indicates that power forwards and centers are, on average, superior rebounder with a percentage of available rebounds successfully recovered, $TRb\%$, of 13.6% and 15.9%, respectively. As a comparison, the sample average of $TRb\%$ is 10%. Wing positions, shooting guards and small forwards, are traditionally great shooters and scorers which is indicated by their rate of three point attempts relative to total field goal attempts of 37.2% and 35.8%, respectively, and high points per game averages. The average point guard is the team's primary facilitator, indicated by an $Ast\%$, the percentage of team field goals assisted, of 27.6% which exactly doubles the sample average. While this is a vary narrow picture of the multidimensional performance requirements in NBA games, it still shows that there are heterogeneities between positions. The standard position classification will thus serve as our baseline measure for prototypes which will latter on be compared with more sophisticated prototype

[15]Possessions end by field goal attempts, free throws and turnover. See Section 4.1 for an extensive discussion of the variables used in for the empirical analysis.

categorizations.

Table 2: Summary statistics - comparison of positions

	$3Par$	$TRb\%$	$Ast\%$	$Usg\%$	Pts/g	N
PG	0.324 (0.147)	0.059 (0.014)	0.276 (0.085)	0.207 (0.046)	10.789 (5.291)	475
SG	0.372 (0.157)	0.064 (0.017)	0.140 (0.067)	0.201 (0.047)	10.868 (5.269)	501
SF	0.358 (0.177)	0.088 (0.021)	0.105 (0.054)	0.181 (0.047)	9.823 (5.476)	469
PF	0.153 (0.193)	0.136 (0.032)	0.089 (0.046)	0.191 (0.047)	9.879 (5.392)	501
C	0.024 (0.069)	0.159 (0.031)	0.080 (0.045)	0.180 (0.052)	9.090 (5.037)	440
Total	0.250 (0.205)	0.100 (0.046)	0.138 (0.094)	0.192 (0.049)	10.111 (5.335)	2,386

Notes: Means calculated over all active players from the 2009/2010 season to the 2015/2016 season; Standard Deviations in parenthesis.
Data obtained from http://www.basketball-reference.com on 30th of October, 2016.

4 Data and econometric framework

4.1 Data

The utilized data contains performance measures, player characteristics and salary information for 884 athletes from the 2009/2010 to the 2015/2016 season, resulting in an unbalanced panel with 2,386 observations. We excluded observations of athletes who played fewer than 100 minutes in the season and/or got payed less than the minimum annual salary.[16] Performance statistics are collected from Basketball-reference.com and NBA.com. Salary statistics were drawn from ESPN.com, and Basketball-reference.com. A variables description and simple summary statistics are provided in Table 3.

We collect two different individual performance measures for NBA players, Win Shares (WS) and Value over Replacement Player (VORP), which are publicly available at Basketball-reference.com. Both are based on box score data, a variation of production variables collected by the NBA for every official game, and combine the performance dimensions into one single production variable. The most important difference between the two variables is the method of estimating individual player production with box score variables. While VORP utilizes a $+/-$ method, that is, the positive or negative margin the team performed relative to its opponents while the athlete performed on the court, WS is based on techniques introduced by Oliver (2004) to decompose individual production into contribution parts and assign them to the responsible athletes. That being said, VORP and WS are highly correlated in our sample, with a correlation coefficient of 0.912. Appendix A provides a detailed overview on how both measures are calculated.

The box score captures the official statistics collected for every official game by the NBA. A typical game has 48 minutes, although some games may exceed this if the score is tied after the regular playing time. Statistics collected and used in this paper include the amount of games each player participated

[16] NBA teams are able to sign free agent athletes for up to two 10 day contracts per season. The agreed base annual salary is adjusted for the number of working days. Due to possible bias of the results and the low number of observations that display a salary below the respective minimum wage, we decided to exclude athletes on 10 day contracts. Moreover, athletes who played less than 100 minutes during a season are excluded in order to account for season-ending injures.

in during the regular season and the average amount of minutes an athlete played per game. Further, the amount of points scored is recorded and the average points per game during a season together with efficiency estimates (e.g., percentage of scoring attempts converted) serve as an approximation of scoring ability. Scoring attempts in the NBA are referred to as field goal attempts and may yield two or three points depending on the distance to the basket if converted successfully. Moreover, the athlete receives two (three) free throws if he is fouled during a field goal attempt or in case the opposing team has already exceeded a threshold of fouls committed. Free throws are unopposed attempts close to the basket. The box score also includes assists (a pass by the athlete that leads to a basket), rebounds (gaining possession of the ball after a missed field goal attempt), steals (actively gaining possession of the ball from the opponent), blocks (legally deflecting an opponent's field goal attempt) and turnovers (losing possession of the ball). All the box score variables enter the analysis as season per game averages in order to capture a robust estimate of an athlete's performance related market value.

There is a large body of literature utilizing pure box score data to measure athlete performance such as Kopkin (2012), Stiroh (2007) and Yang and Lin (2012). With the utilization of more advanced productivity measures, we intend to capture dimensions of performance that are neglected when focusing on simple box score data. WS and VORP are adjusted for the performance of teammates and opponents and account for the pace of a game. These adjustments are important since box score variables scale with the amount of possessions and playing time of athletes. Measures that account for these factors are therefore able to better estimate the individual contribution to a team's overall success. That being said, the chosen performance variable still struggles to identify individual contributions on the defensive end and complementary contributions of athletes to productivity of their teammates. However, we are not too concerned about these shortcomings as Berri, Brook, and Schmidt (2007) and Kuehn (2017) showed that both defensive as complementary contributions are hardly valued in the NBA labor market and individual salaries are mostly driven by individual offensive contributions.

4.2 Econometric framework

This paper focuses on the contract bargaining outcomes between NBA teams and athletes. We utilize panel data to control for unobserved heterogeneity between individuals exploiting within-individual variation. The utilized data is compiled at a regular seasonal basis but does not include any information about contract status. Since contracts in the NBA may exceed one season, we have to control for autocorrelation of individual salaries over time. The basic econometric specification thus reads as following:

$$W_{i,t} = \alpha W_{i,t-1} + \beta' y_{i,t-1} + \delta' \omega_{c,t-1} + \kappa' x_{i,t} + \lambda_t + \gamma_i + \epsilon_{i,t}, \tag{9}$$

where $W_{i,t}$ is the log of the individual wage in period t, $y_{i,t-1}$ denotes the individual performance in period $t-1$ measured via WS and VORP, $x_{i,t}$ is a vector of individual time-varying characteristics and $\epsilon_{i,t}$ is an *iid* error term with $\epsilon_{i,t} \sim (0, \sigma_\epsilon^2)$. γ_i represents (time-invariant) individual fixed effects capturing unobserved between-player heterogeneity. λ_t controls for common time-effects by means of seasonal dummy variables. $\omega_{c,t-1}$ is a vector of variables representing prototype wages. Time-dependence in wages is modeled with an AR(1) process in individual wages with the corresponding coefficient α. The remaining parameters to be estimated are collected in the vectors β', δ' and κ', respectively.

Table 3: Variable definitions and descriptive statistics

Variable	Description	Mean(SD)	N
W	Annual Salary in 100,000 (2016 \$)[a]	61.607 (57.275)	2,364
WS	Estimated Productivity - Win Shares	3.523 (2.888)	2,386
$VORP$	Estimated Productivity - Value over Replacement Player	0.894 (1.419)	2,386
Age	An athlete's age	26.696 (4.178)	2,386
$All-Star$	Dummy variable: equals 1 if the athlete was named an NBA All-Star, voted by fans and coaches	0.075 (0.264)	2,386
$Rookie$	Dummy variable: equals 1 if the athlete is still in his rookie contract	0.302 (0.459)	2,386
$Games$	Number of games played	64.972 (14.149)	2,386
$Minutes$	Number of average minutes played per game	24.381 (7.521)	2,386
$Points$	Number of average points per game	10.111 (5.335)	2,386
$Rebounds$	Number of average rebounds per game	4.275 (2.429)	2,386
$Assists$	Number of average assists per game	2.213 (1.887)	2,386
$Turnover$	Number of average turnover per game	1.393 (0.746)	2,386
$Steals$	Number of average steals per game	0.768 (0.409)	2,386
$Blocks$	Number of average blocks per game	0.494 (0.480)	2,386
$Ast\%$	An estimate of teammates' field goals the athlete assisted for while on the floor	0.138 (0.094)	2,386
$TRb\%$	An estimate of available rebounds successfully executed	0.100 (0.046)	2,386
$ORb\%$	An estimate of available offensive rebounds successfully executed	0.053 (0.039)	2,386
$DRb\%$	An estimate of available defensive rebounds successfully executed	0.148 (0.059)	2,386
$Efg\%$	An estimate of shooting efficiency accounting for higher value of three-point field goals	0.498 (0.049)	2,386
$3Par$	A measure of the athlete's frequency of three-point field goal attempts	0.250 (0.205)	2,386
$Dbpm$	Estimated impact on defense	-0.056 (1.730)	2,386
$Usg\%$	An estimate of the percentage of team possessions used by the athlete	0.192 (0.049)	2,386

Notes: Means and standard deviations are calculated by pooling data from the 2009/2010 season to the 2015/2016 season. See Table B2 in Appendix B for the calculation process for the transformed variables $Ast\%$, $ORb\%$, $DRb\%$, $Efg\%$ and $Usg\%$.

[a]Annual Salaries are deflated with respect to the salary cap, the maximum budget teams are allowed to spend on salaries without league penalty. See Section 3.1 for a detailed discussion.

Estimating (9), by means of a fixed effects (FE) estimation controls for individual characteristics that may affect estimated coefficients if omitted. However, the inclusion of the lagged dependent variable on the RHS of the equation introduces an endogeneity problem, (Nickell, 1981). Arellano and Bond (1991) proposed a dynamic model that utilizes an instrumental variable approach in a GMM framework, referred to as "difference GMM" in the literature, to estimate the coefficient of lagged independent variables. Since $W_{i,t-2}$ is highly correlated with $W_{i,t-1}-W_{i,t-2}$, but not with $\epsilon_{i,t}-\epsilon_{i,t-1}$, as long as the error terms are not serially correlated, the authors proposed to use it as an instrument for $W_{i,t-1}-W_{i,t-2}$. Further, contemporaneous realizations and up to two lags of the independent variables may serve as additional instruments.

Blundell and Bond (1998) proposed a slightly different estimator, referred to as "system GMM estimator". This method is an augmented version of the GMM estimator, which utilizes the equation in levels and first differences to obtain additional instruments. The authors showed that the difference GMM estimator tends to be biased if the autocorrelation coefficient is close to unity or the variance in the individual-specific error term is relatively large.

The core principal of GMM is to weight the moments of the two stage least squares (2SLS) estimator to satisfy all moment conditions in a finite sample.[17] The GMM estimator is efficient if the methods

[17]For an introduction in linear generalized method of moments estimation see Baum, Schaffer, and Stillman (2003) and for an application in STATA see Roodman (2006).

are weighted in inverse proportion to their variances and covariances, which, however, are unknown ex-ante. Hence, in a first GMM regression, the moments are weighted by an arbitrary matrix, mostly assuming homosekdasticity. The residuals of the first regression may then be used to construct a matrix that accounts for heteroskedasticity and within-individual covariances in a second estimation, referred to as two-step GMM. This analysis will focus primarily on two-step system GMM estimations of the dynamic model, utilizing the Windmeijer (2005) error correction. Following Roodman (2009), we report the number of instruments applied, standard autocorrelation tests for the error term and the Hansen (1982) J test statistics for the validity of the overidentifying restrictions.

4.3 Prototype wages and cluster analysis

The main hypothesis of this paper is that individual wages are, in addition to past performance also affected by evaluations of past performances of similar athletes. The definition of similarity is key, since categorization is a relative process. Therefore, we apply different cluster-specifications which are, in turn, tested against each other.

Let $\{1, ..., i, ..., C\} \in c \subseteq N$ be the representative cluster of individual i, a subset of all individuals N, based on n performance characteristics. Then the average cluster-specific wage,

$$\omega_{c,t} = \frac{\sum_{j=1}^{C} W_{j,t}}{C}, \tag{10}$$

represents the relative average market value of cluster c in period t, referred to as prototype wage for individual i in period t. Following the psychological theory discussed in Section 2, we hypothesize that NBA teams may base their payment decision (at least) partly on one-period lagged prototype wages in order to estimate the athlete's future expected production.

The main hypothesis of this paper is that $\delta' > 0$, i.e. that an athlete's individual wage is positively and significantly affected by one-period lagged average cluster-specific income. Hence, an increase in prototype wage in period $t-1$ should positively impact individual wages holding individual productivity, time-varying and time-constant individual characteristics constant. On the other hand, in case wage decisions are solely based on assessing the players' individual characteristics, $\delta = 0$ would be expected.

As highlighted in Section 3.4, the simplest way for to categorize NBA athletes is to consider the five prespecified official positions. However, this specification may neglect a lot of useful information that would suggest a categorization in more than five groups or based on factors that are not captured by this classification. To account for this, we utilize an hierarchical clustering algorithm to identify groups of athletes depending on specified productivity characteristics in order to offer a more detailed analysis of potential prototypes.[18]

One of the most widely used clustering method is the k-means algorithm, introduced by MacQueen (1967). The algorithm categorizes N observations from an n-dimensional space into K groups so that the similarities of observations within groups are high and the similarities between the group

[18] In the economics literature, hierarchical cluster algorithms have been utilized e.g., to identify potentially failing banks (Alam et al., 2000), to classify hedge funds based on their investment strategy (Das, 2003) and to categorize firms according to their coordination strategies in global markets (Roth, 1992).

averages are low. Formally, let $X = \{x_{i,j}\}, i = 1, 2, ..., N, j = 1, 2, ..., n$ be the set points in R^n over N observations to be clustered into a set $C = \{c_k\}, k = 1, 2, ...K$ of K clusters. Further, let μ_k be cluster k's centroid. The k-means algorithm minimizes the objective function,

$$J(C) = \sum_{k=1}^{K} \sum_{x_{i,j} \in c_k} \parallel x_{i,j} - \mu_k \parallel^2, \tag{11}$$

the sum of squared residuals between every point in c_k and the cluster specific centroid over all cluster K. The algorithm starts with an initial partition with K clusters, assigns each point to a cluster and calculates the centroids. These steps are repeated until the algorithm converges to a local minimum of the objective function, in that the assignment of new centroids does not change from the previous step. The k-means algorithm requires user input about the number of groups observations are clustered in, K, and the n dimensions clustered on.

In our framework we utilize the k-means algorithm to categorize NBA athletes in homogeneous groups with respect to a number of performance measurements. Thereby, the goal is to describe the role of an NBA player on the court as closely as possible and to be able to cluster athletes accordingly. We are aware that classification is something subjective and vague in nature and it is therefore a difficult task to identify the appropriate specification of dimensions and number of groups used by teams to compare athletes with each other. Hence, the clustering of observations will be tested carefully.

According to Jain (2010) the most common method to identify the number of most reasonable groups is to compare the within group sum of squared residuals (WSS) of possible number of clusters K given by equation (11). The WSS will naturally decrease and converge to zero as K approaches the number of individuals and we are looking for a solution at which the convergence of WSS is slowing down, thus indicating that the marginal reduction of the within-cluster sum of squares of adding additional cluster decreased. This method is loosely referred to as "elbow method" due a kink of the WSS plot on the number of clusters K. Using a similar approach, we utilize the proportional reduction of WSS denoted as PRE_K of each possible cluster solution K compared to the one-step previous solution $K - 1$:

$$PRE_K = \frac{WSS(K-1) - WSS(K)}{WSS(K-1)}. \tag{12}$$

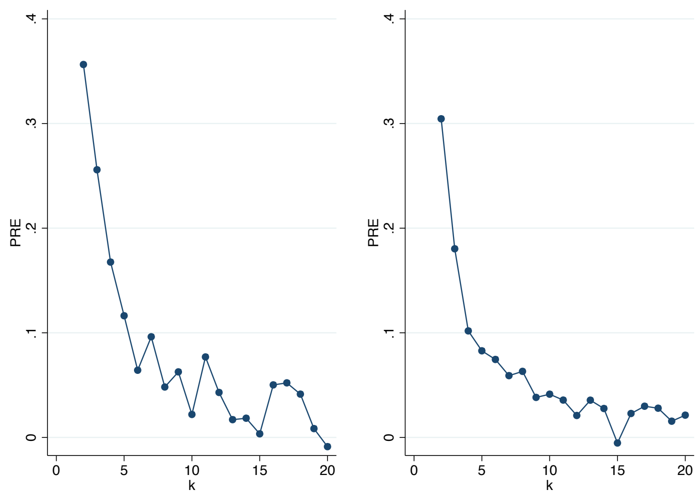
As with WSS, PRE_K converges to zero as K increases. A solution candidate would display a positive spike in the PRE graph on K as it reduces the within-cluster sum of squares notably compared to the solution with $K-1$ groups.

This paper considers two different specifications to define athlete roles on the basketball court. The first specification utilizes simple box score variables in per game averages over a season such as points, assists and rebounds per game. The second specification relies on transformed variables that account for playing time and pace of teams. Figure 1 presents the PRE graph for the two specifications. The first specification with respect to the box score variables suggests $K = 11$ as a resonable solution candidate since the PRE graph displays a significant spike. For the specification with respect to the transformed variables, the PRE graph displays no obvious spikes. The solution with eight clusters ($K = 8$) offers the greatest reduction of WSS compared to the solution $K-1$ for all solutions with $K > 6$ and thus will be used in the consecutive analysis.[19]

[19] As a robustness check, we conducted estimations with the prototype wage variables for the cluster solution $K = 7$

See Table B3 in Appendix B for summary statistics of the prototype variables utilized in our analysis and the figures in Appendix C for cluster-specific time series of prototype wages over the sample period. Figure C1 refers to the time series of prototype wages for the five official positions in the NBA while Figure C2 displays the time series of prototype wages based on the simple box score variables and eleven clusters. Figure C2 presents the time series with respect to transformed variables for each of the eight respective prototypes.

Figure 1: PRE of two alternative cluster specifications



Notes: Both graphs present the PRE for differing K but a constant vector of standardized variables as input for the k-means algorithm, where $PRE_K = \frac{WSS(K-1)-WSS(K)}{WSS(K-1)}$. The variables utilized in panel a are points, assists, rebounds, turnover, steals and blocks per game. The variables utilized in panel b are points per game, ast%, ORb%, DRb%, efg%, 3PAr, dbpm and usg%. For the definition of the variables please see Table 3 and Table B2 in Appendix B.

5 Results

This section reports and discusses the estimation results for the econometric specification discussed in Section 4.2. In particular we offer an empirical test for the prototype wage hypothesis by applying different cluster-specifications for the construction of potential prototypes. The categorization based on the official field positions serves as the baseline and will be compared to more sophisticated specifications. If NBA teams really base their payment decision on a comparison of the athlete to his peers, prototype wages are expected to affect individual wages after controlling for individual performance (and other characteristics).

5.1 Main findings

In the consecutive discussion we rely on a slightly modified specification of equation (9) which accounts for the empirically constructed prototype wages. In particular, the model reads as:

with respect to box score variables and for the cluster solution $K = 13$ with respect to transformed variables. System GMM estimations report similar results and are available from the authors upon request.

$$W_{i,t} = \alpha W_{i,t-1} + \beta y_{i,t-1} + \delta' \omega_{i,t-1} + \kappa' x_{i,t} + \lambda_t + \gamma_i + \epsilon_{i,t}, \tag{13}$$

where $\omega = (\omega_{pos}\ \omega_{11}\ \omega_8)'$ represents the prototype wage vector. ω_{pos} is the prototype wage with respect to the official positions, ω_{11} is based on points, assists, rebounds, turnover, steals and blocks per game considering 11 groups, and ω_8 is the prototype wage constructed from points per game, ast%, ORb%, DRb%, efg%, 3PAr, dbpm and usg% considering 8 clusters. The elements of δ are the coefficients of main interest. The application of prototype heuristic in wage bargaining would suggest that at least one of these coefficients is statistically significant and positive. All prototype wage variables are expressed in million USD and thus the coefficients can be interpreted as percentage change in individual wages when the prototype wage increases by $1 million.

Furthermore, due to obvious multicollinearity in our productivity variables (the bivariate correlation coefficient for *WS* and *VORP* amounts to 0.915) we only include *WS* in equation (13) to measure individual performance. This choice for *WS* is based on initial regressions in which both variables are included simultaneously but no information on prototype wages have been included. In this setting *WS* turned out to be statistically significant throughout while once we we control for *WS*, the coefficient on *VORP* becomes insignificant.[20] However, in our sensitivity analysis we investigate this issue further by providing alternative specifications for individual productivity. Furthermore, and in order to account for the institutional regulations in the NBA wage setting process $x_{i,t}$ includes age and age-squared together with a contemporaneous and a lagged rookie dummy variables. The former accounts for a potential non-linear wage-age premium where wages would likely increase with a decreasing rate with age. The rookie dummies intend to control for highly regulated market entry wages as explained by the NBA's draft system (see Section 3.2).

Table 4 reports system GMM estimation results for equation (13). Column (1) presents results when only considering prototype wage with respect to the five official positions. Columns (2) and (3) separately include the prototype wages based on the two preferred numbers of clusters amounting to 11 groups for simple box score data and to 8 groups for the transformed box score variables. Column (4) simultaneously accounts for all three different potential prototype wages. Furthermore, we also include dummy variables for the different prototype groups in order to control for remaining unobserved time-invariant differences across these cohorts.

At the bottom of Table 4, we report the relevant test statistics for the validity of the obtained system GMM estimates. In particular, the model would be misspecified when finding a remaining significant AR(2) process in the error term. As indicated by the reported p-values we do not find any evidence for remaining auto-correlation of order 2 and thus the model seems to accurately capture the dynamics in NBA wages over time. Furthermore, the Hansen J test allows to assess the overidentification restrictions necessary for the instrumenting strategy to provide consistent parameter estimates. Across all four specifications we are not able to reject the null hypothesis concerning the exogeneity of the instruments which provides us with confidence on the validity of the identified estimates.

The coefficient on the one-period lagged dependent variable is statistically highly significant in all specifications and amounts to a point estimate of about 0.47 to 0.51, indicating the need to control for persistence in NBA wages over time. The parameters associated with the other covariates collected in $x_{i,t}$ are well in line with our expectations. In particular, NBA wages tend to increase with a player's age but at a decreasing rate. This is suggested by the positive and significant parameter for the linear

[20] These estimation results are available from the authors upon request.

age term identified across all four different specifications and negative but smaller estimates associated with squared age. In a similar vein and on average, rookies earn substantially less when individual performance is held constant. NBA teams pay on average 9.8% less for rookies compared to what a similar athlete would be worth. Moreover, the negative premium increases to about 32% in the last year of an athlete's rookie contract. That being said, athletes tend to be overpaid by an average of 21.3% in the first year of their first non-rookie contract, probably to account for their losses during the previous contract.[21] With regard to individual productivity we also find a robust and positive relationship. This finding provides evidence for an individual productivity wage channel through which NBA players with better performance are compensated with higher wages.

Table 4: Main estimation results

	Dependent Variable: Log Salary in 100,000 (2016 $)			
	(1)	(2)	(3)	(4)
W_{t-1}	0.506***	0.473***	0.503***	0.483***
	(0.057)	(0.060)	(0.058)	(0.059)
WS_{t-1}	0.085***	0.040***	0.061***	0.038***
	(0.009)	(0.005)	(0.007)	(0.006)
$\omega_{pos,t-1}$	0.021			0.014
	(0.021)			(0.019)
$\omega_{11,t-1}$		0.036***		0.033***
		(0.007)		(0.008)
$\omega_{8,t-1}$			0.021***	0.001
			(0.006)	(0.006)
Age_t	0.225***	0.263***	0.229***	0.252***
	(0.058)	(0.056)	(0.056)	(0.055)
Age_t^2	-0.004***	-0.005***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Rookie_t$	-0.338***	-0.311***	-0.330***	-0.319***
	(0.064)	(0.066)	(0.065)	(0.065)
$Rookie_{t-1}$	0.267***	0.213***	0.245***	0.214***
	(0.056)	(0.055)	(0.057)	(0.055)
Dummies position	YES	NO	NO	YES
Dummies 11 cluster	NO	YES	NO	YES
Dummies 8 cluster	NO	NO	YES	YES
Instruments	33	39	36	52
Arellano-Bond AR(2) (p-value)	0.940	0.536	0.891	0.682
Hansen J (p-value)	0.253	0.221	0.235	0.119

Notes: Standard Errors are clustered with respect to individuals and are reported in parentheses. Estimates are based on two-step system GMM with the Windmeijer (2005) error correction using three lags to instrument for the lagged dependent variable in differences. All estimations include year-specific dummy variables. *, **, *** ...significant at 10%-, 5%- and 1%-level, respectively

[21] These are point estimates from column (2) in Table 4 and should be interpreted carefully. While we can conclude that rookies earn considerably less to what they would be worth according to their performance, the magnitude of the negative premium probably increases more gradually during the rookie contract duration. The model falls short to report this due to the limitations of the variable to only one lag. The same reasoning applies to the overpayment in the first non-rookie contract.

With regard to the role of prototype heuristics for wage setting in NBA contract negations, the coefficient on position-specific average wages is statistically insignificant. Once we control for time-varying and time-constant individual effects together with overall time-effects, the (one-period lagged) average market value of the position a player is allocated to has no further impact on the wages he is able to negotiate. When considering the prototype wage specification with respect to simple box score data and dividing athletes into eleven groups, the coefficient on prototype wage is positive and statistically significant at the 1% level. Accordingly, a \$1 million increase in an individuals prototype wage increases his wage next year by 3.6% on average, holding everything else constant. Moreover, the coefficient corresponding to individual performance is more than halved in magnitude, indicating prototype wages indeed matter. Column (3) concentrates on transformed box score variables which account for playing time and team pace. The coefficient on prototype wages from eight clusters is again positive and significant at the 1% confidence level. Thus, a \$1 million increase in an individuals prototype wage – ceteris paribus – increases his next year's wage by 2.1% on average. Again, the inclusion of prototype wage reduces the parameter for individual productivity, although the decrease is less severe as compared to Column (2).

Column (4) finally reports system GMM results when simultaneously including all three prototype wages together with group-specific dummy variables. Once we include prototype wages based on simple box score variables resulting in eleven cohorts, the coefficient for the more sophisticated measure based on transformed variables and eight groups becomes statistically insignificant while the effect of the position specific prototype wage $\omega_{pos,t-1}$ remains insignificant. Taken all the findings on prototype wages from Table 4 together we are able to provide robust evidence for a behavioral component in wage negotiations which is not negligible. In particular, managers of NBA teams seem to rely on more sophisticated prototype heuristics as compared to simply pay their players wages that are affected by the average wage level of the official playing position. On the other hand, when controlling for relatively straight forward performance measures for the peers, the most sophisticated indicators also do not seem to be very relevant. Put differently, the wage negotiation process in the NBA seem to be driven by relatively simple prototype heuristics based on standard performance measures which are typically also discussed a lot in sport media and among basketball fans.

5.2 Sensitivity analysis

When interpreting the main results for the role of prototype wages in NBA contract negotiation outcomes, a possible source of concern is that the coefficient on prototype wage may be (partly) driven by performance aspects not captured by the *WS* variable. Table 5 presents results from dynamic system GMM fixed effects estimation for a more general individual productivity specification reading as:

$$W_{i,t} = \alpha W_{i,t-1} + \beta' y_{i,t-1} + \delta\omega_{11,t-1} + \kappa' x_{i,t} + \lambda_t + \gamma_i + \epsilon_{i,t}, \tag{14}$$

where $y = (WS\ \ VORP\ \ All{-}Star)'$ now represents the performance vector considering three different dimensions of individual productivity. $VORP$ is the alternative performance measure discussed in previous sections and $All{-}Star$ is a dummy variable equal to one if the athlete was voted into the All-Star game. Past selections may positively influence an athlete's wage even after controlling for individual performance. More popular athletes probably boost game attendance numbers and the overall popularity of the team. Hence, NBA teams may pay a premium for All-Stars independent of their on court productivity. Moreover, the positive effect of prototype wage may be partly driven by such popularity effects if athletes that belong to certain classifications are simply more likely to be elected to All-Star games than others.

Table 5 reports results from system GMM estimation considering different specifications of equation (14). The positive coefficient of prototype wage seems robust to the inclusion of any additional performance measures and also remains remarkably stable in quantitative terms. Thus, the prototype effect for individual wages is driven by other channels than performance aspects not captured by the production variable used in Section 5.2. Column (2) reports results with both previously discussed performance variables, WS and $VORP$. $VORP$ has no statistical significant effect on individual wages once we control for WS. However, the inclusion of the All-Star dummy of the previous season has a negative effect on the WS coefficient, thus indicating that the positive effect of individual performance is overstated in previous specifications where we did not account for this popularity proxy. The coefficient on $All-Star$ is statistically significant on a 5% confidence level and suggests that individual wages increase on average by 12% if an athlete has been voted into the All-Star game. This effect seems quite high but is not too surprising since popular athletes increase team revenues through additional channels than just their sole performance.

Previous sections utilized the full panel data set and we modeled the wage bargaining results in the NBA by utilizing dynamic panel methods. This approach allows to (i) control for unobserved time-fixed heterogeneity across individuals and (ii) control for persistence in individual wages due to the fact th bvat most contracts are binding for more than just one single year. However, the fact that we do not observe contract value but rather annual wage could bias our estimation results.

In order to account for this issue, we try to identify an athlete's contract year and, in a next step, restrict the analysis to observations in which an athlete is on the first year of a contract. Since minor wage adjustments during running contracts happen quite frequently and the variable is adjusted for salary cap inflation, we restrict the wage variable to observations at which the an annual real salary increased or decreased by at least 15% compared to the previous year. This restricts the sample to 617 salary observations with a mean of \$5.778 million and a standard deviation of \$4.837 million. Compared to the original sample, both the mean and the standard deviation decreased slightly from \$6.16 million and \$5.73 million, respectively. Moreover, the restricted sample includes 353 individuals compared to the previous specification with 490 individuals. The loss of individuals can be explained by the chosen identification method of first years in new contracts. Individuals who only had one contract in the sample period are not able to experience a 15% wage change and are thus dropped from the sample. Furthermore, we are not able to calculate the first difference of the dependent variable if there is a gap in an athlete's observed time-period and we, thus, may miss some contract years.

Column (5) in Table 5 presents estimation results for the restricted sample. The restricted set is still an unbalanced panel but the average number of observations per individual decreased significantly to 1.7. The low number of observations per individual makes it impossible to additionally control for persistence in individual wages. However, due to the fact that we only investigate the first year of each new contract, this issue should be of minor relevance. Heterogeneity across individuals is controlled for by applying the simple fixed-effects (within) estimator. In terms of statistical significance and the direction of the estimated effects, the results are again remarkably stable. The positive age effect seems to be larger while only the contemporaneous rookie status seems to matter. At this point, we would like to point out that the included rookie-contract observations in the restricted sample are exclusively the fourth-year team option of such contracts which require NBA teams to offer a wage increase

Table 5: Estimation results: Sensitivity analysis

	Dependent Variable: Log Salary in 100,000 (2016 $)				
	(1)	(2)	(3)	(4)	(5)
W_{t-1}	0.484***	0.472***	0.483***	0.483***	
	(0.061)	(0.060)	(0.059)	(0.059)	
WS_{t-1}		0.048***	0.034***	0.043***	0.073***
		(0.010)	(0.006)	(0.010)	(0.021)
$VORP_{t-1}$	0.063***	-0.020		-0.020	
	(0.011)	(0.020)		(0.020)	
$All-star_{t-1}$			0.116**	0.118**	
			(0.050)	(0.050)	
$\omega_{11,t-1}$	0.038***	0.037***	0.034***	0.035***	0.054**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.022)
Age_t	0.268***	0.263***	0.263***	0.264***	0.482***
	(0.057)	(0.056)	(0.056)	(0.056)	(0.162)
Age_t^2	-0.005***	-0.005***	-0.005***	-0.005***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$Rookie_t$	-0.315***	-0.311***	-0.307***	-0.306***	-0.460***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.099)
$Rookie_{t-1}$	0.217***	0.211***	0.212***	0.210***	0.123
	(0.056)	(0.056)	(0.056)	(0.056)	(0.097)
Instruments	39	40	40	41	-
Arellano-Bond AR(2) (p-value)	0.584	0.517	0.574	0.554	-
Hansen J (p-value)	0.199	0.218	0.201	0.200	-

Notes: Standard Errors are clustered with respect to individuals and are reported in parentheses. Estimates in columns (1) - (4) are based on two-step system GMM with the Windmeijer (2005) error correction using three lags to instrument for the lagged dependent variable in differences. Fixed effects estimates in column (5) restrict the dependent variable to periods in which the first difference of annual salary is outside the interval $[0.85, 1.15]$ and standard errors are clustered with respect to athletes. All estimations include year-specific dummy variables. *, **, *** ... significant at 10%-, 5%- and 1%-level, respectively

by a minimum of 25% relative to the previous salary. We conclude, that rookies in their final year of the harshly regulated rookie contracts are highly underpaid relative to what they would be worth according to their individual performance. However, we are unable to confirm the previously discovered overpayment of athletes in their first non-rookie contract. The impact of individual productivity as well as for our preferred prototype wage measure, are comparable to our main findings. The positive impact of performance on individual wages, however, increased. The point estimate of prototype wage slightly increased as well as the coefficient's standard error which yields a p-value of 0.016. That being said, the significance of the findings are pointing again to the important role which prototype heuristics seem to play in NBA wage negotiations. Accordingly, a $1 million increase in prototype wage raises an athlete's first-year wage of the new contract by 5.4% on average, holding everything else constant.

6 Discussion and Conclusions

This paper builds on an agency model that analyzes contract design when the agent's actions cannot be observed directly by the principal. In this standard model, workers face a prevailing wage and then decide how much effort to supply. The principal's offered compensation depends on estimates of the agent's ability and willingness to show effort during the contract. Since neither of these variables is directly observable, the principal judges the agent's value based on past output which is imperfectly correlated with effort and ability. The uncertainty of this process provides room for behavioral influences. There is a limited but growing body of literature on psychological consequences for contract design that analyzes wage preferences of agents and principals' judgment bias regarding performance.[22]

This research focuses on the principal's payment decision, assuming that agents always choose the optimal effort level given an offered wage compensation scheme. Referring to the theory of prototype heuristics by Kahneman and Frederick (2002), we argue that NBA teams base their assessment of an athlete's productivity on a comparison to the evaluated performance of similar athletes in the past. Moreover, athletes are compared to the prototype of their role, represented by average values of salient properties of the homogeneous group an athlete belongs to. The paper uses different cluster-specifications based on performance measurements to identify athletes that fulfill similar roles on NBA teams. The average real wage of an athlete's group serves as a measures for the relative market value of the cluster. The main hypothesis of this paper is that an athlete's individual wage is positively affected by the (past) prototype wage of the agent's representative cluster.

Utilizing dynamic fixed effects models, the results show a statistically significant effect of one-period lagged prototype wage after controlling for the athlete's past individual performance and other time-fixed and time-varying individual characteristics. Moreover, the comparison of different cluster specifications yields a preferred type of categorization on which NBA teams seem to base their assessment of a player. Accordingly, NBA teams tend to compare athletes based on their performances in measurable outcomes such as points, assists, rebounds, turnovers, steals and blocks per game. Based on our estimates, individual wages increase by 3.6% per $1 million in one-year lagged cluster-specific average wages when considering 11 distinct prototypes. This finding offers evidence that NBA teams' payment decisions are positively linked to past season's average wage of an athlete's prototype and, thus, indirectly on past average performance of the assigned role, independent on how much value the athlete may offer the team. The non-significant effects of alternative prototype definitions indicates that (i) NBA teams may neglect the simplistic classification in positions and categorize athletes in more than just five types explicitly considering likely role-heterogeneity within positions and (ii) NBA teams prefer rather visible characteristics to compare athletes to each other (box score variables) and neglect more sophisticated dimensions that may affect an athlete's accumulated statistics over a season such as playing time and team pace.

By studying the labor market in the NBA, this paper analyzes the link between relative market value of agents in a setting that offers publicly accessible performance measures of rather high quality. One can easily imagine settings where individual performance is much more difficult to assess and, thus, employers find it much more difficult to decompose the causal effect of performance and the design of incentive contracts is therefore even more challenging. In such settings, the consequences of moral hazard are likely to be even worse in that the uncertainty about an employee's value for the employer increases. Hence, we would argue that our findings provide rather robust evidence of a predictable

[22]See Camerer and Malmendier (2012) for a literature review on what they call "Behavioral Economics of Organizations".

inefficiency in contract designs under uncertainty, which may even increase with difficulty for the principal to identify the individual productivity and her contribution to the overall output.

References

Alam, P., D. Booth, K. Lee, and T. Thordarson (2000). The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study. *Expert Systems with Applications 18*, 185–199.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies 58*(2), 277–297.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Baum, C. F., M. E. Schaffer, and S. Stillman (2003). Instrumental variables and GMM: Estimation and testing. *Stata Journal 3*(1), 1–31.

Berri, D. J., S. L. Brook, and M. B. Schmidt (2007). Does one simply need to score to score? *International Journal of Sport Finance 2*(4), 190.

Bertrand, M. and S. Mullainathan (2001). Are CEOs rewarded for luck? The ones without principals are. *Quarterly Journal of Economics 116*(3), 901–932.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115–143.

Camerer, C., L. Babcock, G. Loewenstein, and R. Thaler (1997). Labor supply of New York City cabdrivers: One day at a time. *Quarterly Journal of Economics 112*(2), 407–441.

Camerer, C. and U. Malmendier (2012). Behavioral economics of organizations. In *Behavioral Economics and Its Applications*. Princeton University Press.

Das, N. (2003). Hedge Fund classification using K-means clustering Method. In *9th International Conference on Computing in Economics and Finance* 11–13.

Fehr, E. and L. Goette (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *American Economic Review 97*(1), 298–317.

Frederick, S. and B. Fischhoff (1998). Scope (in) sensitivity in elicited valuations. *Risk Decision and Policy 3*(2), 109–123.

Grossman, S. J. and O. D. Hart (1983). An analysis of the principal-agent problem. *Econometrica 51*(1), 7–45.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica 50*(4), 1029–1054.

Harris, M. and B. Holmström (1982). A theory of wage dynamics. *Review of Economic Studies 49*(3), 315–333.

Hart, O. D. and B. Holmström (1986). *The theory of contracts*. Department of Economics, Massachusetts Institute of Technology.

Holmström, B. (1979). Moral hazard and observability. *The Bell Journal of Economics 10*(1), 74–91.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *Review of Economic Studies 66*(1), 169–182.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters 31*(8), 651–666.

Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist 58*(9), 697.

Kahneman, D. and S. Frederick (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In *Heuristics and Biases: The Psychology of Intuitive Judgment* 49– 81. Cambridge University Press.

Kliger, D. and A. Kudryavtsev (2010). The availability heuristic and investors' reaction to company-specific events. *Journal of Behavioral Finance 11*(1), 50–65.

Kopkin, N. (2012). Tax Avoidance How Income Tax Rates Affect the Labor Migration Decisions of NBA Free Agents. *Journal of Sports Economics 13*(6), 571–602.

Kuehn, J. (2017). ACCOUNTING FOR COMPLEMENTARY SKILL SETS: EVALUATING INDIVIDUAL MARGINAL VALUE TO A TEAM IN THE NATIONAL BASKETBALL ASSOCIATION. *Economic Inquiry*, n/a– n/a.

Lee, B., J. O'Brien, and K. Sivaramakrishnan (2008). An analysis of financial analysts' optimism in long-term growth forecasts. *Journal of Behavioral Finance 9*(3), 171–184.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability* 281– 297. Oakland, CA, USA.

National Basketball Association (2011). *NBA collective bargaining agreement.*

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica 49*(6), 1417–1426.

Oliver, D. (2004). *Basketball on paper: Rules and tools for performance analysis.* Washington D.C.: Potomac Books, Inc.

Roodman, D. (2006). How to do xtabond2: An introduction to difference and system GMM in Stata. *Center for Global Development working paper*.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics 71*(1), 135–158.

Roth, K. (1992). International configuration and coordination archetypes for medium-sized firms in global industries. *Journal of International Business Studies 23*(3), 533–549.

Shiller, R. J. (1999). Human behavior and the efficiency of the financial system. *Handbook of Macroeconomics 1*, 1305–1340.

Spear, S. E. and S. Srivastava (1987). On repeated moral hazard with discounting. *Review of Economic Studies 54*(4), 599–617.

Stiroh, K. J. (2007). Playing for Keeps: Pay and Performance in the NBA. *Economic Inquiry 45*(1), 145–161.

Tversky, A. and D. Kahneman (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology 5*(2), 207–232.

Tversky, A. and D. Kahneman (1974). Judgment under uncertainty: Heuristics and biases. *Science 185*(4157), 1124–1131.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics 126*(1), 25–51.

Yang, C.-H. and H.-Y. Lin (2012). Is there salary discrimination by nationality in the NBA? Foreign talent or foreign market. *Journal of Sports Economics 13*(1), 53–75.

Appendix A: Calculation of individual performance variables

This appendix gives a brief overview of both, the WS and VORP calculations, based on the articles available at Basketball-reference.com. Both calculations utilize individual-specific and team-specific variables. In what follows we refer to the former with the subscript i and to the latter with the subscript tm. League-wide averages are referred to with the subscript lg.

Value over Replacement Player ($VORP$)

Developed by Daniel Myers[23], $VORP$ measures athlete productivity per share of minutes played during a season. The basis for the calculation is a statistical plus-minus method, called "Box Plus Minus" (BPM), which estimates the marginal productivity of a player per 100 possessions in comparison to the league average. For example, a team with a mean BPM of +6 outscores an average other NBA teams by 6 points per 100 possessions.

The basis for the BPM calculation is an regularized adjusted plus-minus ($RAPM$)[24] sample from the 2000/2001 to the 2013/2014 season. A variety of box-score based variables are chosen as independent variables in a regression to estimate their impact on $RAPM$ and the following coefficients are estimated:

$$\begin{aligned} BPM_i = 0.123 * MPG_i + 0.120 * ORb\%_i - 0.151 * DRb\%_i + 1.256 * Stl\%_i + \\ 0.532 * Blk\%_i - 0.306 * Ast\%_i + 0.921 * (Tov\%_i * Usg\%_i) + \\ 0.711 * Scoring_i + 0.726 * (Ast\%_i * TRb\%_i)^{1/2}, \end{aligned} \tag{15}$$

where $Scoring_i = Usg\%_i * (1 - Tov\%_i) * [2 * (TS\%_i - TS\%_{tm}) + 0.017 * Ast\%_i + 0.298 * (3PAr_i - 3PAr_{lg}) - 0.213]$.[25]
BPM data is adjusted by playing time to receive an estimate of value generated by an athlete. Since BPM is centered around the league average at 0, values for athletes below the average would be concave in the amount of playing time. Hence, the variable is adjusted to represent value produced relative to a hypothetical "replacement level player" defined as an athlete on minimum salary and/or an athlete not part of a team's regular rotation, whose BPM is defined to be -2.[26] An individual's contribution during a regular season is calculated as $VORP_i = [BPM_i - (-2.0)] * T_i$, where T_i represents the individual share of total available playing time.

[23] See www.basketball-reference.com/about/bpm.html

[24] $RAPM$ is a lineup based variable of individual production. Every possession of a NBA Game features ten observations, five players of team A and five players of team B. In a sequence of possessions, not interrupted by a substitution, these ten independent variables affect the dependent variable margin which is defined as points scored of team A minus points scored of team B. An athletes individual contribution is then calculated by solving the system of equations over one/multiple seasons. Additionally, ridge-regression analysis as introduced by **?** is utilized to account for outliers as a consequence of vast differences in minutes on the field. We refer an interested reader to http://www.82games.com/comm30.htm for the original article on adjusted the adjusted plus-minus measure.

[25] See basketball-reference.com/about/bpm.html for an extensive Discussion about the independent variables chosen for the regression. And table B2 in Appendix B for a description of the variables with the exception of MPG, which is the average amount of minutes per game played by an athlete.

[26] The definition of replacement level is especially difficult in the NBA since there is (limited) incentive to hire athletes below replacement level due to development reasons in the case of very young players or tactical reasons due to the setup of the draft process of the NBA as explained in Section 3.2.

Win Shares (WS)

WS is based on methods developed by Oliver (2004) and is defined as the sum of offensive and defensive WS to account for value added while the own team is in possession of the ball and while the opponent is.

The offensive WS are based on:

$$PointsProduced_i = (FgPart_i + AstPart_i + FtPart_i)* \\ (1 - \frac{ORb_{tm}}{ScPoss_i} * ORbWeight_{tm} * Play\%_i) + \frac{1}{2}ORbPart_i, \tag{16}$$

where $FgPart$, $AstPart$, $FtPart$ and $ORbPart$ are partial credits for field goals scored, field goals assisted, free throws converted and offensive rebounds, respectively[27], $Play\%_i$ is the percentage of possessions the team scored and $ORbWeight_{tm}$ is an estimate of the value of offensive rebounds.[28] Individual points produced are then compared to expected points produced, given by $0.92 * PPP_{lg} * Poss_i$, where PPP_{lg} are the league-wide average points per possession and $Poss_i$ is the number of individual offensive possessions.[29] The difference yields the athlete's marginal offense which is divided by marginal points per win, $PPG_{lg} * \frac{Pace_{tm}}{Pace_{lg}} * \frac{1}{3}$, where PPG_{lg} are the league's average points per game, $Pace_{tm}$ is the team's average number of possessions per 48 minutes and $Pace_{lg}$ the league-wide average number of possessions per 48 minutes. The multiplication with $1/3$ is due to the definition of three Win Shares being equal to one win. An athlete's offensive WS are then calculates as "marginal offense" divided by "marginal points per win".

The core for the defensive WS is formed by an athlete's individual defensive Rating ($DRtg_i$) developed by Oliver (2004),

$$DRtg_i = DRtg_{tm} + 0.2 * [100 * OPPP_{tm} * (1 - Stop\%_i) - DRtg_{tm}], \tag{17}$$

where $OPPP_{tm}$ is the number of points scored by the opponent per scoring possession, $DRtg_{tm}$ is the team specific defensive rating, defined as points allowed per 100 possessions and $Stop\%$ is an estimate of the rate an athlete forces a defensive stop.[30] The formula accounts for the fact that defense is a team effort and adjusts the team's defensive rating according to individual success while assuming that defensive possessions are smoothly distributed among the five players on the court (0.2 coefficient). Marginal defensive ($MDef_i$) is then calculated by comparing the individual defensive rating to the

[27] Field goals, for example, are often assisted by other athletes. The calculations are based on estimates of the value of assists, which is subtracted from the scorer's credits and reflected in the assisting athlete's AST Part. For the detailed calculations see Oliver (2004) Appendix A.

[28] $ORweight_{tm} = \frac{(1-OR\%_{tm})*Play\%_{tm}}{(1-OR\%_{tm})*Play\%_{tm}+OR\%_{tm}*(1-Play\%_{tm})}$

[29] Expected points produced are weighted by 0.92 to adjust it to "replacement level", hence, to assure that no significant sub-sample of total athletes has negative points produced.

[30] $Stop\%_i = \frac{Stops_i*MP_j}{DPoss_{tm}*MP_i}$ where MP_j is the number of minutes played by the opposing player j, $DPoss_{tm}$ is the number of team-specific possessions on defense and stops are a function of steals, blocks and defensive rebounds. See Oliver (2004) for an extensive explanation.

expected one given by the league average:

$$MDef_i = \frac{MP_i}{MP_{tm}} * DPoss_{tm} * (PPP_{lg} * 1.08 - \frac{DRtg_i}{100}), \tag{18}$$

where the coefficient of 1.08 is simply an adjustment for "replacement level" to assure that no significant sub-population exhibits a negative marginal defense. As for offensive WS, the marginal defense is divided by marginal points per win, $PPG_{lg} * \frac{Pace_{tm}}{Pace_{lg}} * \frac{1}{3}$, to calculate the defensive WS.

Total individual WS is simply the sum of offensive and defensive WS. The variable is designed as to estimate individual contribution to team wins. Hence, individual WS of all athletes on a specific NBA team should add up approximately to the team's regular season wins. According to http://www.basketball-reference.com/about/ws.html, the root mean squared error of this comparison is 3.41 wins since the 1962-63 season.

Appendix B: Tables

Table B1: Maximum and minimum annual salary in the NBA

Years in the NBA[a]	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16
Panel A: Maximum annual salary							
0-6	13,520,500$	13,603,750$	12,922,194$	13,668,750$	13,701,250$	14,746,000$	16,407,500$
7-9	16,224,600$	16,324,500$	15,506,632$	16,402,500$	16,441,500$	17,695,200$	19,689,000$
10+	18,928,700$	19,045,250$	18,091,071$	19,136,250$	19,181,750$	20,644,400$	22,970,500$
Panel B: Minimum annual salary							
0	457,588$	473,604$	473,604$	473,604$	490,180$	507,336$	525,093$
1	736,420$	762,195$	762,195$	762,195$	788,872$	816,482$	845,059$
2	825,497$	854,389$	854,389$	854,389$	884,293$	915,243$	947,276$
3	855,189$	885,120$	885,120$	885,120$	916,099$	948,163$	981,348$
4	884,881$	915,852$	915,825$	915,852$	947,907$	981,084$	1,015,421$
5	959,111$	992,680$	992,680$	992,680$	1,027,424$	1,063,384$	1,100,602$
6	1,033,342$	1,069,509$	1,069,509$	1,069,509$	1,106,942$	1,145,685$	1,185,784$
7	1,107,572$	1,146,337$	1,146,337$	1,146,337$	1,186,459$	1,227,985$	1,270,964$
8	1,181,803$	1,223,166$	1,223,166$	1,223,166$	1,265,977$	1,310,286$	1,356,146$
9	1,187,686$	1,229,255$	1,229,255$	1,229,255$	1,272,279$	1,316,809$	1,362,897$
10+	1,306,455$	1,352,181$	1,352,181$	1,352,181$	1,399,507$	1,448,490$	1,499,187$

Notes: Numbers obtained from National Basketball Association (2011) and http://www.cbafaq.com/salarycap.htm on 30th of October, 2016.
[a]An athlete is credited with a year of service as long as he is on a NBA team's active or inactive list for at least one day during the season.

Table B2: Transformed variables of individual performance

Variable	Definition	Description
PT	$\frac{MP}{MP_{tm}/5}$	Estimated share of total Playing Time.
$TRb\%$	$100 * \frac{TRb}{PT*(TRb_{tm}+TRb_{opp})}$	An estimate of available total rebounds successfully executed.
$ORb\%$	$100 * \frac{ORb}{PT*(ORb_{tm}+DRb_{opp})}$	An estimate of available offensive rebounds successfully executed.
$DRb\%$	$100 * \frac{DRb}{PT*(DRb_{tm}+ORb_{opp})}$	An estimate of available defensive rebounds successfully executed.
$Stl\%$	$100 * \frac{Stl}{PT*Poss_{opp}}$	An estimate of opponents' possessions that ended in a steal by the player.
$Blk\%$	$100 * \frac{Blk}{PT*(Fga_{opp}-3Pa_{opp})}$	An estimate of opponents' two-point field goal attempts blocked by the player.
$Ast\%$	$100 * (\frac{Ast}{PT*Fg_{tm}} - Fg)$	An estimate of teammates' field goals the player assisted for.
$Usg\%$	$100 * \frac{Fga+0.44*Fta+Tov}{PT*(Fga_{tm}+0.44*Fta_{tm}+Tov_{tm})}$	An estimate of the percentage of team possessions used by the player.
$Tov\%$	$100 * \frac{Tov}{Fga+0.44*Fta+Tov}$	An estimate of Turnovers per 100 possessions.
$EFg\%$	$\frac{Fg+0.5*3P}{Fga}$	A measure of shooting efficiency including three-point field goals.
$TS\%$	$\frac{Pts}{2*(Fga+0.44*Fta)}$	A measure of shooting efficiency including three-point field goals and free throws.
$3Par$	$\frac{3Pa}{Fga}$	A measure of the player's frequency of three-point field goals.

Table B3: Prototype wage variables in $1 million

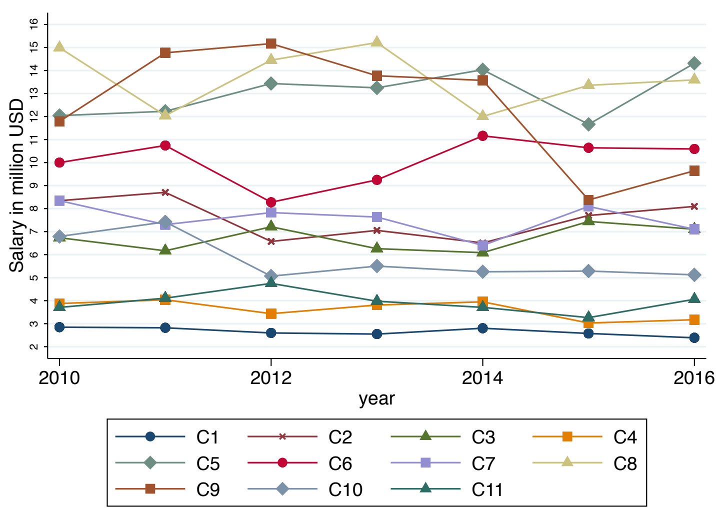
	Mean (SD)	**Min**	**Max**
	Positions		
PG	5.383 (0.416)	4.690	5.986
SG	5.689 (0.508)	5.062	6.316
SF	6.076 (0.664)	5.033	7.228
PF	6.553 (0.504)	6.231	7.728
C	7.169 (0.599)	6.361	8.106
	Clustering Solution A[a]		
C1	2.650 (0.163)	2.387	2.849
C2	7.526 (0.802)	6.509	8.705
C3	6.736 (0.525)	6.087	7.441
C4	3.616 (0.372)	3.030	4.038
C5	12.922 (0.901)	11.662	14.315
C6	10.066 (0.958)	8.277	11.162
C7	7.546 (0.616)	6.401	8.347
C8	13.586 (1.182)	12.005	15.214
C9	12.195 (2.509)	8.377	15.169
C10	5.622 (0.769)	5.066	7.421
C11	3.934 (0.419)	3.264	4.750
	Clustering Solution B[b]		
C1	4.231 (0.383)	3.558	4.781
C2	3.217 (0.512)	2.456	4.122
C3	4.245 (0.404)	3.699	4.961
C4	6.322 (0.532)	5.670	7.410
C5	5.277 (0.459)	4.777	5.982
C6	13.212 (1.176)	11.822	15.468
C7	5.285 (0.509)	4.314	6.055
C8	11.596 (1.239)	9.802	13.230

[a]With respect to points, assists, rebounds, turnover, steals and blocks per game.
[b]With respect to points per game, ast%, ORb%, DRb%, efg%, 3PAr, dbpm and usg%.

Appendix C: Figures

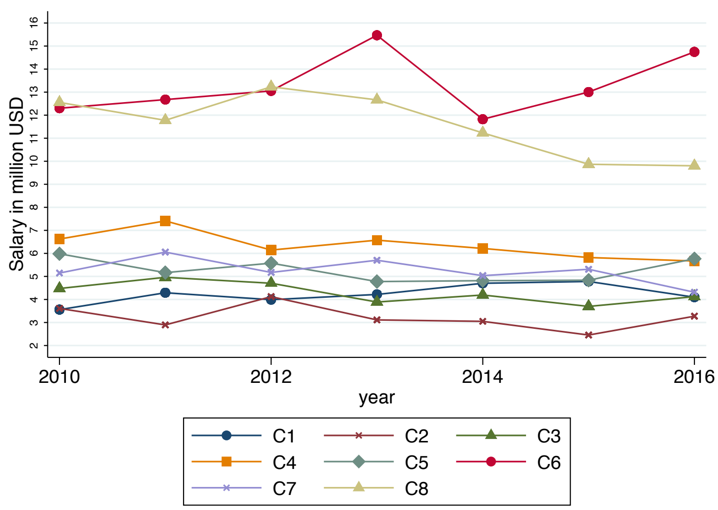
Figure C1: Prototype wage with respect to Positions

Figure C2: Prototype wage with respect to Cluster Solution A[a]



[a]With respect to points, assists, rebounds, turnover, steals and blocks per game.

Figure C3: Prototype wage with respect to Cluster Solution B[a]



[a]With respect to points per game, ast%, ORb%, DRb%, efg%, 3PAr, dbpm and usg%.