Free Agent Migration in Major League Baseball

by

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Abstract

When a player begins his career in Major League Baseball, the rights to his services are the exclusive property of his current team. But after six years of service, baseball players earn the right to declare free agency when their contracts expire. Because there is a rich statistical record for player characteristics, baseball free agency provides an excellent setting for studying migration patterns in labour markets. This paper investigates several elements of free agent movements. We first study the relationship between team characteristics and success in retaining and signing free agents using linear regression techniques. The most pertinent factors are found to be home market size and the number of free agents on a team. A probit model is also estimated to determine which factors affect the likelihood that an athlete will switch teams. While the link between gains from moving and actual migration is tenuous, the evidence does suggest that the strength of the relationship varies with player abilities. The allocation of marginal players is considerably more random compared with non-marginal players.

Acknowledgments

How all occasions do inform against me,
And spur my lit review! What is a grad,
If his chief good and market of his time
Be but to sleep and feed? a beast, no more.
Sure, he that had us write such large discourse,
Looking before and after, perceived not
A reason that our learning and hard-earned skills
Would fust in us unused. Now, whether it be
Academic oblivion, or some lazy habit
Of thinking too little on the event,
A thought which, when provoked, hath been duly shuffled
Off to littered sideline, I do not know
Why yet I live to say "This thing's to do;"
Sith I have cause and will and strength and means
"To do't". Examples gross as earth exhort me:
Witness this army of M.A.s so eager
Led by ambition and dreams of tenure,
Whose spirit with scholarly intent
Makes mouths at the invisible event,
Exposing what their data doth imply
To all that uncertain judgment, even for
A slip of paper? Rightly to be great
Is not to write without great argument,
But greatly to find some story in the numbers
When degrees are at the stake. How stand I then,
That have but an abstract left to pen,
Some few acknowledgements outstanding,

And let all sleep? While, to my shame, I see
The thundering steps of a latter class,
That, to their credit and my enduring shame,
Go forth from Dunning Hall, essays complete
And final grades adorned on transcripts,
With no more fees to pay nor colleagues
To cruelly inquire? O, from this time forth,
My thoughts be 'Submit!', or be nothing worth!

Sincerest thanks to my family for agreeing to never bring this essay up in conversation unless I do so first, to Professor Abbott for his guidance and always helpful comments, and to Abner Doubleday for providing me with the source material. Apologies to Shakespeare.

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1 Introduction

Major league baseball's (MLB) labour market has a rich and unique history, and has spawned substantial economic research. MLB was traditionally a very monopsonistic market. Until 1976, a 'reserve clause' in the league's constitution gave total control over the allocation and compensation of players to the owners. Under the system, the rights to a player's services belonged in perpetuity to his team unless traded or released. Since this meant a player was only allowed to negotiate with one team, his bargaining position was severely limited. From a player's rookie season to his retirement, the team for which he played and the salary he received was virtually dictated to him by the owners.

Because of the monopsonistic nature of the market, players were historically paid salaries well below their contributions to club profits. In a seminal article, Scully (1974) estimated a simple model of salary determination in which players receive a wage equal to their marginal revenue products less monopsony rents. Salaries were found to be just 15 to 20% of the predicted marginal revenue products. The disparity between productivity and remuneration became more pronounced as a player's skill level increased. On the whole, the reserve clause imposed a large economic loss on professional baseball players, with star players suffering the largest degree of exploitation.

A series of rulings in the mid 1970s overturned the old, exploitative system and transferred some of the bargaining power from the owners to the players. These changes led to a substantial rise in player compensation, reflecting the shift of market power to the players. As it stands today, there are three tiers of players, each with its own level of bargaining power. All players with fewer than six years of experience are still subject to the reserve clause. However, all player with at least three years of major league experience and 17% of two-year players are eligible for salary arbitration. With six years of experience, a player can make his services available to the highest bidder by filing for free agency. The allocation and compensation of this final group of players is determined solely on player and team characteristics.

It is with the third tier of players—free agents—that this paper is concerned. We are particularly interested in the allocation of players in this group across teams. While players in the first two tiers have little or no say in what team they play for, there is an open market for free agents. What factors, then, influence a free agent's ultimate destination?

Free agent movements are investigated by estimating several migration models. These analyses are designed to bring three key elements of this particular labour market to light. First, we seek to identify team characteristics that influence success at signing and retaining free agents. For example, do good teams in large markets have a natural recruiting advantage? Second, we examine the extent to which player migration is affected by the potential gains from moving. Third, we will empirically test whether the pattern of player migration differs between marginal and non-marginal players.

The remainder of the paper is organized as follows. Section 2 reviews the chief strands of economic research related to MLB labour markets. The seminal contributions to the literature are included, as well as those papers most closely related to this one. Section 3 discusses the basic theory that motivates the main question this paper seeks to answer. The next two sections describe the methodology used to explore those problems and report the results of the research. In section 4, we develop an empirical model based on net team-level player flows whereas we approach the migration problem by using binary response models in Section 5. Finally, Section 6 summarizes the results and the conclusions that can be drawn.

2 Literature Review

The introduction of final offer arbitration and free agency in 1976 has generated an interesting research literature. The abundance and availability of performance statistics and other player data make it an attractive field for testing economic theories. Two main categories of problems have received particular attention from economists. The first set explores the effect of different levels of bargaining power on player salaries, contracts, and other related issues. The second type of problem considers the impact of free agency on player movements.

It is well-established in the literature that player salaries are determined chiefly by performance, experience, and status. But the degree of bargaining power is also a significant factor. Several studies (Kahn, 1993; Gustafson and Hadley, 1991; Gustafson and Hadley, 1995; Bodvarsson and Banaian, 1998) find that eligibility for free agency or arbitration leads to a large increase in salary relative to comparable ineligible players, suggesting that market structure plays an important role in determining player contracts. Furthermore, the presence of an institutional wage structure for lower-tier players is indicated by the tendency for salaries to vary on the basis of performance only after players qualify for arbitration. In addition, Marburger's (1996) research suggests that while arbitration-eligible salaries continue to be suppressed below competitive market levels at first, they approach free agent salaries as experience increases. Eventually, a player can expect to receive a salary under final offer arbitration that is comparable to what he would receive on the free agent market. In other words, each successive year of arbitration eligibility reduces monopolistic exploitation more than the last.

The relationship between negotiations in the market for arbitration-eligible players and negotiations in the market for free agents has also been explored. Miller (2000) argued that salaries are determined according to different incentive structures in the two systems, but that the outcomes were not independent of each other. Statistical analysis demonstrated that while there was indeed a significant structural difference, there also existed a significant positive relationship between compensation levels for players of comparable ability under both systems. In other words, the existence of a free market for more experienced players raises the general level of salaries such that higher salaries are also awarded under the arbitration system.

Many other factors affecting player compensation have been discussed in the literature, including racial discrimination (Fizel, 1996; Bodvarsson and Banaian, 1998; Bodvarsson and Pettman, 2002), home city climate (Krautmann and Novak, 2004), and the approach of retirement (Horowitz and Zappe, 1998). Other studies have examined the relationship between compensation and contract length. For example, Maxsy (1998) added contract length to a wage equation and found it to be positively related to player compensation. However, Krautmann and Oppenheimer (2002), using a more sophisticated two-stage least squares approach, find evidence to the contrary, suggesting that returns to performance decrease as contract length increases.

The second major category of research is related to the impact of free agency on the allocation of players and by extension the competitive balance of the league. It is to this part of the literature that our paper belongs. Under the reserve clause, player migration was determined solely by the preferences of the owners. These owners often justified the exploitative system by appealing to concerns about league domination. In a free market, it was claimed, all the best players would migrate to just a few teams and the competitive balance of the league would be undermined. The reserve clause, in contrast, allows teams to hold onto their stars.

This argument conflicts with the well-known results of the Coase Theorem, which states that the actual assignment of property rights has no effect on the allocation of resources. It is certainly true that the distribution of property rights will impact the welfare of the agents involved. In our case, players capture a much greater portion of the rents they generate under free agency than under the reserve clause. But the Coase Theorem implies that the system has no bearing on allocative outcomes. For example, suppose that team A controls the rights to a player who would actually be more valuable on team B. One should expect the owners to negotiate a mutually beneficial deal in which the player is traded to team B. And if the same player becomes a free agent, team B would be willing to outbid the other team for his services. The outcome is identical in both cases. Thus, as long as owners are profit maximizers, certain players will move to certain teams; the movement of players from team to team should be independent of the distribution of gains from migration.

Although some studies focus simply on identifying factors that influence migration patterns, the issue of player mobility is more frequently cast as an empirical test of this theorem. The basic question is whether the introduction of free agency altered the movement of players across teams. Pre-1976 owners claimed that it would. Proponents of the Coase Theorem say otherwise. But such questions are most appropriately settled using empirical evidence.

There are three basic empirical approaches to issues of player mobility in the literature. The first, and least sophisticated, approach investigates the impact of institutional changes on the league's competitive balance. For example, Horowitz (1997) finds that free agency has had a distinctly negative impact on the competitive balance of the National League (results for the American League are inconclusive). Similarly, casual observation of win-loss records leads Surdam (2006) to conclude that individual teams experience wide swings in success across periods with different institutional structures. These types of results are used as indirect evidence against the invariance proposition of the Coase Theorem. It is argued that if migration patterns were truly the same under all player rights regimes, one would not see such significant changes in the competitive balance or in individual team success.

Another approach uses aggregate player movements to investigate the factors that influence the movement of free agents. For example, Cymrot (1983) estimated a migration equation using team and player data from the 1976–79 seasons. The evidence indicates that players tend to move to teams for which they have a relatively high value. A subsequent estimation of an salary equation suggests that this pattern exists because compensation levels are related to the expected contributions to team revenues. Teams that would derive greater financial benefit from a player's inclusion on their roster are able to offer a higher salary and are consequently a more successful recruiter. In practical terms, this means that teams based in large and growing cities, as well as struggling teams, are more likely to retain and attract free agents because they receive greater marginal revenues from a given player's production. The results of this study suggest that fears of a competitive imbalance driven by free agency are mostly unfounded. It is true that large market teams do have an advantage, but population growth also matters. More importantly, high-quality teams tend to *lose* free agents. The combination of these effects makes domination by a select few teams less likely.

A third approach is to examine mobility from an individual player perspective. For example, Hylan, Lage, and Treglia (1996) collect data on all pitchers who played between 1961 and 1992. Their panel data set, easily the largest in this literature, contains 11,699 pitcher-year observations. Using a wide range of explanatory variables, they use a probit analysis to identify the determinants of player migration. They find that more talented players are less likely to move, and that longevity increases the likelihood of migration. In addition, pitchers on teams with higher winning percentages or in larger markets are less likely to move. The impact of population is expected, but the effect of team success is the opposite of what Cymrot (1983) found. Most importantly, their results reject the invariance proposition of the Coase Theorem by finding that seasoned pitchers are much less likely to move under free agency than under the old reserve clause regime.

Many of these studies incorporate an estimate of the gains from moving or staying and then relate these gains to the actual pattern of migration. If the Coase theorem holds, the relationship between the distribution of gains and player movement will be the same under both systems. Cymrot and Dunlevy (1987) compute the estimated gain from moving for 307 position players who played in MLB in 1978–1980, some of whom were eligible for free agency and some of whom were not. However, the potential gain from moving was only significant for players who were eligible for free agency. This result casts doubt on the validity of the Coase Theorem by suggesting that market structure matters when it comes to the allocation of players across teams.

Their analysis also suggests that there are unobservable personal characteristics that make some players more likely to migrate than others.

Similar findings appear in Krautmann and Oppenheimer (1994). Their study covered the 1989–1991 seasons and restricted the sample to 136 high-impact players. They compute a player's marginal product on his original team and his hypothetical marginal product on other teams before estimating the probability of migration using a logit model. They find that free agents do not migrate to teams where they are best able to help win games but instead tend to stay in larger markets. Their empirical results suggest that player preferences are important, that large-city teams have a recruiting advantage, and that the allocation of labour is probably different under free agency than under the reserve clause system.

In contrast to these studies, Cymrot, Dunlevy, and Even (2001) use data from the 1979–80 off-season to show that the predicted gains from moving have a significant impact on player migration regardless of free agent status. These results support the Coase Theorem, but it must be noted that the majority of studies in this area have found the opposite. In general, there is consensus in the literature that market size and team success are important determinants of player movements, while some notable studies have also attributed a role to player preferences.

3 Theoretical Discussion

As discussed in the previous section, baseball players with at least six years of experience at the major league level can declare free agency when their contracts expire. In this paper, we consider only the market for free agents. If we assume that no market participant or group of participants engages in anti-competitive strategies (e.g., collusion among owners), it is safe to treat the labour market as competitive. Consequently, a free agent will be paid his marginal revenue product (MRP) which consists of two components: (1) the team's marginal revenue (MR); and (2) the player's marginal product (MP). Since teams will make salary offers to a free agent based on the expected MR and MP, teams with characteristics that increase the MR or the MP will tend to be more successful at signing free agents.

However, salary may not be the only argument in a baseball player's utility function. Their migration decisions may also be influenced by other sources of income and non-pecuniary benefits. We assume that free agents consider all these factors and maximize their utility when making a migration decision. As such, the probability that a player will switch teams is directly related to the expected gains:

$$P_i = f(\Delta MP_i, \Delta MR_i, \Delta NBINC_i, \Delta NONPEC_i) \tag{1}$$

where

P_i = the probability that player i migrates;

ΔMP_i = the change in player i's marginal product if he migrates;

ΔMR_i = the change in marginal revenue if player i migrates;

$\Delta NBINC_i$ = the change in player i's non-baseball income if he migrates;

$\Delta NONPEC_i$ = the change in player i's non-pecuniary benefits if he migrates.

Equation (1) is the basis for all the empirical analysis contained in this paper. The variables included in the migration models we develop are designed to represent one or more of the arguments in this function. The underlying premise of these exercises is that teams value players differently. If the market responds efficiently to these differences in player evaluation, we should expect players to move to teams on which they will generate greater income by increasing their MP and/or their MR. Other things being equal, then, the allocation of free agents should depend on the gains from moving.

To test the importance of these gains it is necessary to construct suitable estimates. Since the gains from moving are a product of team attributes as well as individual player performance, the first step is to identify the relevant team characteristics. Team characteristics can be expected to enter the equation in several ways. The literature suggests that home city population, population growth, and team quality are important in determining a player's MP and MR.

Population is expected to have a positive effect on the MR of a baseball player's performance. Teams in larger markets generally have a larger fan-bases, increasing demand for tickets and broadcasting rights. Free agents should therefore be more valuable in big cities than in small cities. Market size also affects a player's potential for non-baseball income. Players on teams based in large centres have greater public profiles. These profiles help attract corporate endorsements and create greater opportunities for post-baseball employment. For the same reasons, the population growth rate is also expected to influence player mobility. Personnel decisions are made not only with respect to current demand but also with respect to future demand, especially when multiple year contracts are involved. A team with a growing fan-base will expect marginal revenues to increase over time so that players become more valuable over the duration of the contract. Thus, free agents will tend to move from teams in small and stagnant cities to teams in large and rapidly-growing cities, ceteris paribus.

The theoretical impact of team quality is less straightforward. A player's MP is not only affected by his performance but also by the performance of his teammates. A more talented player creates more runs, but the abilities of his teammates largely determine how those runs are converted into wins. Indeed, successful teams probably have many high quality players already. Then, if the principle of diminishing returns holds, the potential *marginal* contribution of any one player should be greater on a poor team than on a good team. A player's production will usually be more valuable to the team that struggles to win games. Free agents, then, should migrate away from good teams and toward poor teams.

But there are other factors to consider. A baseball team does not merely seek to maximize regular season profits. There are many benefits (monetary and otherwise) from making the playoffs and winning divisional titles, league pennants, and the World Series. A high quality player may actually be more valuable to a team that finishes just short of a playoff spot. That player could be the final piece needed to push the team into the post-season. Or, he could turn a perennial contender into a bone fide front runner. Thus, it is not clear that the relationship between a player's MP and team revenues should be monotonically negatively.

We should also take player preferences regarding team quality into account. Although it is certainly not a baseball player's sole motive when making migration decisions, most professional athletes desire to play on a winning team. Success is generally more satisfying than failure. Furthermore, a great deal of anecdotal evidence suggests that many players, especially athletes who have yet to win a championship and are near the end of their career, will try to move to a contending team. Thus, team quality should be positively related to the non-pecuniary benefits from moving. The various ways that team quality influences player movements makes the direction of the net effect theoretically ambiguous.

A necessary task in this type of research is to ensure that the market is appropriately defined. It may not be the case that all baseball players migrate according to the same process. Specifically, there are good reasons to believe that marginal players should be treated differently than non-marginal players. When a clubs management makes personnel decisions, their primary concern is with the non-marginal players that will form the core of the team. Marginal players, on the other hand, are secondary concerns. These athletes are signed as platoon or utility players, or simply to fill holes in rosters. Not only do they make less crucial contributions to their team's success, they possess less unique skills and exist in far greater numbers than than non-marginal players, making them highly inter-changeable with one another. It is much easier to find substitutes for bench players than it is to find adequate replacements for a starting centrefielder. For these reasons, it would not be surprising if the migration pattern of marginal players differed significantly from that of non-marginal players.

4 Net Player Flows

In this section, we investigate the impact of team characteristics on the flow of free agents from team to team. Team characteristics influence the salaries and non-pecuniary benefits that can be offered to players. For example, we expect teams in populous and rapidly-growing cities to attract more free agents because those markets have greater demand for spectator sports. Higher demand translates into higher marginal revenues, allowing salary offers to rise. The empirical model is borrowed with modifications from Cymrot (1983). His results, based on data from the 1970s, confirmed that players tend to move to teams for which they have a relatively high monetary value. We seek to replicate and extend his results using recent data. The model is:

$$NET_{it} = a + b_1 WINS_{i,t-1} + b_2 POP_{it} + b_3 GROWTH_{it} + X_{it} b_4 + e_{it} \qquad (2)$$

where

NET_{it} = net flow of free agents for team i prior to season t;

$WINS_{i,t-1}$ = team i's wins in year $t-1$;

POP_{it} = population of team i's home market area in year t (in millions);

$GROWTH_{it}$ = growth rate of team i's home market area over the five years ending in year t;

X_{it} = a vector of other explanatory variables; and

e_{it} = error term.

Equation (2) will be estimated using linear regression techniques.

4.1 Data

The sample includes one observation for each of the thirty major league teams over three off-seasons: 2005-06, 2006-07, and 2007-08. There are 90 observations in all. One important deviation from Cymrot (1983) is that we restrict our attention to position players only. The earlier study considered both pitchers and non-pitchers. Because these two types of players arguably belong to two different markets, we feel that this will not adversely affect the analysis.

The database for this study was built by the author using several sources. The chief source was ESPN, which publishes extensive statistical and biographical data for MLB on its website. The vast majority of offensive statistics, player characteristics and history, and team-related data were taken from that source. Other Internet–based sources were used to fill in any gaps that existed. Data for a few variables were collected using other sources, all explicitly stated in the text.

The dependent variable NET can be measured in several ways. A fairly simple measure is the difference between players signed and lost in a given offseason. We call this variable NETFLOW. However, since not all players contribute equally to the team's success, NETFLOW is not altogether satisfactory. It would be preferable to weight players according to performance. An alternate measure that overcomes this difficulty is NETRC. Runs Created (RC) is a summary statistic that, as its names suggests, estimates the number of runs a player created for his team. NETRC, then, is the difference between the total RC of players signed and the total RC of players lost. It is possible for a team to have a negative NETFLOW but a positive NETRC if, for example, it loses two marginal players but signs one very productive player. To avoid problems associated with one-year aberrations in performance, we compute two different NETRC variables. The first uses the previous seasons data only. The other averages each players statistics over the previous three years.[1]

Three different sets of population data from the 2006 U.S. Census are used. POP1 is the 2006 population of the home city's Primary Metropolitan Statistical Area (PMSA). POP2 substitutes the 2006 population of the home city's Consolidated Metropolitan Statistical Area (CMSA) if it exists.[2] However, the best performing

[1]Cymrot used the same NETFLOW variable and a weighted average based on estimates of players marginal revenue products

[2]If an area that qualifies as a Metropolitan Statistical Area has a census population of 1 million or more, two or more PMSAs may be designated within it if they meet certain standards. When

variable is POP3, which equals POP2 for cities with only one team. For cities with two teams, POP3 equals one-half POP2 (e.g. Chicago) or the respective PMSA figure where appropriate (e.g. San Francisco and Oakland).

The GROWTH variable is intended to capture expectations of future demand. GROWTH1 is the population growth rate for the PMSA and GROWTH2 is the population growth rate for the CMSA over the period 2000–2006.

Demographics and team quality, however, are not the only variables that describe a team. For that reason, several other data are also collected and considered. Attendance, for example, is measured in two ways. ATTAVG is the average attendance at home games in the previous season while ATTPCT is the average attendance as a percentage of stadium capacity, also in the previous season. PAYROLL is the total amount of player salaries from the previous season. The variable PROSPECTS is a ranking that reflects the quality of a teams farm system. Data unavailability necessitated the use of two different sources to construct this variable. We use the organizational talent rankings produced by Baseball Prospectus for years 2007 and 2008 and a similar ranking produced by Baseball America for 2006. The dummy variable GM is coded 1 if the team has appointed a new general manager since the start of the previous season and coded 0 otherwise. Two measures for quality of life are also collected. Both are published rankings of North American cities based on a wide range of factors that affect liveability including crime, climate, and amenities. QOL1 is taken from the Places Rated Almanac and QOL2 is taken from Cities Ranked and Rated. Finally, the variable NFA counts the number of players on a team that declare free agency in the relevant off-season.

For ease of reference, the definitions for all of these variables are displayed in Table 1. Descriptive statistics are displayed in Table 13.

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multiple PMSAs exist within one metropolitan area, it is called a CMSA.

Table 1: Definitions of Variables in Net Migration Equations

Variable	Definition
NETFLOW	Free agents signed less free agents lost
NETRC	Free agents signed less free agents lost, weighted by the Runs Created statistics.
WINS	Team wins
POP1	Population of home city's PMSA
POP2	Population of home city's CMSA
POP3	Population of home city's CMSA, except where more than one team can be found in the CMSA. Then equal to the PMSA population or one half of the CMSA population.
GROWTH1	PMSA population growth rate, 2000-2006
GROWTH2	CMSA population growth rate, 2000-2006
ATTAVG	Average attendance in previous season
ATTPCT	Average attendance as a percentage of stadium capacity in previous season
PROSPECTS	Ordinal ranking of prospect pool
PAYROLL	Total player compensation
GM	Dummy equal to 1 if the team has a new general manager, and equal to 0 otherwise.
QOL1	Ordinal ranking of city's quality of life, as per Places Rated Almanac
QOL2	Ordinal ranking of city's quality of life, as per Cities Ranked and Rated
NFA	Number of players on a team eligible for free agency

4.2 Empirical Results

We first restrict the explanatory variables to only those considered by Cymrot (1983). That is: team quality, population, and population growth. Table 2 reports the results.

Whereas Cymrot found only weak evidence that free agents migrate from good teams to poor teams, here we see that the coefficient on the WINS variable is not only negative but also highly significant. The population variables all have positive signs, a fact that corresponds well with Cymrot's results, but they are statistically insignificant. The only major departure is that the coefficients on the growth variables have negative, albeit statistically insignificant, signs. Cymrot found the opposite: in the 1970s, teams in fast-growing cities were considerably more successful at signing

Table 2: Net Free Agent Migration by Team, 2006-2008

	(1) NETFLOW	(2) NETRC[1]	(3) NETRC[1]	(4) NETRC[1]	(5) NETRC[2]
Intercept	5.1514[a]	318.29[a]	335.69[a]	335.44[a]	293.67[a]
	(3.27)	(3.89)	(4.05)	(4.14)	(4.05)
Wins	-0.0642[a]	-3.8878[a]	-4.1925[a]	-4.2899[a]	-3.973[a]
	(-3.20)	(-3.78)	(-3.98)	(-4.16)	(-4.11)
POP1		0.5554			
		(0.23)			
POP2			1.8772		
			(0.81)		
POP3	0.0579			4.5819	5.75
	(0.76)			(1.17)	(1.63)
GROWTH1		-0.9574			
		(-0.64)			
GROWTH2	-0.0331		-1.093	-1.3672	-1.95
	(-1.13)		(-0.73)	(-0.91)	(-1.45)
N	90	90	90	90	90
R^2	0.11	0.16	0.16	0.17	0.17
R^2adj	0.08	0.13	0.13	0.14	0.14
p(anova)	0.0161	0.0022	0.0015	0.0011	0.0011

[a]Significant at the 1% level (two-tail test)

[b]Significant at the 5% level (two-tail test)

[c]Significant at the 10% level (two-tail test)

1. NETRC is computed using each player's average Runs Created over the previous three seasons.
2. NETRC is computed using only the previous season's Runs Created.
3. Figures in parentheses are t-ratios for corresponding coefficient estimates.

free agents. Indeed, the current result is peculiar. What reason is there for teams in cities with high growth rates to be less successful at recruiting free agents than teams in stagnant cities? A possible explanation for this curiosity is found by observing that the cities which have grown fastest in recent years (e.g. Phoenix, Tampa Bay, Miami) are not traditional baseball markets. The most established teams are typically based in slower growing cities (e.g. Chicago, San Francisco, Philadelphia). In fact, the attendance data displayed in Table 15 suggests that population growth and demand for baseball are *negatively* correlated. It is this spurious relationship that the GROWTH variables are capturing. Consequently, attendance variables will henceforth be substituted for GROWTH variables.

Cymrot only considered three factors in his analysis. While interesting results were generated with regards to these variables, the overall explanatory power of the migration model is poor. The R-squared values from the regressions reported in Table 2 range from 0.11 to 0.17. A useful task, then, would be to identify other variables that influence the flow of free agents from one team to another. To belong to the true migration equation, candidate explanatory variables must help explain either team profits or player welfare.

For example, organizational depth would decrease the cost associated with losing a player to free agency. A team with solid prospects in its minor league system will be less concerned with losing players on the current roster. If the team has players in its system that are ready to replace the departing free agent, it will gladly allow the player to leave. Then it can insert the much cheaper player into its line-up. Replacing veterans with minor league prospects also cuts down on transaction costs associated with pursuing free agents. Other things being equal, free agents should move from teams with good prospects to teams that lack them.

Another factor that may affect a team's decision to offer a contract to a free agent is the current size of its payroll. A high payroll reflects the resources and willingness to spend a lot of money on player salaries, implying that the team will be more inclined to offer large contracts to free agents. Moreover, the proportional cost of signing (or re-signing) a free agent will be smaller for a high payroll team than a small payroll team. On the other hand, a team with a high payroll may have already reached its maximum feasible level of player salaries. In that case, it will look to shed salary rather than add it. As a result of this conflict, the direction of the effect is theoretically ambiguous.

Like most professional sports teams, the individual responsible for player personnel decisions on a major league baseball club is the General Manager (GM). The GM is the executive that oversees selections at the entry draft, negotiates player contracts, engages in trades with other teams, and dismisses players whose services are no longer desired. More than anyone else, it is the GM who shapes and gives character to the team. His job security also depends on the team's success. If the team underachieves over an extended period, the GM will eventually be held to account and dismissed. A new GM will then be appointed and charged with the task of rebuilding the team. Regime changes are frequently (at least, anecdotally) associated with extensive changes to the team's roster. Thus, the appointment of a new GM is expected to influence the migration of free agents to and from a baseball team. The direction of this influence, however, is theoretically ambiguous. A new GM may be less inclined to re-sign inherited free agents but may be more inclined to sign other free agents. The net result is not clear ex ante.

Another factor that should be considered is the number of players on a team who are entering free agency. Other things being equal, we should expect teams with a higher number of free agents to have more difficulty in retaining their players. A large amount of human and financial resources are required to sign free agents. With many free agents, these resources will be spread too thinly to re-sign all of them. And since the team has undoubtedly foreseen the situation, it has likely made plans (through trades or the draft) to ensure its roster is complete for the next season. It is also possible that some of these players were 'rentals' acquired at the trade deadline for the stretch run and playoffs. For all these reasons, the expected direction of the effect is negative.

Finally, quality of life issues may also affect migration decisions. If players consider the overall liveability of their team's home market, clubs based in attractive locations will have an advantage in recruiting free agents. There is some anecdotal evidence that players prefer desirable cities such as San Diego or San Francisco. If this is true, players should be expected to migrate to teams based in more desirable cities.

The vector of additional explanatory variables in Equation (2) is therefore given by:

$$X_{it} = [PROSPECTS_{it}, PAYROLL_{i,t-1}, GM_{it}, NFA_{it}, QOL_{it}] \quad (3)$$

where

$PROSPECTS_{it}$ = quality of team i's prospects in season t;

$PAYROLL_{i,t-1}$ = payroll of team i in season $t-1$ (in millions);

GM_{it} = indicator variable for a change in executive control of team i before season t begins;

NFA_{it} = the number of players on team i who are eligible for free agency prior to year t; and

QOL_{it} = the quality of life in team i's city.

To see whether any of these factors are important, we re-estimate the migration equation. We also substitute ATTPCT for GROWTH. Thus, the new model is:

$$\begin{aligned} NET_{it} &= a + b_1 WINS_{i,t-1} + b_2 POP_{it} + b_3 ATTPCT_{i,t-1} + b_4 PROSPECTS_{it} \\ &\quad + b_5 PAYROLL_{i,t-1} + b_6 GM_{it} + b_7 NFA_{it} + b_8 QOL_{it} + e_{it} \quad (4) \end{aligned}$$

The results of the estimation are displayed in Table 3. The dependent variables are NETFLOW and NETRC, where the RC statistic is averaged over the previous three seasons. The variables PROSPECTS, PAYROLL, GM, QOL1, QOL2, and NFA are all defined as in Section 4.1. Note that PROSPECTS and the QOL variables are rankings where lower numbers indicate superiority. Because we predict that the impact of organizational depth on a team's net flow of free agents will be negative, the coefficient on PROSPECTS is expected to be positive. Similarly, since quality of life should have a positive effect, the coefficients on the two QOL variables are expected to be negative.

Unlike population growth, the variable ATTPCT has the expected sign in each regression. However, it is only significant at the 10% level in the last specification. The only other statistically significant variable among the other new ones is NFA

Table 3: Extended Net Free Agent Migration by Team, 2006-2008

	(1) NETRC	(2) NETRC	(3) NETRC	(4) NETRC	(5) NETRC	(6) NETRC	(7) NETRC	(8) NETFLOW
Intercept	302.17[a]	309.91[a]	304.75[a]	286.41[a]	308.88[a]	307.02[a]	262.48[a]	3.519[a]
	(3.71)	(3.77)	(3.73)	(3.98)	(3.91)	(3.85)	(3.27)	(2.32)
Wins	-4.025[a]	-4.073[a]	-4.3602[a]	-3.602[a]	-4.099[a]	-4.081[a]	-3.185[a]	-0.0459[b]
	(-3.55)	(-3.56)	(-3.55)	(-3.50)	(-3.57)	(-3.60)	(-2.88)	(-2.19)
POP	2.8124	2.5496	2.7693	6.9529	2.7135	2.9536	9.1974[c]	0.1959[b]
	(0.61)	(0.49)	(0.60)	(1.63)	(0.59)	(0.61)	(1.80)	(2.03)
ATTPCT	0.08335	0.09889	0.1300	0.6175	0.1443	0.1169	0.8789	0.0248[c]
	(0.13)	(0.12)	(0.21)	(1.06)	(0.22)	(0.18)	(1.12)	(1.67)
PROSPECTS	0.3703						0.3395	0.0117
	(0.33)						(0.33)	(0.59)
PAYROLL		0.02498					-0.3736	-0.01093
		(0.05)					(-0.79)	(-1.22)
GM			5.1536				-3.0882	-0.1936
			(0.20)				(-0.13)	(-0.42)
NFA				-21.55[a]			-23.57[a]	-0.50[a]
				(-4.29)			(-4.38)	(-4.87)
QOL1					0.02455		-0.1500	-0.00249
					(0.17)		(-1.03)	(-0.90)
QOL2						5.1536		
						(0.17)		
N	90	90	90	90	90	90	90	90
R^2	0.16	0.16	0.16	0.31	0.16	0.16	0.32	0.31
R^2adj	0.12	0.12	0.12	0.27	0.12	0.12	0.25	0.24
p(anova)	0.0056	0.0059	0.0058	0.0000	0.0058	0.0058	0.0001	0.0001

[a]Significant at the 1% level (two-tail test)
[b]Significant at the 5% level (two-tail test)
[c]Significant at the 10% level (two-tail test)
1. NETRC uses each player's average Runs Created over the previous three seasons.
2. Figures in parentheses are t-ratios for corresponding coefficient estimates.

which enters negatively and highly significantly into each specification where it is included. As the theory suggests, players are more likely to leave teams that have a greater number of free agents. Indeed, the other factors have little impact on the flow of free agents. A test for the joint significance of PROSPECTS, PAYROLL, GM, and QOL1 in specifications (7) and (8) yielded P-values of .77 and .68 respectively. Since the effect of PAYROLL and GM was theoretically ambiguous, it is not that surprising that these variables are insignificant here. One explanation for the insignificance of PROSPECTS is that the variable is not measured precisely enough. Although the organizational rankings are good indicators of the overall level of talent in a team's farm system, it does not specify how that talent is distributed. If the team has strong pitching prospects but its free agents are middle infielders then organizational depth is not very relevant. There would have to be a coincidence of demand and supply within the minor league system for prospect depth to affect free agent decisions.

Because the factors which influence a free agent to sign with one team may be different from those which affect his decision to leave another, we follow Cymrot (1983) and separate each of the dependent variables into two components. NETGAIN is the number of new players signed and NETLOSS is the number of players not re-signed. Similarly, RCGAIN is the sum of the RC of new players signed while RCLOSS is the sum of RC of players not re-signed. We now re-estimate the migration equation using these gain and loss variables as the dependent variable. The results are displayed in Tables 4 and 5.

The variables POP and ATTPCT are measures of market size. The former enters positively and significantly into specification (1) while the latter does the same in specification (2). Thus, there is some evidence that teams in stronger baseball markets are more successful at recruiting free agents. However, there is no evidence that teams in smaller markets are more likely to lose free agents. This distinction, also apparent in Cymrot's (1983) findings, is important. The size of the market does not appear to be affect a player's decision to leave his current team. But once a player begins to search for a new team, he is more likely to end up in one of the larger markets.

Cymrot (1983) found that free agents are more likely to leave good teams but are no more likely to sign with poor teams. In our analysis, the implication of the empirical evidence has shifted. That is, good teams are *not* more likely to lose free agents but poor teams *are* significantly more likely to recruit them. It seems, then, that once a player hits the free agent market, it is more likely that he will be recruited by a poor team than by a good team.

The GM variable was initially included to reflect the impact of a regime change. It was hypothesized that teams with new GMs will be less likely to resign players and more likely to add new players. Since there is no theory to predict the net effect of

Table 4: Gainers and Losers of Free Agents, Part 1

	(1) NETGAIN	(2) RCGAIN	(3) NETLOSS	(4) RCLOSS
Intercept	4.555^a	187.32^a	-0.0583	-64.853
	(3.54)	(3.17)	(-0.05)	(-1.02)
Wins	-0.0459^b	-2.585^a	0.0184	1.183
	(-2.50)	(-3.06)	(1.04)	(1.31)
POP	0.1469^b	5.538	0.1048	3.816
	(1.97)	(1.62)	(1.46)	(1.04)
ATTPCT	0.0121	1.277^a	0.00618	0.627
	(1.17)	(2.70)	(0.62)	(1.24)
N	90	90	90	90
R^2	0.09	0.14	0.08	0.11
R^2adj	0.06	0.11	0.05	0.08
p(anova)	0.0402	0.0042	0.0607	0.0206

Table 5: Gainers and Losers of Free Agents, Part 2

	(5) NETGAIN	(6) RCGAIN	(7) NETLOSS	(8) RCLOSS
Intercept	4.7107^a	208.24^a	0.4449	-30.585
	(3.59)	(3.54)	(0.57)	(-0.61)
Wins	-0.0497^a	-2.896^a	0.0058	0.5614
	(-2.71)	(-3.52)	(0.53)	(0.80)
POP	0.1102	3.0632	-0.0194	-1.645
	(1.46)	(0.90)	(-0.43)	(-0.57)
ATTPCT	0.0078	1.0012^b	-0.00834	0.00379
	(0.75)	(2.16)	(-1.35)	(0.01)
NFA	0.1897^b	11.486^a	0.6446^a	26.838^a
	(2.13)	(2.88)	(12.14)	(7.90)
GM	0.0532	-11.639	0.2127	-8.327
	(0.13)	(-0.61)	(0.84)	(-0.52)
N	90	90	90	90
R^2	0.14	0.22	0.67	0.49
R^2adj	0.09	0.18	0.65	0.46
p(anova)	0.0262	0.0006	0.0000	0.0000

[a]Significant at the 1% level (two-tail test)

[b]Significant at the 5% level (two-tail test)

[c]Significant at the 10% level (two-tail test)

1. All RC statistics used in calculating the dependent variables are three year averages.

2. Figures in parentheses are t-ratios for corresponding coefficient estimates.

these moves, the insignificant results in the Table 3 regressions may not be an accurate indicator of this variables importance. We continued to add GM as an explanatory variable to see if becomes significant when gains and losses are considered separately. But even when this analytic change was made, there is no evidence that a regime change leads to increased player migration.

In contrast, very strong conclusions can be drawn regarding the impact of the NFA variable. It enters positively and significantly into every specification where it is included. Teams with many free agents are therefore more likely to add new players and also more likely to lose current players. Of course, this fairly self-evident statement will surprise no one. What we really want to know is whether the number of free agents impacts one side of the equation more than the other. And since the coefficients and t-statistics for the NFA variable are considerably greater when the dependent variables is NETLOSS or RCLOSS, we see that the impacts are much larger when it comes to losing players. It is also true that the improvement in explanatory power from included NFA is far greater on the 'loss' side.[3]

Another issue to address is whether marginal players migrate according to a different pattern than non-marginal players. We test this proposition by dividing players into two subgroups. We define non-marginal players as those who averaged more than 250 at bats per season over the previous three years. NETRC, RCGAIN and RCLOSS are computed for the non-marginal and marginal players of each team in each year. Thus, there are two 90 observation samples for each dependent variable. The results of the subsequent estimations and test scores are displayed in Table 6. They strongly indicate that the two subgroup do in fact migrate along different lines. The inclusion of the NFA variable magnifies the structural differences between the two groups because it is much more important for the migration pattern of non-marginal free

[3]For example, the R-squared values for specifications (7) and (8) are .67 and .49 whereas the equivalent regressions in specifications (3) and (4) have R-squared values of just 0.08 and 0.11. In contrast, the explanatory power of the free agent inflow equations in (5) and (6) does not improve by nearly the same extent.

agents.[4] By decomposing the sample in this way, we also observe that the negative impact of team quality on net migration is only significant for non-marginal players.

Table 6: Migration Patterns of Marginal and Non-Marginal Free Agents

	NETRC		RCGAIN		RCLOSS	
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Marg.	Marginal	Non-Marg.	Marginal	Non-Marg.	Marginal
Intercept	301.2^a	-14.765	255.0^a	3.356	-76.18	18.12
	(4.12)	(-0.70)	(3.59)	(0.19)	(-1.50)	(1.26)
WINS	-3.53^a	-0.0721	-2.939^a	0.03186	0.5905	0.1037
	(-3.37)	(-0.24)	(-3.28)	(0.13)	(0.81)	(0.51)
POP3	-3.37	-0.24	-3.28	0.13	0.81	0.51
	(1.55)	(0.18)	(1.50)	(-0.16)	(-.038)	(-0.46)
ATTPCT	0.286	0.3316^c	0.7745	0.0711	0.489	-0.2605^b
	(0.48)	(1.94)	(1.52)	(0.50)	(1.18)	(-2.23)
NFA	-20.41^a	-1.137	9.116^b	1.252	29.53^a	2.393^b
	(-3.99)	(-0.77)	(2.08)	(1.02)	(8.33)	(2.39)
N	90	90	90	90	90	90
R^2	0.30	0.05	0.17	0.02	0.54	0.10
R^2adj	0.26	0.01	0.13	-0.02	0.52	0.05
p(anova)	0.0000	0.3557	0.0032	0.7158	0.0000	0.0698
Chow F-Test	6.68		24.12		49.56	
Combined SSR	763047		794926		751091	

[a]Significant at the 1% level (two-tail test)

[b]Significant at the 5% level (two-tail test)

[c]Significant at the 10% level (two-tail test)

1. All RC statistics used in calculating the dependent variables are three year averages.
2. Figures in parentheses are t-ratios for corresponding coefficient estimates.

5 Probability of Player Migration

Recall that the probability of a player switching teams is a function of the expected changes in marginal product, marginal revenue, non-baseball income, and non-pecuniary benefits. We rewrite migration equation (1) here for ease of exposition:

$$P_i = f(\Delta MP_i, \Delta MR_i, \Delta NBINC_i, \Delta NONPEC_i) \tag{5}$$

[4]If NFA was excluded from this part of the analysis, the Chow F-test statistics would be 3.454, 22.434, and 21.981.

where

P_i = the probability that player i migrates;

ΔMP_i = the change in player i's marginal product if he migrates;

ΔMR_i = the change in marginal revenue if player i migrates;

$\Delta NBINC_i$ = the change in player i's non-baseball income if he migrates; and

$\Delta NONPEC_i$ = the change in player i's non-pecuniary benefits if he migrates.

In this section we will estimate the migration equation in (5) using a probit model. Before we can accomplish this goal, however, we must first compute estimates of the gains from moving. Two different methods to compute the estimated gains are employed. The following sub-section describes the data and the construction of the gain variables. The empirical results are then reported in the next sub-section.

5.1 Data

In the previous section, the data were organized by team. We now classify the observations by player. As before, the sample consists of all players eligible for free agency prior to the 2006, 2007, and 2008 seasons. The sample is further restricted to players who signed a contract with a major league team for the next season. There are therefore no observations on players who retired from professional baseball, remained unsigned, or left for another league (e.g. independent baseball or the Japanese leagues). The collected data pertain either to the personal preferences of the player or the gains from moving. There are 285 observations but salary data was only available for 224. As before, the main data source was ESPN.

The personal preferences of a free agent are expected to influence the likelihood of switching teams. Several variables are incorporated into the model to account for these effects. Because migration history is probably an important determinant of current migration, the number of team changes since the player began his major league career (MOVES) and the number of years that the player has been with his current team without interruption (TENURE) are included. Older players, however, are more likely to have played for more teams. But younger players, because they are subject to the reserve clause for the first several years of their careers, are more likely to have longer tenures on their current team. To control for such differences, we follow Krautmann and Oppenheimer (1994) by including a cross-term between AGE and MOVES (MOVEAGE) and between AGE and TENURE (TENAGE). The variable TRADED is a dummy variable equal to one if the player was traded to his current team during the previous season. Many mid-season trades of impending free agents are made to improve a team for the post-season. It seems likely that these 'rental players' are not part of the team's long term stategy. Finally, a quality of life variable (QOL1) is included to control for differences in the desirability of cities.

To compute the gains from moving, we use two different methods, described in fuller detail below. The first method estimates the change in marginal product while the second estimates the change in salary. Both methods make use of the summary statistic RC. This statistic has been little used in the literature. Indeed, none of the works reviewed in Section 2 made use of it. The advantage that RC has over more common statistics such as slugging percentage is that RC captures and evaluates a broad range of offensive skills to estimate a player's total offensive output.

5.1.1 Method I: Estimating the Change in Marginal Product

The construction of this variable is adapted from a similar exercise in Krautmann and Oppenheimer (1994). The idea here is to approximate how output will change if a certain free agent is added to the team's roster (it's input mix). If we make the relatively safe assumption that revenues and team success are positively related—which is the case as long as fans prefer watching a winning team—output can be safely defined as team wins. The measure of offensive input is team runs created (TRC). Since only position players are included in the data set, it is appropriate to use actual team runs allowed (TRA) as the defensive input. The general form of the production function is given by:

$$WINS_k = f(TRC_k, TRA_k) \tag{6}$$

Following Krautman and Oppenheimer, we estimate a Cobb-Douglas production function because it allows for non-constant returns using data from all thirty teams covering the 2005–2007 seasons. A fixed effects panel approach is used to estimate the function. In natural logarithms (t-statistics in parentheses):

$$\ln WINS_{kt} = \underbrace{4.0707}_{(5.33)} + \underbrace{0.87}_{(7.98)} \ln TRC_{kt} - \underbrace{0.83}_{(-10.48)} \ln TRA_{kt} \tag{7}$$

If we treated this data as a cross-sectional set, the estimated coefficient on $\ln TRC_k$ would be slightly higher at 0.89. The empirical relationship between WINS and offensive performance is used to calculate the hypothetical contribution of each free agent on every team. Player i's predicted MP on the k^{th} team is given by:

$$MP_{ik} = \frac{\partial WINS_k}{\partial TRC_k} \cdot \frac{\partial TRC_k}{\partial L_{ik}} \tag{8}$$

where ∂L_{ik} indicates the hypothetical inclusion of the i^{th} player on the k^{th} team.

But given our estimated Cobb-Douglas production function in Equation (7), we can rewrite Equation (8) as:

$$MP_{ik} = 0.87 \cdot \frac{WINS_k}{TRC_k} \cdot \frac{\partial TRC_k}{\partial L_{ik}} \tag{9}$$

The last term, $\frac{\partial TRC_k}{\partial L_{ik}}$, is the free agent's marginal contribution to the k^{th} team's offensive performance. It is generated by computing the k^{th} team's hypothetical offensive performance as though player i was actually on the team. One complication is that the addition of a player to a roster necessitates the subtraction of another player. But which athlete should be subtracted? The most obvious choice is the player on the k^{th} team that plays the same position as player i. But this is not always be the correct procedure. Although players generally specialize at one position, most are capable of fielding others as well. For example, in the 2007–08 off-season, the Milwaukee Brewers signed free agent centrefielder Mike Cameron. The current centrefielder, Bill Hall, remained on the team and moved to third base while the current third basemen, rookie–of–the–year Ryan Braun, began patrolling left field. It was the leftfielder, Geoff Jenkins, that changed teams. He moved to the Philadelphia Phillies to play right field. As this example illustrates, it would be an enormous task to identify the player who should be subtracted on each team for every free agent in the data set.

Instead, we subtract a hypothetical 'average' player. He creates the average number of runs per at bat for that team. This player is replaced by player i in such a way that the teams total at bats remains unchanged. The formula is:

$$\begin{aligned} \frac{\partial TRC_{k,t-1}}{\partial L_{ik}} &= \frac{TAB_{k,t-1} - AB_{i,t-1}}{TAB_{k,t-1}} \cdot TRC_{k,t-1} + RC_{i,t-1} - TRC_{k,t-1} \\ &= RC_{i,t-1} - AB_{i,t-1} \cdot \frac{TRC_{k,t-1}}{TAB_{k,t-1}} \end{aligned} \tag{10}$$

where

$TRC_{k,t-1}$ = total runs created for team k in season $t-1$;

$TAB_{k,t-1}$ = total at bats for team k in season $t-1$;

$AB_{i,t-1}$ = at bats for player i in season $t-1$; and

$RC_{k,t-1}$ = runs created for player i in season $t-1$.

The marginal contribution will be positive for player i on teams whose 'average player is worse than him and negative on teams whose average player is better than him. Using the marginal contributions calculated according to Equation (10) and team win-loss records, we can use Equation (9) to compute the marginal product of each free agent in our data set on each of the thirty major league teams. This information is used to construct two different variables to measure MP_i. Denoting the player's maximum hypothetical marginal product as MP_{ik*} and the marginal product on his current team as MP_{ik}, we define:

$DIFFMP_i = MP_{ik*} - MP_{ik}$

This variable is the maximum potential gain from moving. Note that $DIFFMP_i$ is non-negative because it must be true that $MP_{ik*} \geq MP_{ik}$. The second variable, $NUMMP_i$ is the number of teams on which the player's hypothetical marginal product is greater than his current marginal product. That is, $NUMMP_i = \text{COUNT}(MP_{ik*} > MP_{ik})$. Whereas $DIFFMP_i$ measures the size of the potential gain, $NUMMP_i$ measures the potential level of competition in the bidding process.

We also compute the difference between a player's slugging percentage in the season prior to free agency and his lifetime slugging percentage. Since performance has a natural evolution over the course of a player's career, this variable, $IMPSLG$, is used to capture expectations about future changes in performance.

The final variable used to measure the gains from moving is metropolitan population ($POP3$). Teams located in big cities tend to generate greater revenues for each unit of output produced. Hence, the free agent's incremental contribution to the teams offensive production will be more highly valued in larger markets. And, as was discussed above, population also proxies the potential for non-baseball income-generating activities during a players active career and in retirement.

5.1.2 Method II: Estimating the Change in Salary

This procedure involves estimating a wage equation for baseball free agents that relates compensation to personal and team characteristics. These estimates are used to predict a free agent's salary under an alternate scenario. For a mover, we calculate the salary he would have hypothetically earned had he re-signed with his original team; for a non-mover, we predict the salary he would have earned had he switched teams. One difficulty is selecting the appropriate team characteristics. This is not a challenge for movers since we simply substitute his original team's characteristics. But the task is not as simple for non-movers because it is not obvious which team they would have moved to. To overcome this problem, we follow the example set in the literature and use team characteristics that are average for the entire league.[5]

The wage equation takes the form:

$$LNSAL_i = a + b_{1i}PC_i + b_{2j}MC_j + b_{3k}TC_k + e_i \tag{11}$$

where

$LNSAL_i$ = natural logarithm of player i's salary;

PC_i = personal characteristics, $i = 1, ..., 7$;

MC_i = market characteristics, $j = 1, ..., 3$;

TC_i = team characteristics, $k = 1, ..., 4$; and

e_i = error term.

The sample used for estimating Equation (11) is the set of free agents from the off-seasons prior to the 2006, 2007 and 2008 major league seasons. This is the same data set that we have used throughout the paper. The definitions for the variables in the log-salary equation are displayed in Table 7 and the estimated equation is reported in Table 17, found in Appendix C.

There is no evidence that the wage equation for non-marginal and marginal players is different at any conventional level of significance.[6] The estimated equation (11) is used to calculate the hypothetical salaries and also to generate predicted salaries for players whose salary data is missing. These variables are all converted into millions of dollars before calculating the gain from moving:

$$GAIN = SAL - HSAL \text{ for movers; and} \tag{12}$$

$$GAIN = HSAL - SAL \text{ for non-movers.} \tag{13}$$

where

$HSAL$ = each player's hypothetical annual salary.

[5]Cymrot and Dunlevy (1987) and Cymrot, Dunlevy, and Even (2001) do the same to overcome the problem.

[6]The Chow F-test statistics is 0.3390 with a p-value of 0.9880.

Table 7: Definitions of Variables in Salary Equation

Variable	Definition
LNSAL	Natural logarithm of player salary, averaged over the duration of the contract
RC	Runs created
RCAVG	Average runs created over previous three seasons
ALLSTAR	Number of times selected to the all-star game plus one if selected in the previous season
RACE	Dummy variable equal to unity for non-whites and equal to zero for whites
EXPER	Years of major league experience
EXPERSQ	Years of experience squared
MIDFIELD	Dummy variable equal to unity for catchers, second basemen, shortstops, and centrefielders; and equal to zero otherwise
SAME	Dummy variable equal to unity if the free agent re-signed and equal to zero if the free agent changed teams
YR07, YR08	Dummy variables for year in the free agent market
WINS	The number of team wins in the previous season
POP3	Population of the team's home city
ATTPCT	Average attendance by percentage of capacity filled in previous season
NFA	Number of players on the team eligible for free agency

If the pattern of player movements is at least partly determined by the gains from moving, then we expect GAIN to be positive for movers and negative for non-movers. Descriptive statistics of SAL, HSAL, and GAIN are given for both movers and non-movers in Table 8. We see that movers tend to have lower salaries than non-movers. Also, the mean value of $GAIN$ for movers is positive and the mean value of GAIN for non-movers is negative, which is what the theory suggests.

Table 8: Descriptive Statistics for Salaries and Gains

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
			Movers		
SAL	159	3.3355	3.7566	0.400	18.100
HSAL	159	2.9098	2.9442	0.449	24.730
GAIN	159	0.4257	2.2795	-7.730	11.126
			Non-Movers		
SAL	65	3.7568	4.7721	0.400	27.500
HSAL	65	3.6018	7.6908	0.524	60.895
GAIN	65	-0.1549	4.5534	-7.246	33.395

A glance at the data for non-movers shows that there is at least one extreme observation in the non-movers subset, where the hypothetical salary is $60.9 million per year and the associated gain is $33.4 million. Table 9 lists all observations for which the absolute value of the gain from moving is greater than $5 million. There are seven observations in the upper tail and four in the lower tail.

Table 9: Extreme Gains from Moving

Player	SAL	HSAL	GAIN	Year	Team 1	Team 2
Alfonso Soriano	17.00	24.73	-7.73	2007	WSH	CHC
Aramis Ramirez	15.00	7.75	-7.39	2007	CHC	CHC
Mike Lowell	12.50	6.97	-5.53	2008	BOS	BOS
Barry Bonds	15.80	10.71	-5.09	2007	SF	SF
J.D. Drew	14.00	7.44	6.56	2006	LAD	BOS
Jose Guillen	12.00	5.19	6.81	2008	SEA	KC
Andruw Jones	18.10	10.88	7.22	2008	ATL	LAD
Torii Hunter	18.00	10.39	7.61	2008	MIN	ANA
Carlos Lee	16.65	6.03	10.62	2007	TEX	HOU
Gary Sheffield	14.00	2.87	11.13	2007	NYY	DET
Alex Rodriguez	27.50	60.89	33.39	2008	NYY	NYY

Team 1 is the player's team prior to free agency

Team 2 is the player's team prior to free agency

We observe that the only truly extreme observation is Alex Rodriguez in 2008. The estimated salary equation predicts that his salary would have been $60.9 million had he migrated. In fact, he re-signed with the New York Yankees for less than half that amount and still remained the games highest paid player. Part of this curious result is due to the fact that he is easily the most productive offensive player in the sample. Because he already plays on baseball's best offensive team, migrating to a poor quality team would likely increase his MP by a large amount. This is why the model predicts such a high salary. However, no team in baseball has the financial resources to take on so large a salary. When Rodriguez opted out of the last three years of his previous deal (which paid him $25 million per year) he expected several teams to bid aggressively for his services. The response from other teams, however, was almost non-existent. The only team that had serious interest in signing him (to a large degree because it was the only team that could afford to pay him anything close to what he wanted) was his original team, the New York Yankees. He ultimately signed with the team for much less than what he initially expected. Rodriguez's migration decision is therefore unlike the other players in this sample since his level of compensation effectively restricts him to playing for one team. For that reason, we exclude this observation from the rest of the analysis.

As before, the variable $IMPSLG$ is included to account for a player's natural development path: that is, to capture expectations about future changes in performance. The market size variable, $POP3$, is not needed to control for differences in MR because it has already been accounted for in $GAIN$. However, we still include POP because of its impact on non-baseball sources of income.

5.2 Empirical Results

The last step in this analysis is to determine if and how the probability of migration is affected by the gains from moving and the player's personal preferences. We estimate the following models:

$$\begin{aligned} MIGRATE &= a + b_1 DIFFMP + b_2 NUMMP + b_3 IMPSLG + b_4 POP3 \\ &\quad + b_5 TENURE + b_6 TENAGE + b_7 MOVES + b_8 MOVEAGE \\ &\quad + b_9 TRADED + b_{10} QOL1 \end{aligned} \tag{14}$$

$$\begin{aligned} MIGRATE &= a + B_1 GAIN + B_3 IMPSLG + B_4 POP3 + B_5 TENURE \\ &\quad + B_6 TENAGE + B_7 MOVES + B_8 MOVEAGE + B_9 TRADED \\ &\quad + B_{10} QOL1 \end{aligned} \tag{15}$$

where

$$\begin{aligned} MIGRATE &= 1 \text{ if the player signed with another team; or} \\ &= 0 \text{ if the player re-signed with his original team.} \end{aligned}$$

The variables reflecting the gains from moving ($DIFFMP$ and $NUMMP$; and $GAIN$) are all expected to have a positive impact on the probability of migration. Similarly, the sign on $POP3$ should be negative because market size also affects the gains to the player and his team. If these theoretical considerations hold in the data, it means that a player is more likely to migrate if there are realizable gains associated with changing teams. In other words, the market really does allocate resources efficiently across teams. The expectation for $IMPSLG$ is somewhat less clear. If a players most recent performance is above his career trend, it may indicate that the player is moving upward on his learning curve. In this case the effect on expected gains will be positive. However, if general managers interpret improved performance as an aberration they will expect the player to regress to his mean in the following seasons. This latter interpretation would depress expectations of future gains and the direction of the effect will be negative.

The next variables in the equation represent the player's migration history. The sign on the $TENURE$ variable is expected to be negative. The longer a player has been with his current team, the greater is his attachment to the community. The opportunity costs of uprooting his family and moving to another city will be larger. It can also be noted that this variable may also negatively influence the gains from moving. The longer a player stays with a particular baseball club, the more team-specific human capital he acquires (e.g. leadership) and the greater his public profile (which helps in generating non-baseball income) becomes. In contrast, the variable MOVES is expected to have a positive effect on the probability of migration. A player who has demonstrated a tendency to move from team to team in the past is more likely to switch teams again. Of course, a player may become tire of constant relocation so there is some theoretical ambiguity. The sign on $TRADED$ is expected to be positive. Most midseason trades occur near the trading deadline. These trades are not usually intended to establish new long-term player-team relationships. Rather, the typical transaction involves a good team giving up young prospects in order to acquire soon to be free agents for the post–season. Other things being equal, then, one does not expect these ‘rental players to re-sign with the team to which they were dealt. Finally, the quality of life in a city is expected to reduce the probability of players migrating away from that locations team. Because $QOL1$ is a set of city rankings (i.e., a higher rank indicates a less desirable location), the predicted sign of its coefficient is positive.

Equations (14) and (15) are estimated as probit models. We also separate the sample into marginal and non-marginal players and re-estimate the migration equations for the two sub-groups. The results for all specifications are reported in Table 10.

In each specification in Table 10, the sign of the coefficient on $TENURE$ is positive. This suggests that migration history affects the probability of current migration in a way that is opposite of what was predicted. However, the cross-term included to control for differences in age corrects this puzzling anomaly. The positive coefficient on $TENURE$ is a reflection of the reserve clause. Long periods of non-migration are imposed on young players when they enter the league. Thus, it is often the case that younger player have long tenures with their current teams. But because $TENAGE$ enters negatively into every specification, the direction of tenure's effect is as predicted for more experienced players. For instance, if a 25–year–old and 35–year–old player who both have six years of tenure and are otherwise identical become eligible for free agency, the older one is less likely to migrate. The younger player's tenure is due to the reserve clause and does not indicate a personal preference against moving. Interestingly, the variables $TENURE$ and $TENAGE$ are only significant when the sample includes all players or only non-marginal players. A player's tenure with his current team does not appear to matter if the player has marginal talents.

It was noted previously that there are two probable effects related to the number of prior moves. A player who has moved frequently in the past may be relatively more willing to move again. On the other hand, the player may have developed an aversion to constant uprootedness. The combination of the negative sign on $MOVES$ and the

Table 10: Probit Estimates of the Migration Equations

	(1) All Players	(2) Non-Marg.	(3) Marginal	(4) All Players	(5) Non-Marg.	(6) Marginal
Intercept	0.6574[b]	0.7847[b]	0.7866	0.5970[c]	0.6417[c]	0.9961
	(2.36)	(2.14)	(1.37)	(1.86)	(1.70)	(1.27)
DIFFMP	0.4985[c]	0.00184	0.3315			
	(1.77)	(0.0045)	(0.28)			
NUMMP	-0.0186	-0.0070	-0.0063			
	(-1.30)	(-0.31)	(-0.24)			
GAIN				0.1868[a]	0.2021[a]	0.5974
				(3.45)	(3.48)	(1.22)
POP3	-0.0357	0.0431	-0.1457[b]	-0.0275	0.04792	-0.2079[b]
	(-0.97)	(0.86)	(-2.35)	(-0.77)	(1.08)	(-2.53)
IMPSLG	-1.190	-2.098	-0.9073	-0.927	-1.4731	-0.9461
	(-1.20)	(-1.31)	(-0.66)	(-0.74)	(-0.84)	(-0.37)
TENURE	0.6997[b]	0.5942[c]	0.7822	0.6754[b]	0.6200[c]	-.0661
	(2.33)	(1.83)	(0.85)	(1.96)	(1.71)	(-.04)
TENAGE	-0.01987[b]	-0.01743[b]	-0.0223	-0.01858[b]	-0.01789[c]	-0.0006
	(-2.49)	(-2.04)	(-0.92)	(-2.05)	(-1.79)	(-0.02)
MOVES	-0.3217	-0.5036	-0.2380	-0.4452	-0.6961	-0.2455
	(-1.14)	(-1.30)	(-0.47)	(-1.33)	(-1.62)	(-0.31)
MOVEAGE	0.0091	0.0121	0.0091	0.01216	0.0166	0.0105
	(1.22)	(1.17)	(0.66)	(1.36)	(1.44)	(0.49)
TRADED	0.1176	0.1281	-0.0328	0.1428	0.2463	-0.3504
	(0.54)	(0.45)	(-0.0805)	(0.58)	(0.83)	(-0.59)
QOL1	0.0015	0.0021	-0.0004	0.00237	0.00384	0.0004
	(0.81)	(0.85)	(-0.16)	(1.13)	(1.33)	(0.12)
N	284	186	98	223	168	55
LR chi2(9)	15.79	13.15	10.45	23.20	26.03	14.86
Prob>chi^2	0.1058	0.2157	0.4022	0.0058	0.0020	0.0949
pseudo R2	0.0479	0.0654	0.0834	0.0868	0.1362	0.2031

[a]Significant at the 1% level (two-tail test)

[b]Significant at the 5% level (two-tail test)

[c]Significant at the 10% level (two-tail test)

Figures in parentheses are t-ratios for corresponding coefficient estimates.

positive sign on $MOVEAGE$ suggests that the second effect is dominant. But no clear conclusions since the estimates never reach conventional levels of significance.

There is insufficient empirical evidence to claim authoritatively that players who were traded in the middle of a season are more likely to switch teams during the subsequent off-season. It is possible that the sample contains too few observations in which $TRADED = 1$ to generate precise results in this regard.

There is a considerable difference in the effectiveness of the variables used to reflect the gains from moving. Specifications (1) to (3) use the variables based on estimates of MP whereas specifications (4) to (6) use variables based on an estimated salaries. The second set vastly out-performs the first. The variable $GAIN$ is significant at the 1% level for all players and for non-marginal players. Conversely, the variable $DIFFMP$ is only significant at the 10% level in specification (1) and is not even close to a conventional level of significance when the sample is separated into the two classes of players. The coefficient on the variable $NUMMP$, which was intended to reflect the strength of bidding competition, is insignificant everywhere. Tests for the joint significance of all variables used to reflect the gains from moving (i.e. $POP3$ and $IMPSLG$ too) are reported in Table 11. The P-values from these tests demonstrate that the first set of explanatory variables is substantially less effective at explaining migration patterns of baseball free agents.

Table 11: Testing Joint Significance of Gains from Moving Variables

	Specification	Chi^2	P-value
Set 1	(1) All Players	5.66	0.2259
	(2) Non-Marginal Players	2.54	0.6373
	(3) Marginal Players	7.66	0.1050
Set 2	(4) All Players	12.90	0.0049
	(5) Non-Marginal Players	13.10	0.0044
	(6) Marginal Players	6.97	0.0727

Looking at specifications (4) to (6), what observations can be made regarding the importance of the gains from moving? For one, we see that the variable $GAIN$ is highly significant, at least as long as non-marginal players are concerned. These results correspond well with Cymrot and Dunlevy (1987) and with Cymrot, Dunlevy and Even (2001). Those earlier studies also attributed a substantial role to the predicted gains from moving in explaining player migration. It is notable that the significance of the $GAIN$ variable disappears when we restrict the sample to only marginal players. It seems, then, that the relationship between the predicted gains from moving and the actual probability of migration is considerably stronger for non-marginal players. This result supports our earlier hypothesis that the two categories of players would migrate according to different processes. In particular, the migration process of marginal players appears to be more random and only loosely related to expected gains.

The method used to compute $DIFFMP$ and $NUMMP$ was modified from a similar one used by Krautmann and Oppenheimer (1994). Our method differs in how the marginal contributions are computed and in how production is modeled and estimated. The results, however, are unfortunately similar. The authors of the earlier paper found that the expected gains from moving were insignificant in every specifications of their model. Free agents, it appeared, did not migrate to teams where they were best able to help win games. It is perhaps not surprising, then, that the estimations in specifications (1) to (3) produced a similar triviality. A possible explanation for the insignificance is that the potential impact any one position player can have on a team's success is relatively small. Alex Rodriguez, who has the largest $DIFFMP$ by far, would generate just 3.15 additional wins on the worst offensive team in baseball compared to his previous team, the best offensive team in baseball (New York Yankees). Only 33 out of 285 players in the sample would contribute at least one extra win on their most productive team.

It is also possible that the method of estimating the gains from moving is to blame for the disappointing results in specifications (1) to (3). Recall that the variables $DIFFMP$ and $NUMMP$ are computed using an estimate of each players marginal product for the team on which he would be most productive. But since the principle of diminishing returns implies that players tend to be most productive on the poorest teams, it is highly probable that this team is the same for the majority of the players. For example, if each of the 100 free agents in the 2006–2007 sub-sample migrated to their hypothetically most productive team, then 88 would have signed with the hapless Pittsburgh Pirates, 6 with the Oakland Athletics, 5 with the Tampa Bay Devil Rays, and 1 with the Los Angeles Dodgers. But this is an impossible scenario. Moreover, once one player signs with a team, the potential contribution of all other free agents will change. Thus, most players will not—indeed, cannot—migrate to the team on which they would theoretically be most productive. In fact, only one player in the 2006–2007 sub-sample made an optimal move.

The problem, then, might be that we are using MP_{ik*}, a players maximum hypothetical marginal product, when it is not clear that MP_{ik*} is even relevant. Note that the more effective second method uses ex post salary data whereas the first method uses only ex ante predictions. Rather than MP_{ik*}, it might be better to consider the predicted MP on the team a player *actually* signs with. To that end we define a new variable as follows:

$$\begin{aligned} MPGAIN &= MP_{new} - MP_{old} \text{ for movers; and} \\ &= MP_{hyp} - MP_{old} \text{ for stayers.} \end{aligned} \tag{16}$$

where

MP_{new} = Predicted marginal product of player i on his new team;

MP_{old} = Predicted marginal product of player i on his old team; and

MP_{hyp} = Predicted marginal product of player i on a team with average team characteristics.

A problem we faced earlier arises here as well. To what team would a player have moved had they not stayed where they were? Our previous, though somewhat unsatisfactory, solution was to posit a team whose characteristics were equal to the league average. We adopt the same solution in this case.

Table 12: Substituting MPGAIN for DIFFMP in Probit Migration Models

	All Players	Non-Marginal	Marginal
Intercept	0.9864[a]	1.0358[b]	1.0417
	(2.97)	(2.40)	(1.58)
MPGAIN	0.4322[c]	0.3477	0.249
	(1.69)	(1.14)	(0.27)
NUMMP	-0.019	-0.0219	-0.0159
	(-1.39)	(-1.10)	(-0.71)
POP	-0.0343	0.037	-0.1353[b]
	(-0.96)	(0.76)	(-2.30)
IMPSLG	-1.2867	-2.531	-0.9108
	(-1.28)	(-1.54)	(-0.67)
TENURE	0.7473[b]	0.6352[c]	0.6639
	(2.43)	(1.91)	(0.75)
TENAGE	-0.0209[a]	-0.0186[b]	-0.0193
	(-2.55)	(-2.11)	(-0.83)
MOVES	-0.3939	-0.5697	-0.2897
	(-1.37)	(-1.45)	(-0.56)
MOVEAGE	0.0105	0.0138	0.0102
	(1.38)	(1.32)	(0.74)
TRADED	0.1677	0.1297	0.0538
	(0.77)	(0.46)	(0.14)
QOL1	0.0015	0.0024	-0.00058
	(0.81)	(0.94)	(-0.20)
N	284	186	98
LR chi2	15.61	14.44	10.91
Prob>chi^2	0.1112	0.1538	0.3647
Pseudo R2	0.0473	0.0718	0.0871

[a]Significant at the 1% level (two-tail test)

[b]Significant at the 5% level (two-tail test)

[c]Significant at the 10% level (two-tail test)

Figures in parentheses are t-ratios for corresponding coefficient estimates.

Substituting $MPGAIN$ for $DIFFMP$ in Equation (14), we re-estimate the probit model. The results, as reported in Table 12, are unconvincing again. The revised method slightly improves the empirical results for the non-marginal sub-sample. However, the improvement insufficient to generate any definite conclusions. We must say, then, that there is either a deeper flaw in this method or that free agent flows are generally unrelated to expected changes in marginal product.

6 Conclusion

In the world of professional team sports, athletes are constantly moving from team to team. Rosters are often dramatically reshaped between seasons, so much so that teams can take on entirely new personae. When comparing professional sports with other industries, this rapid turnover in the main productive input—the athletes themselves—stands out as a distinguishing feature. The allocation of players across teams is typically conducted via several different methods, including trades, amateur drafts and waivers. This paper used data from Major League Baseball to explore one such method: free agency. The lack of league-imposed regulations in the free agent market makes it an ideal setting for studying player allocation. To conduct the research, empirical analyses were based on several earlier studies. Because the articles in question used data from the 1970s or 1980s, this paper has the added contribution of updating earlier results with recent data.

In studying the migration patterns of MLB free agents, this paper had three chief aims. First, we sought to identify team characteristics that were correlated with successful recruitment. We found some evidence that teams in stronger baseball markets are significantly more successful at signing free agents. By market "stength", we mean both size and fan intensity. This result will not surprise baseball enthusiasts familiar with the business practices of cash–rich teams like the New York Yankees, Boston Red Sox, and Chicago Cubs.

The empirical evidence also showed that poor teams are more successful recruiters. They stand to benefit more from an athlete's talents than good teams, and therefore offer larger contracts. However, the most important factor in determining free agent flows between teams is the number of free agents each team has. When a team has a lot of players with expiring contracts, it has great difficultly maintaining its roster through free agency. With recruiting resources (both human and financial) stretched thin, such a team inevitably loses more players than it retains.

The second goal of this research paper was to determine how closely the probability of migration is related to the potential gains from switching teams. Basic economic theory suggests that players will move to the team on which their skills are most highly valued. To test this proposition, a migration model was estimated using probit analysis. The results, however, were largely disappointing. Of the two methods used to quantify the gains from moving, only one—estimating the change in player salary—met with any degree of success. But even when the estimations showed that the gains from moving were statistically significant, the overall explanatory power of the migration model was low.

This paper's most unique contribution to the literature is its comparison of marginal and non-marginal players. The empirical evidence consistently showed that these two types of players (low and high type) migrate according to different patterns. For example, the relationship between the gains from moving and the probability of migration is considerably stronger for the non-marginal subgroup. The allocation of marginal players, who are less vital to team success and more substitutable, is more random and only loosely related to expected gains. This confirms that recruitment efforts are generally focused on impact free agents, while players of lesser talent are secondary concerns.

On the whole, it seems that the link between gains from moving and actual migration is tenuous. Individual athletes do not always move to the team on which they are best able to help win games. But this outcome is still informative. The degree of randomness in the allocation of free agents is greater than anticipated, an instructive result in its own right. In such an environment, a well-managed team that pursues a more systematic and scientific approach to free agency could extract an advantage over its rivals.

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A Tables of Descriptive Statistics

Table 13: Descriptive Statistics of Team Variables, 2006-2008

Variable	Obs	Mean	Std. Dev	Min	Max
WINS	90	81	9.97	56	100
POP1	90	5.040	4.26	1.5	18.8
POP2	90	5.884	4.55	1.5	18.8
POP3	90	4.361	2.29	1.5	9.9
GROWTH1	90	6.17	6.49	-2.5	24.2
GROWTH2	90	6.53	6.35	-2.5	24.2
PAYROLL	90	77.75	33.34	15.0	208.31
PROSPECTS	90	15.49	8.72	1	30
GM	90	0.167	0.37	0	1
QOL1	90	48.1	66.73	1	330
QOL2	90	104.2	74.52	7	273
NFA	90	3.167	1.92	0	9

Table 14: Descriptive Statistics of Player Variables, 2006-2008

Variable	Obs	Mean	Std. Dev	Min	Max
MIGRATE	284	0.7324	0.4435	0	1
DIFFMP	284	0.5256	0.4602	0	2.74
NUMMP	284	15	8.701	0	29
GAIN	223	0.1086	2.186	-7.73	11.13
POP3	284	4.827	2.541	1.51	9.948
IMPSLG	284	-0.0229	0.0796	-0.5	0.493
TENURE	284	2.437	2.73	0	19
TENAGE	284	84.71	102.25	0	798
MOVES	284	3.31	2.415	0	11
MOVEAGE	284	116.9	90.93	0	418
TRADED	284	0.2007	0.4012	0	1
QOL1	284	38.95	51.26	1	330

Table 15: Population Growth and Attendance, 2005-2007

Team	City	Growth	2007		2006		2005	
			ATTAVG	ATTPCT	ATTAVG	ATTPCT	ATTAVG	ATTPCT
ANA	Anaheim	4.7	41,551	92.2	42,059	93.4	42,033	93.3
ARI	Phoenix-Mesa	24.2	28,598	58.3	25,821	52.7	25,423	51.9
ATL	Atlanta	21	33,891	67.7	31,869	63.6	31,519	62.9
BAL	Baltimore	4.1	27,060	56.2	26,583	55.2	32,404	67.2
BOS	Boston	1.1	36,675	101.4	36,182	100.0	35,166	97.2
CHC	Chicago	4.2	40,153	97.7	39,040	94.9	38,753	98.0
CHW	Chicago	4.2	33,140	81.6	36,511	89.9	28,923	71.2
CIN	Cincinnati	4.7	25,388	60.4	26,351	62.7	23,989	57.0
CLE	Cleveland	-1	28,448	65.6	24,667	56.9	24,664	56.8
COL	Denver	10.5	28,978	57.4	25,999	51.5	23,944	47.5
DET	Detroit	0.4	37,618	93.8	32,048	79.9	25,306	63.1
FLA	Miami	9.1	16,919	46.6	14,384	39.6	22,792	62.7
HOU	Houston	17.5	37,288	91.1	37,318	91.1	34,530	84.3
KC	Kansas City	7.1	19,961	48.9	17,158	42.1	17,356	42.5
LAD	Los Angeles	4.7	47,614	85.0	46,400	82.9	44,489	79.4
MIL	Milwaukee	0.6	35,421	83.5	28,835	68.0	27,296	64.4
MIN	Minneapolis	6.9	28,350	58.2	28,210	58.0	25,168	51.7
NYM	New York City	2.7	47,579	82.9	43,327	75.5	35,217	61.3
NYY	New York City	2.7	52,739	91.8	51,858	90.2	50,499	87.9
OAK	Oakland	1.4	23,726	54.3	24,402	55.9	26,040	59.6
PHI	Philadelphia	2.5	38,374	88.2	34,200	78.6	33,316	76.6
PIT	Pittsburgh	-2.5	22,141	57.7	23,269	60.7	23,003	60.0
SD	San Diego	4.5	34,445	81.0	32,836	77.3	35,400	83.3
SEA	Seattle	7.2	32,992	69.1	30,626	64.1	33,619	70.4
SF	San Francisco	1.4	39,792	95.8	38,645	93.0	39,259	94.5
STL	St. Louis	3.6	43,853	93.6	42,588	90.9	43,647	86.7
TB	Tampa Bay	12.6	17,148	40.7	16,901	38.6	14,052	32.1
TEX	Dallas-Fort Worth	16.3	29,795	60.7	29,490	60.0	31,480	64.1
TOR	Toronto	9.2	29,143	57.7	28,422	56.3	24,724	48.9
WSH	Washington, D.C.	10.3	24,217	53.5	26,582	58.7	33,651	74.4
Correlation with Growth			-0.2335	-0.3598	-0.2150	-0.3327	-0.1766	-0.2884

B Marginal Effects

Table 16: Marginal Effects for Probit Estimations

	(1) All Players	(2) Non-Marg.	(3) Marginal	(4) All Players	(5) Non-Marg.	(6) Marginal
DIFFMP	0.1613	0.0005	0.119			
	(1.77)[c]	(0.00)	(0.28)			
NUMMP	0.006	-0.0021	-0.0022			
	(-1.3)	(-0.31)	(-0.24)			
GAIN				0.0611[a]	0.0593[a]	0.2229
				(3.45)	(3.48)	(1.22)
POP3	-0.116	0.0127	-0.052[b]	-0.009	0.0141	-0.0776[b]
	(-0.97)	(0.86)	(-2.35)	(-0.77)	(1.08)	(-2.53)
IMPSLG	-0.385	-0.6186	-0.3257	-0.3035	-0.4319	-0.3531
	(-1.20)	(-1.31)	(-0.066)	(-0.74)	(-0.84)	(-0.37)
TENURE	0.2264[b]	0.1752[c]	0.2808	0.2211[b]	0.1818	-0.0247
	(2.33)	(1.83)	(0.85)	(1.96)	(1.63)	(-0.04)
TENAGE	-0.0064[b]	-0.0051[b]	-0.008	-0.006[b]	-0.0052[c]	-0.0002
	(-2.49)	(-2.04)	(-0.92)	(-2.05)	(-1.79)	(-0.02)
MOVES	-0.141	-0.1485	-0.0854	-0.1458	-0.2041	-0.0916
	(-1.14)	(-1.30)	(-0.47)	(-1.33)	(-1.62)	(-0.31)
MOVEAGE	0.003	0.0036	0.0033	0.004	0.0049	0.0039
	(1.22)	(1.17)	(0.66)	(1.36)	(1.44)	(0.49)
TRADED	0.03716	0.0367	-0.0118	0.0454	0.0681	-0.1351
	(0.54)	(0.45)	(-0.08)	(0.58)	(0.83)	(-0.59)
QOL1	0.0005	0.0006	-0.0002	0.0008	0.0011	0.0002
	(0.81)	(0.85)	(-0.16)	(1.13)	(1.33)	(0.12)
N	284	186	98	223	168	55
LR chi2(9)	15.79	13.15	10.45	23.20	26.03	14.86
Prob>chi^2	0.1058	0.2157	0.4022	0.0058	0.0020	0.0949
pseudo R2	0.0479	0.0654	0.0834	0.0868	0.1362	0.2031
obs. P	0.7324	0.7688	0.6633	0.713	0.744	0.6181
pred. P	0.7412	0.7816	0.677	0.7352	0.7837	0.6425

[a]Significant at the 1% level (two-tail test)
[b]Significant at the 5% level (two-tail test)
[c]Significant at the 10% level (two-tail test)
Figures in parentheses are t-ratios for corresponding coefficient estimates.

C Salary Equation Estimation

Table 17: Salary Equation

Variable	Coefficient	t-statistic
Intercept	-1.285	-3.17
RC	0.014	5.86
RC3	0.0159	5.46
ALLSTAR	0.0427	1.88
MIDFIELD	0.1426	1.75
EXPER	0.0378	0.81
EXPERSQ	-0.0023	-1.07
RACE	0.1252	1.57
STAY	0.0961	1.06
YR07	0.3053	3.32
YR08	0.2676	2.66
WINS	-0.0020	-0.45
POP3	-0.0062	-0.38
ATTPCT	0.0050	1.92
NFA	-0.0386	-1.78
N	224	
R^2	0.692	
R^2adj	0.671	
p(anova)	0.000	

[a]Significant at the 1% level (two-tail test)
[b]Significant at the 5% level (two-tail test)
[c]Significant at the 10% level (two-tail test)