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Shirking in MLB

Shirking behavior is a critical topic of study in economics and psychology, with broad implications for organizational productivity, contract structures, and managerial practices. Shirking refers to the measurable decline in effort or productivity when employees face reduced incentives to perform, which could be when employees have increased job security and compensation. This phenomenon arises when monitoring is limited or incentives are misaligned, creating opportunities for employees to exert less effort, or shirk, without immediate consequences. Research in this area aims to uncover how employment contract structures and managerial strategies can either mitigate or exacerbate this behavior.

In professional sports, particularly in Major League Baseball (MLB), shirking has become a pressing issue due to the unique structure of player contracts in a league without a salary cap. MLB contracts often involve long-term commitments to players with significant financial guarantees, offering players high job security and, in many cases, limited performance-based incentives. Once players secure these lucrative multi-year guaranteed contracts, the external pressure to perform may diminish due to increased job security and compensation, potentially leading to declines in effort and output. These performance declines can negatively impact team success, flexibility with roster construction, and payroll efficiency, making shirking behavior a necessary concern for MLB front offices.

This study examines shirking in MLB, focusing on the relationship between contract terms, such as contract length and salary, and player performance post-signing. The analysis for this study defines shirking as the decline in Wins Above Replacement (WAR) between the contract year (final year of a player's current deal or arbitration) and the first year of the new deal. WAR aggregates multiple dimensions of performance, encompassing offensive and defensive metrics for hitters, and pitching effectiveness for pitchers. By analyzing the year-to-year change in WAR, this study provides a quantitative basis for evaluating the extent and predictors of shirking behavior.

A key contribution of this research is the integration of recent player data and the application of predictive modelling to evaluate past cases of shirking behavior, and forecast potential future shirking behavior for players in the 2025 free agent class. Using Generalized Additive Models (GAMs), the analysis identifies key factors – such as salary change, age, and contract length – that influence changes in WAR after players sign new contracts. These models provide insights into the risks of performance decline for certain free agents, especially ones who receive longer contracts, offering a data-driven approach for contract negotiations and roster planning. By bridging theory and practice, this research equips MLB front offices with tools to better manage the risks of long-term, high-value contracts.

The study highlights the challenges of balancing player compensation with performance incentives in a highly competitive environment. While long-term financial guarantees are often necessary to secure high-end talent and drive team success, they also carry the risk of shirking, especially in MLB where contracts are predominantly guaranteed and lack performance-based incentives. By incorporating over a decade of recent data and employing statistical modelling techniques, this research provides a deep understanding of shirking behavior and extends the analysis to include predictions for future free agents. The findings of the study revealed a negative relationship between salary increases, contract length and changes in WAR, indicating that longer contracts and greater pay raises are associated with larger declines in the first year of the new contract post-signing, suggesting potential reduction in effort or performance incentives.

The primary research question guiding this study is: To what extent does shirking behavior impact player performance following the signing of a contract, and can this behavior be effectively predicted for future free agents? Addressing this question serves a dual purpose of analyzing past relationships between contract terms and performance, while also forecasting shirking behavior for upcoming free agents. By achieving these objectives, the research contributes to the existing literature on shirking in professional sports and offers useful applications for MLB front offices to optimize roster construction while also understanding the risks associated with large contracts.

This paper aims to enhance the understanding of shirking behavior in MLB, providing a framework to evaluate its factors and consequences. The use of past player analysis as well as using the predictions for future shirking represents a novel approach that is new to the existing literature. As MLB teams continue to navigate the challenges of roster construction in an era of increasing salaries and player mobility, as well as increased differences in payroll between the big market and small market teams, the insights from this research can help inform decisions related to contract terms and performance. By shedding light on the risks associated with different contract types, this study seeks to inform better decision making, ensuring that teams are aware of the potential risks to maximize player and team performance.

Literature Review

Shirking behavior refers to a reduction in employee effort, normally associated with job security, increased compensation, or challenges in monitoring employee performance. According to Antosc (2020), shirking is particularly relevant in jobs with limited oversight, where employees can exert reduced effort without facing immediate repercussions. In professional sports, shirking can manifest when athletes reduce effort after securing a long-term contract, an issue that can be detrimental to a team's front office, as it potentially reduces the teams roster flexibility and declines team success.

Sports presents a unique lens to study shirking behavior, as performance metrics are highly quantifiable compared to other realms of shirking study in the workforce. Marks (2017) analyzed shirking in the NFL and found it is relatively limited due to NFLs structure of most contracts not being fully-guaranteed. Players who underperform are at risk of being cut in the NFL, especially when they have no more guaranteed money remaining on their contract, which discourages shirking.

In MLB, where contracts are fully guaranteed, and there is no salary cap, and no limits to the amount of money or years a team can sign a player for, the potential for shirking is higher. However, Taylor (2016) challenged this assumption, finding that MLB players on long-term deals often maintain or exceed the expected performance levels of their contracts, suggesting that other factors, such as intrinsic motivation or team culture, may mitigate shirking. Barnes (2016) introduced the concept of "surplus value" to assess whether a players performance justified their salaries, using machine learning to compare player performance against contract values. This metric provides an interesting approach to shirking by identifying instances where guaranteed contracts might increase potential shirking behavior.

Player salaries in professional sports are determined by a combination of factors including historical performance, market demand, and perceived future value. Magel (2015) explored salary determinants in MLB, finding that stats such as games played and total bases were significant predictors of batter salaries, while strikeouts, saves and ERA were significant for pitchers. Similarly, Rosen (2016) examined salary structures in the NBA and aimed at determining salaries based on their contributions to a team's regular season success. Lucifora (2003) looked at Italian League Soccer (futbol for those of you across the pond) introducing the "superstar effect", where elite players earn disproportionately higher salaries due to factors including a lack of consensus on the best players, differing playing styles, and difficulty in isolating a player's contributions to the team. While Lucifora (2003) focuses on soccer, the implications for MLB are the same: superstar players may command salaries that exceed their statistical contributions because of their branding and fan appeal. These studies highlight the challenges of predicting salaries, particularly in leagues like MLB, where guaranteed money can disconnect pay from future performance.

Advancements in machine learning have significantly enhanced the ability to accurately predict player performance. Watkins (2020) applied XGBoost to forecast MLB player statistics, demonstrating that machine models outperformed traditional regression methods in terms of prediction accuracy. This approach allows for the inclusion of nonlinear relationships and interactions between variables, allowing the model to better understand the trends in the data. Nguyen (2021) used random forests to predict NBA player performance and popularity trends using metrics like win shares and all-star probability. Sun (2022) pushed these methods further and used long short-term memory (LSTM) networks to analyze MLB performance trained on historical data. These studies demonstrate the effectiveness of advanced techniques in predicting performance in professional baseball.

While advancements in machine learning have refined the ability to predict player performance, these tools create opportunities to analyze behavioral trends, such as the contract year phenomenon and its implications for effort and performance consistency. The “contract year phenomenon” describes players' tendency to perform better than their average performance in their contract year in hopes of getting a more lucrative contract for the following season. While this can show motivation, it raises concerns about consistent effort across the entire duration of the contract and potential shirking behavior. Francis (2006) investigated this issue in the NBA, and found that player performance often declines in the contract year, challenging the idea of the contract year phenomenon. Koschmann (2017) also explores shirking in the NBA to investigate whether players exert less effort over the course of the contract and then intensify performance in the contract year to enhance their chances of getting more money. The results also revealed a negative relationship between contract years and performance, suggesting that the pressure of the contract year does not enhance performance. In MLB, O’Neill (2019) examined the year-to-year change in performance between contract year and first year of the following contract and found players perform better in the first year, but the results also found a negative relationship for contract length. This means that players tend to perform worse in the first year of longer contracts, possibly showing the effects of job security on shirking behavior.

Performance under pressure reflects an athlete’s ability to perform in high stakes situations and often intersects with shirking behavior, as both are shaped by psychological demands. Factors like anxiety, responsibility, fatigue and attention shifts play key roles in influencing performance (Murayama, 2010). Galilee (2018) found that NBA teams facing elimination in the playoffs perform worse at home when their opponents aren’t under the same pressure of elimination. Zheng (2011) revealed that NBA players tend to “choke” during late game free throws due to psychological pressures, even when accounting for shooter characteristics. Morgulev (2019) found no evidence that momentum from late-game comebacks improves NBA overtime outcomes. Hsu (2019) showed that environmental factors have more of an effect on NFL kicker performance than psychological factors. Pitts (2022) examined how drafting a first-round quarterback affects an incumbent quarterback's performance when he is under pressure of job termination, and found that there is no significant change in performance. These findings align closely with the contract year phenomenon, where players face heightened pressure to perform in difficult situations. The interplay between the stakes of contract year performance and high-pressure performance highlights how athletes respond to the pressure of gaining significant financial rewards, revealing the potential for both elevated performance and choking under the pressure.

Methodology/Data

The data for this study was collected from multiple sources and before filters were added, the primary dataset included contracts signed between 2011 and 2024, focusing on players that ranked within the top 500 salaries each year. This restriction of only including the top 500 salaries ensured the inclusion fo high-earning players and excluding low-tier players who don't provide much value. By concentrating on high-value contracts, the analysis highlight the financial dynamics and incentives influencing MLB's elite players.

Contract and free-agent data were sourced from Spotrac, a database that provides information on salaries, contract terms and transaction details. Key variables extracted from here included salary, contract length, contract start and end years, as well as the list of free agents for the 2025 offseason. Performance metrics including Wins Above Replacement (WAR), were obtained from Fangraphs through direct access of the website and the baseballr package in R. WAR served as the primary dependent variable for analyzing year-to-year performance changes, and additional metrics were used for predicting future salary and contract length. Demographic data, collected from the mlb_people function in baseballr, identified player birthplaces, enabling analysis of potential differences in shirking tendencies between internation and domestic-born players. Lastly, city population data was collected from the maps package in R to provide insights into a team's market size, a critical factor impacting salaries and performance pressures due to disparities in financial resources, media presence, and fan expectations. Together, these data enable an in-depth exploration of the relationship between player performance, contract terms and external influences.

The primary objective of this study was to examine shirking behavior – whether players demonstrate decreased effort or performance after signing long-term contracts. To investigate this phenomenon, year-to-year changes in WAR were analyzed, focusing on the transition from the contract year to the first year of the free-agent contract. Generalized Additive Models (GAMs) were employed for their flexibility in capturing linear and nonlinear relationships between predictors and outcome variables. This allows the model to uncover subtle patterns and trends for certain variables that can't be accomplished with traditional linear models.

The study was conducted separately for batters and pitchers, as their relevant performance metrics differ, and this allows us to see if there are any variations in shirking behavior between batters and pitchers. Arbitration deals – contracts offered to players that have three to six years of service time – were excluded from the analysis. These deals are typically one year agreements based on previous season performance and do not offer the same level of financial security as free-agent contracts, making them less relevant for examining behavior trends, including shirking, that are more likely to emerge in the context of high-value, multi-year free-agent contracts. This exclusion allows for a clearer focus of the dynamics of performance and job security. Following the exclusion of arbitration deals, the resulting datasets consisted of 898 year-to-year observations for batters and 885 for pitchers, focusing only on the change between contract year and the first year of a free agent contract.

To examine the change in WAR between the contract year and first year of the free-agent contracts, the following GAM model was specified for both batters and pitchers:

$$WAR\ Change \sim s(Age) + Salary\ Change + Contract\ Length + Market\ Size + New\ Team + Multiple\ Teams + New\ Team * Market\ Size + International + Contract\ Type\ FA\ to\ FA$$

The independent variables used in the model were selected to capture the diverse factors influencing player performance and contract dynamics. Age is a critical factor in understanding player performance over time as it reflects the natural career trajectory of athletes, including peak performance years and eventual decline due to aging. By using the smoothing spline in the GAM, the model accounts for the nonlinear relationship of age on performance. Changes in player salary between contracts was included to reflect the financial incentives tied to new deals. A significant increase in salary might reduce a players motivation to exert maximum effort, while a minor change or a decrease in salary could reflect diminished performance and market value. Contract length is another crucial variable, as longer contracts create greater job security and may influence performance incentives. While longer contracts may help teams secure marquee talent (Juan Jose Soto Pacheco), they may also reduce motivation to maintain peak performance, especially in a league where contracts are typically fully guaranteed. By including contract length, the model examines whether it correlates with performance patterns indicative of shirking behavior.

Market size is another variable included as teams in larger markets often have greater financial resources and increased media scrutiny which can add pressure to players especially after signing large contracts. In Major League Baseball there is a substantial disparity in market size and payroll among teams. Large market teams like the Los Angeles Dodgers, New York Mets, and New York Yankees typically have the ability to sign players to lucrative contracts, whereas smaller market teams like the Tampa Bay Rays, Milwaukee Brewers and Cleveland Guardians have tighter budget constraints and lack this luxury. Players in large markets also may face additional performance pressure and media scrutiny, while players in smaller markets may not. This variable accounts for the influence of external factors tied to a player's team environment.

To better understand factors influencing year-to-year changes in WAR, the model also included variables related to team transitions and stability. A binary variable called "new team" was used to indicate whether a player changed teams when signing a new contract.This variable was included because moving to a new team can present adaptation challenges, such as adjusting to a new environment, teammates, and coaching staff, or it can spark renewed motivation to perform and prove one's value. Controlling for new team ensures the model can assess how team changes impact player performance under new contracts.Additionally, playing for multiple teams in a single season may also disrupt a players routine and lead to performance variations, so there was a dummy variable included called multiple_teams equal to 1 if the player played on multiple teams in the first year of the new contract. This helps account for potential instability caused by mid-season trades or other roster changes.

Regarding contract type, it's important to remember that arbitration-to-arbitration deals were excluded from the analysis as I previously mentioned. Since these deals were excluded from the dataset, all of the contracts are either arbitration-to-free-agent (Arb to FA) or free-agent-to-free-agent (FA to FA). This distinction allows the study to focus on how players' performance changes when going from shorter arbitration deals to free agent contracts, compared to when players enter another free agent contract after possibly already having that increased job security of a long-term contract at some part in their careers. The dummy variable contract_type_fa_to_fa equals 1 if a player signed a free agent deal after previously being in another free agent contract.

To account for the effect of market size different depending on whether a player switches teams, the model included an interaction term between market size and the new team dummy variable. This interaction captures how the combination of market size and player movement influences performance outcomes. Additionally, an indicator for international players was included to examine potential differences in shirking behavior between international and domestic players. This variable tests the hypothesis that players from economically disadvantaged backgrounds might be more likely to exhibit shirking tendencies. It was assumed that players from disadvantaged backgrounds might be motivated to maximize their earnings earlier in their careers and exhibit decreased effort once financial goals are achieved. In MLB< many international players come from economically disadvantaged regions, particularly Latin American countries such the Dominican Republic, Venezuela, and Cuba, making this variable especially relevant for understanding patterns of performance and effort.

After learning about the variables in the model, it is useful to look at the summary statistics for the independent variables. This provides an overview of player ages, salary, contract length, market size, team changes, international players and contract types. Summary stats are below:

Table 1

	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Batter Age	22	30	31	33.75	45
Batter Salary	0.615	1.5	3.5	8.47	70
Batter Contract Length	1	1	1	2	13
Pitcher Age	24	30	32	34	43
Pitcher Salary	0.72	2	4	8.5	43.33
Pitcher Contract Length	1	1	1	2	10
Market Size	301561	424096	575250	2830144	8124427

Table 2

Summary Statistic	Pitcher	Batter
Count of new_team	606	633
Count of multiple_teams	127	129
Count of International	189	252
Free-Agent -> Free-Agent Contract	765	788
Arbitration -> Free-Agent Contract	120	110

The summary statistic reveal substantial skewness in salary and contract length. For both batters and pitchers, salaries show significant variation, with a small group of elite players receiving extreme salaries, while most players earn more modest salaries by comparison. The same applies for contract length with most contracts being one to two year deals, while a few secure long-term contracts approaching or exceeding 10 years. This skewness represents the typical contract structure in Major League Baseball and is important to consider when interpreting results, as it may influence the relationships between salary changes contract length, and performance.

In summary, the study uses Generalized Additive Models (GAMs) to assess the relationship between player performance and contract characteristics, allowing us to examine shirking behavior. By considering the range of variables including age, year-to-year change in salary, contract length, market size, dummies for player mobility with new team and multiple team, contract type and international status, this model allows us to capture key factors that may present shirking behavior with the change in salary and contract length, while also controlling for other external variables such as new team and market size that may affect a players performance after signing a new contract. These other variables also allow for a framework for understanding how a player's motivations might shift post-contract. With separate models for batters and pitchers, this allows us to highlight potential differences in shirking tendencies between these two groups of players. The next step in the analysis is to look at the results of these models then use them to forecast performance changes for players currently in the free-agent market for the 2025 offseason.

Results

WAR Change Model Results

Now we will look at the results of the GAMs developed to model the change in WAR for batters and pitchers between the contract year and the first year of the free agent contract. Four models were made all using the same specification previously mentioned. Two models use the full dataset to model changes in WAR separate for batters and pitchers, while the other two do the same except remove outliers in salary to see if that causes any changes in the results. If shirking behavior is present we should see a negative relationship for salary change and contract length on the change in WAR, meaning players are expected to perform worse in the first year after receiving a large, long-term contract. Below are the results of the four models:

Table 3

	Batters	Pitchers	Batters (No Outliers)	Pitchers (No Outliers)
(Intercept)	0.148	-0.019	0.220	-0.023
	(0.226)	(0.182)	(0.234)	(0.183)
SalaryChange	-0.068***	-0.063***	-0.087***	-0.048***
	(0.013)	(0.010)	(0.015)	(0.011)
ContractLength	-0.182***	-0.096*	-0.255***	-0.116**
	(0.035)	(0.038)	(0.048)	(0.041)
MarketSize	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NewTeam	0.272	0.376**	0.206	0.383***
	(0.154)	(0.118)	(0.155)	(0.114)
MultipleTeams	-0.441**	-0.104	-0.461**	-0.082
	(0.153)	(0.128)	(0.146)	(0.122)
International	-0.062	0.027	-0.109	0.055
	(0.118)	(0.107)	(0.117)	(0.102)
ContractTypeFAtoFA	-0.310	-0.182	-0.208	-0.179
	(0.166)	(0.129)	(0.170)	(0.129)
MarketSize:NewTeam	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EDF: s(Age)	4.718***	1.484	5.148***	1.003
	(5.782)	(1.734)	(6.244)	(1.007)

The batters model shows that salary change is a significant predictor of change in WAR with a negative coefficient. This suggests that the greater the salary increase a player receives, the worse their performance may decline the following year in the first year of the new contract, potentially due to a reduction in motivation once financial incentives are reached. Similarly, contract length has a significant negative effect on the change in WAR, meaning that for longer contracts, there is a greater drop in WAR in the first season of longer contracts. This indicates that players with greater job/financial security may have less incentive to sustain high performance over time. The negative coefficient for salary change and contract length are consistent with the idea of shirking behavior, players that receive greater salary increases, and longer contracts have larger drops in WAR in the first year of the new contract.

Other predictors in the model include market size, new team status, and playing for multiple teams during the first season of the new contract. Interestingly, market size does not show a statistically significant effect on WAR change, contrary to the popular belief that players succumb to the pressure of playing in a big market. Similarly, the new team dummy variable and the interaction between new team and market size are not statistically significant. The lack of significance for the new team dummy suggests that changing teams did not have a strong impact on WAR change for batters in this model. The interaction between market size and new team dummy being not statistically significant indicates that the size of the market did not amplify the effect of switching teams. This suggests tar there is not sufficient evidence to conclude that market size or team change affects WAR change, and we fail to reject the null hypothesis that these variables have no effect on WAR change.

The pitchers model, reveals similar trends, with salary change and contract length being significant predictors of WAR change. The salary change coefficient for pitchers is negative, supporting the idea that larger salary increases are associated with a greater decline in performance in year one of a new contract. The effect of contract length on WAR change for pitchers is also negative, suggesting that once job/financial security is achieved players may have less incentive to maintain performance. New team status for pitchers is also positive and significant, indicating that pitchers who change teams between seasons tend to experience improved performance. This could be for a variety of reasons such as access to new pitching coach staffs, and new pitching strategies that better align with pitcher strengths. Additionally, a new team for pitchers may offer a fresh environment, potentially boosting confidence and motivation, leading to better performance on the mound. None of the other variables are significant for pitchers. Also, international status is not statistically significant for neither pitchers and batters, suggesting that there is not sufficient evidence to conclude that a player's socioeconomic status when growing up leads to shirking tendencies.

When salary outliers were removed from the dataset, the results for both batters and pitchers remained consistent with the models using the full dataset including outliers. The coefficients for salary change and contract length remained significant and negative, indicating the removal of outliers did not substantially alter the relationship between these variables and WAR change. Other variables that were only significant for one group stayed the same as well, and the same for variables that were not significant, suggesting that there is no meaningful difference in the overall model performance when outliers are excluded.

To evaluate model performance, I compared the Root Mean Squared Error (RMSE) for full and reduced models for both batters and pitchers using the full dataset. This was done to assess whether including salary change and contract length improves predictive accuracy. Using an 80/20 training/testing split, the models are trained on 80% of the data and tested on the remaining 20%. RMSE values were calculated on the test data. For both batters and pitchers, the full model, which includes salary change and contract length, showed lower RMSE values compared to the reduced model without those two variables, indicating the inclusion of salary change and contract length enhances predictive accuracy in the model. This supports the idea that contract characteristics significantly influence performance changes. RMSE values for the models are in the table below:

Table 4

Model RMSE Analysis	
Model	RMSE Value
Full Batter Model	1.548
Reduced Batter Model	1.629
Full Pitcher Model	1.209
Reduced Pitcher Model	1.228

Predicting Salary and Contract Length

Now that we've examined the result of the WAR change models and validated their predictive accuracy though the RMSE analysis, we turn out attention to predicting the change in WAR for the current free agent class for next season. Since most free agents have yet to sign contracts and their terms are unknown, it is necessary to first create model to predict salary and contract length. These predicted values will serve as inputs for the WAR change model, allowing us to evaluate shirking tendencies for the 2025 free agent class based on projected salary change and contract length.

Four separate models were developed to predict salary and contract length for batters and pitchers, but they share the same set of predictors within each player group. So the two models for batters have the same variables, and the two models for pitchers have the same variables. Each model uses a GAM framework to capture non-linear relationships between the predictors and response variables. GAMs are particularly well suited for this analysis because they use smoothing splines, which allow the model to capture the complex, non-linear relationships between variables. This ensures that features like age, prior performance metrics, and market size are accounted for without imposing linear assumptions. All variables that start with "previous" are based on the contract year.

For batters, the salary and contract length models are expressed as:

$$Salary/Contract\ Length \sim s(Previous\ WAR) + s(Previous\ Salary) + s(Previous\ Contract\ Length) + Contract\ Type\ FA\ to\ FA + s(Previous\ ISO) + s(Previous\ wRc\ Plus) + s(Previous\ Games\ Played) + s(Market\ Size) + New\ Team + s(Age)$$

The model for batters uses several key performance metrics from the contract year to predict salary and contract length. Previous WAR reflects a player's overall value to team success. Previous salary and previous contract length provide historical data and set a baseline for future contracts. Contract Type FA to FA is a dummy variable capturing whether a player is moving from one free agent contract to another. If this variable equals 0, it means the player is going from an arbitration deal to a free agent contract. ISO (Isolated Power) and wRC+ (Weighted Runs Created Plus) measure offensive performance, with ISO focusing on player’s power and ability to hit for extra bases, and wRC+ accounting for overall offensive value. wRC+ is adjusted for ballpark and league environments, average is 100, and if a player has a 120 wRC+ for example, then they are 20% better than league average at hitting. Games played (G) is an indicator of a players durability, which is important if teams want to give a large contract to players. Market size helps represent the economic environment of the team. Age is another crucial predictor as performance peaks when a player is around 27-32 years old then declines as they get older in most case. New Team reflects whether the player is switching teams, which can impact contract values.

For pitchers, the salary and contract length models are expressed as:

$$Salary/Contract\ Length \sim s(Previous\ WAR)\ +\ s(Previous\ Salary)\ +\ s(Previous\ Contract\ Length)\ +\ s(Previous\ Games\ Started)\ +\ Contract\ Type\ FA\ to\ FA\ +\ s(Previous\ IP)\ +\ s(Previous\ FIP)\ +\ s(Previous\ Saves)\ +\ s(Market\ Size)\ +\ New\ Team\ +\ s(Age)$$

The pitcher model similarly includes previous WAR, previous salary, previous contract length, contract type FA to FA, market size, new team dummy and age just like in the batter model. In the models for pitchers, they have specific metrics such as Games Started (GS), which helps get an idea if a pitcher is a starter or reliever, and this may make a difference in salary and contract length, as starters tend to make more money than relievers. Innings pitched (IP) is a measure of durability and workload. Saves (SV) is included as a metric top-end/high-leverage for relievers. Lastly, FIP (Fielding Independent Pitching) is used to measure a pitcher's performance independent of defense. Because FIP only looks at the three true outcomes, walks, home runs and strikeouts, this provides a more accurate reflection of pitcher skills compared to ERA (Earned Run Average).

The contract length outcome in both the batter and pitcher models is modeled as a count variable. To handle this, we used a GAM with a poisson regression and a log link. The poisson regression is commonly used for count outcomes, and the log link ensures the predicted values remain non-negative, as this isn't possible for contract length. While the GAM framework provides the flexibility to model complex, mon-linear relationships with smoothing splines, the poisson regression with the log link allows us to handle the count nature of contract length effectively. For the salary prediction in both models, we use a gamma distribution with a log link. The gamma distribution allows for modeling continuous positive data like salaries, and the log link ensures that the predicted salary values are positive. This is helpful when predicting a skewed distribution that we see in salary, where the majority of players are concentrated in the lower range of salaries with few players having high salaries.

To evaluate the performance of these models, an 80/20 train-test split was applied to the datasets of contracts signed in 2011-2024. The RMSE values from the test sets were calculated to highlight the model's predictive accuracy. The RMSE values for all four models are in the table below:

Table 5

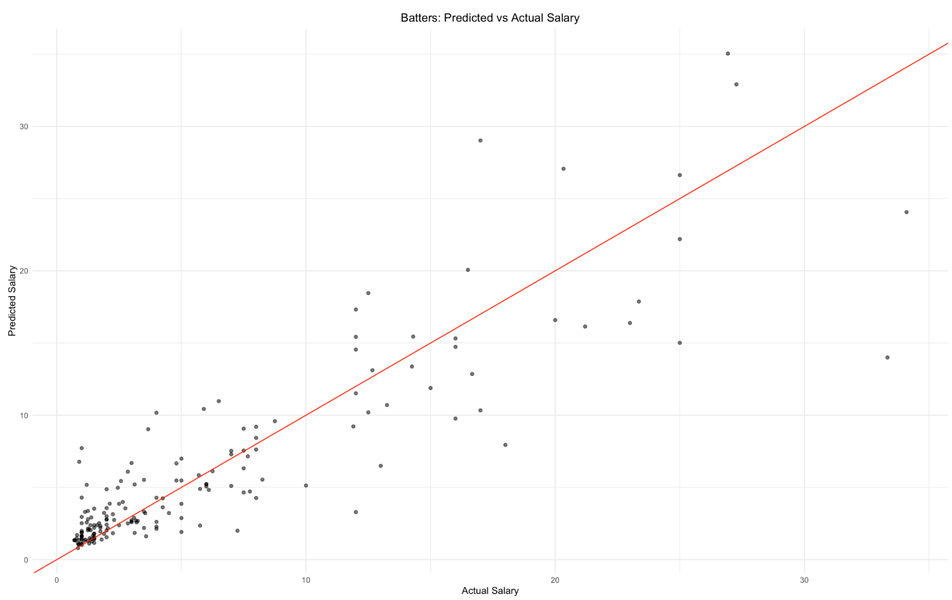
Model Type	Salary RMSE	Contract Length RMSE
Batters	3.2966	1.0329
Pitchers	3.2605	0.9077

These results indicate that the models effectively predict salary and contract length for both batters and pitchers, as reflected by the lower RMSE values. These value mean the average error when predicting salary is approximately $3.3 Million and, and the average error when predicting contract length is about one year. Since salary and contract length have different scales, the values are not directly comparable.

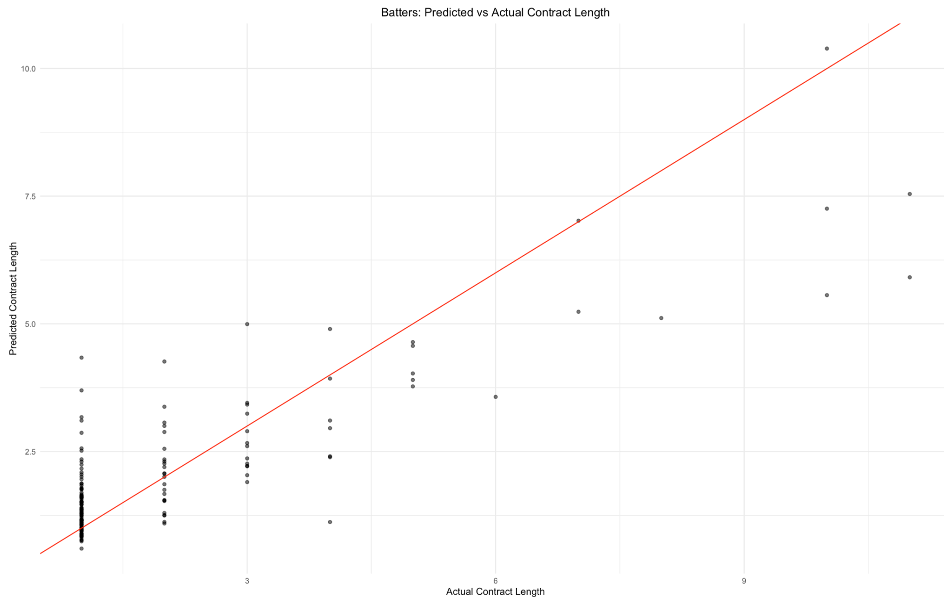
With these models validated, we can now use them to predict the salary and contract length for the 2025 free agent class. These will serve as essential inputs for the WAR change model, allowing us to predict each player's change in WAR for next season, and to assess player performance dynamics based on projected contract terms. The validation process, along with the flexibility of smoothing splines in GAMs to model non-linear relationships, ensures that these models are robust and capable of generating meaningful predictions. After inputting the predicted salary and contract length figures, we can make predictions for the changes in WAR. To further assess the accuracy of the salary and contract length predictions, we now turn to visualising the model performance through scatterplots on the test datasets. These plots compare the predicted values to the actual value, providing a visual representation of the model's predictive strength.

Scatterplots For Salary and Contract Length Predictions

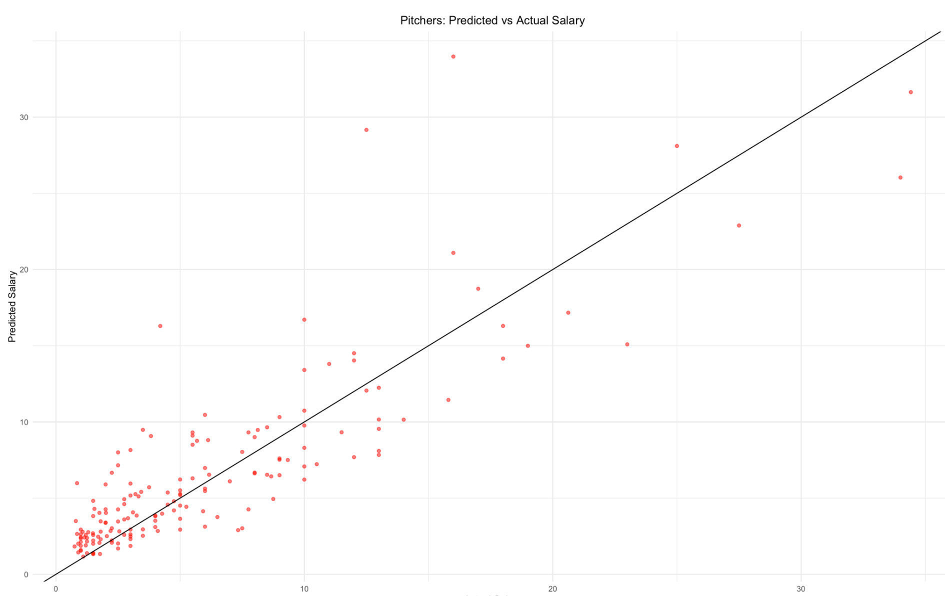
Plot 1



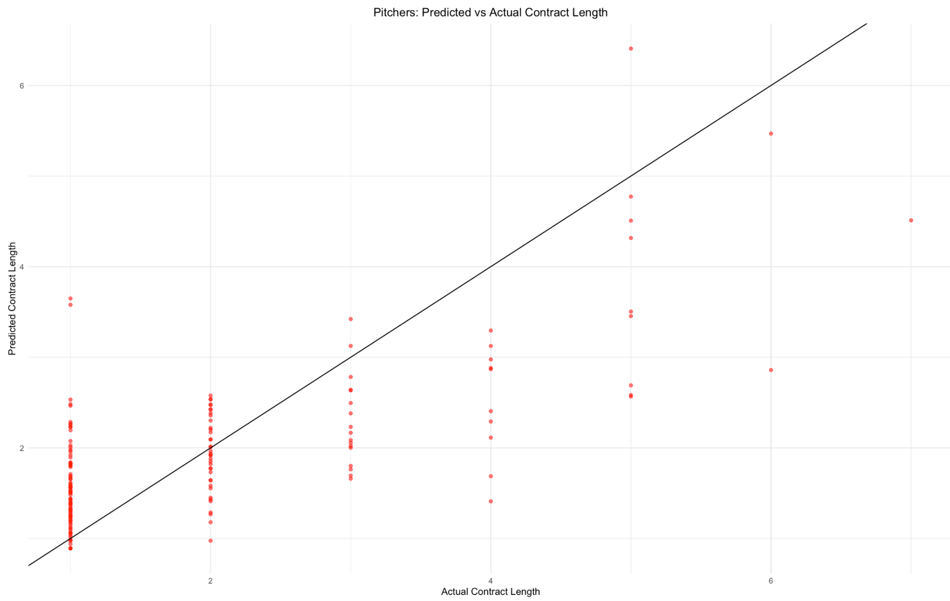
Plot 2


Batters: Predicted vs Actual Contract Length
Predicted Contract Length
Actual Contract Length
10.0
7.5
5.0
2.5
3
6
9

Plot 3


Pitchers: Predicted vs Actual Salary
Predicted Salary
Actual Salary
30
20
10
0
0
10
20
30

Plot 4



Predicting Salary, Contract Length & WAR Change for 2025 Free Agents

With the models for salary, contract length, and WAR change now validated, we can now apply them to forecast outcomes for the 2025 free agents. Using player performance data from the 2024 season, as well as their previous salary and contract length, we predicted the free agent's salary and contract length, providing insight into the financial landscape of the upcoming free agent market. The predicted values for salary and contract length are then used as inputs for the WAR change model to estimate how the player performs in the 2025 season based on shirking variables. The salary change variable in the model is the difference between predicted 2025 salary and actual 2024 salary. Assumptions for some of the other variables in the WAR change model include assigning players to join new teams a value of 1 (New Team = 1), assign the multiple teams dummy a value of 0, and control for the effects of market size by using the average market size. These assumptions simplify the predictions where forecasts for variables such as trades and specific team signings are less feasible.

The tables below display the top 10 and bottom 10 predicted WAR change values for the 2025 free agents, encompassing both hitters and pitcher:

Table 6, Hitter Top 10:

Player Name	Predicted Salary	Previous Salary	Salary Change	Predicted Contract Length	Previous WAR	Predicted WAR Change	Predicted 2025 WAR
Austin Slater	2.86	4.00	-1.14	1.31	-0.15	0.20	0.05
Danny Jansen	5.06	5.20	-0.14	1.77	0.57	0.16	0.72
Alex Verdugo	9.09	8.70	0.39	2.34	0.60	0.11	0.71
Joey Gallo	2.55	5.00	-2.45	1.06	-0.16	0.08	-0.09
Rowdy Tellez	2.28	3.20	-0.92	1.19	-0.47	0.00	-0.47
Adam Frazier	2.07	4.50	-2.43	0.95	-0.58	-0.05	-0.63
Kyle Farmer	5.06	6.30	-1.24	1.45	0.55	-0.09	0.46
Harrison Bader	8.49	10.50	-2.01	2.10	1.32	-0.12	1.20
Justin Turner	6.99	13.00	-6.01	1.48	1.18	-0.15	1.03
Amed Rosario	2.07	1.50	0.57	1.40	0.27	-0.16	0.11

Table 7, Hitter Bottom 10:

Player Name	Predicted Salary	Previous Salary	Salary Change	Predicted Contract Length	Previous WAR	Predicted WAR Change	Predicted 2025 WAR
Juan Soto	33.36	31.00	2.36	16.04	8.14	-1.88	6.26
Willy Adames	30.27	12.25	18.02	5.31	4.75	-1.77	2.98
Anthony Santander	25.48	11.70	13.78	4.28	3.31	-1.34	1.98
Joc Pederson	18.08	12.50	5.58	3.44	2.96	-1.01	1.94
Jurickson Profar	5.70	1.00	4.70	3.28	4.30	-0.92	3.38
Carlos Santana	5.71	5.25	0.46	1.79	3.02	-0.83	2.19
Christian Walker	17.11	10.90	6.21	3.01	3.00	-0.80	2.20
Donovan Solano	1.72	1.00	0.72	1.09	0.78	-0.77	0.02
Yasmani Grandal	2.57	2.50	0.07	1.27	1.96	-0.72	1.24
Travis d'Arnaud	6.19	8.00	-1.81	1.53	1.84	-0.56	1.28

Table 8, Pitcher Top 10:

Player Name	Predicted Salary	Previous Salary	Salary Change	Predicted Contract Length	Previous WAR	Predicted WAR Change	Predicted 2025 WAR
Blake Snell	18.79	31.00	-12.21	2.42	3.07	0.64	3.71
Matt Moore	1.95	9.00	-7.05	0.96	-0.74	0.36	-0.38
A.J. Minter	3.95	6.22	-2.27	1.76	-0.05	0.28	0.23
Michael Soroka	4.03	3.00	1.03	1.80	0.39	0.28	0.67
Wade Miley	2.43	8.50	-6.07	0.88	-0.11	0.27	0.17
Alex Wood	3.55	8.50	-4.95	1.13	-0.06	0.25	0.18
Lucas Sims	2.37	2.85	-0.48	1.54	-0.29	0.22	-0.07
Joe Kelly	2.87	8.00	-5.13	1.13	-0.05	0.21	0.16
Craig Kimbrel	8.38	13.00	-4.62	1.78	0.14	0.11	0.26
Martín Pérez	5.51	8.00	-2.49	1.43	0.53	0.09	0.62

Table 9, Pitcher Bottom 10:

Player Name	Predicted Salary	Previous Salary	Salary Change	Predicted Contract Length	Previous WAR	Predicted WAR Change	Predicted 2025 WAR
Corbin Burnes	30.66	15.64	15.02	4.47	3.74	-1.02	2.71
Max Fried	29.45	15.00	14.45	4.19	3.35	-0.99	2.36
Nick Martinez	18.81	13.00	5.81	3.40	3.47	-0.66	2.80
Tanner Scott	15.36	5.70	9.66	3.94	1.64	-0.64	1.00
Kirby Yates	10.45	4.50	5.95	2.41	1.92	-0.63	1.29
Jeff Hoffman	9.90	2.20	7.70	3.60	2.04	-0.55	1.49
Clay Holmes	13.80	6.00	7.80	3.44	1.20	-0.53	0.66
Jack Flaherty	20.35	14.00	6.35	3.11	3.22	-0.48	2.73
Sean Manaea	18.11	14.00	4.11	2.87	2.78	-0.47	2.31
Nick Pivetta	13.92	7.50	6.42	2.90	2.03	-0.37	1.66

The model's evaluation metrics in the validation process had a salary RMSE of $3.30M for batters and $3.26M for pitchers, and contract length RMSE values of 1.03 years for batters, and 0.91 years for pitchers. Notably, the model predicts that players with the largest projected salary increases will experience the largest declines. However, this outcome is largely a function of the GAM models, as both contract length and salary change were significant and negative. The model could also be overvaluing short-term performance while penalizing long-term risks, which is particularly evident for players whose projected salaries are heavily influenced by external market factors, and not solely based on past performance, as in the case of big names like Juan Soto and Corbin Burnes. Additionally, both salary and contract length are skewed by a small number of high end observations, where only a few players receive extremely high salaries or long-term deals. This skewness can distort predictions for players at the extremes, as the models may struggle to fully capture trends influenced by these outliers.

For the predicted results, Corbin Burnes is projected to have the largest performance decline among pitchers, with a predicted salary of $30.66M, a substantial increase of %15.02M from his previous salary in 2024. He's also projected to have a 4-5 year contract and a WAR decrease of -1.02. The salary and contract length predictions for Burnes appear reasonable for a

30 year old pitcher and aligns with expectations of past performance. The performance decline reflects the challenges of maintaining peak output, particularly following a substantial salary increase, which could cause decrease motivation to perform.

Juan Soto is predicted to have the largest performance decline among batters, with a slight predicted salary increase to $33.36M, and a lengthy predicted contract length of over 16 years. Soto's salary appears to be underpredicted, likely due to the skewness of salary data, and the influence of external market factors that the model doesn't fully understand. Some of these factors could include the fact that Soto is only 26 years old and hasn't reach his prime years, and it's uncommon to have a talent like Soto on the free-agent market at his age. Additionally, because he hasn't reached his prime yet, he'll likely get a higher salary due to projected future performance, not solely based on past performance. Soto's predicted WAR is 6.26, a decline of -1.88 from the 2024 season. While the projected drop reflects the model's tendency to penalize players who receive large contracts, Soto is still projected to be one of the league's elite players.

These results highlight the tradeoff teams must weigh when balancing immediate performance vs long-term performance. While the model provides robust results, players like Juan Soto and Corbin Burnes illustrate the complexities of predicting skewed metrics like salary and contract length. For players like Soto, the underprediction of salary underscores the influence of external market dynamics, and competitive bidding, which can drive actual contract values beyond what the model predicts. In contrast, Corbin Burnes' predicted salary and contract length align more closely with expectations, demonstrating the model's accuracy for certain player types. Additionally, the assumptions made for market size and new team variables in the model introduces further challenges, as actual outcomes can vary significantly depending on the financial market players enter. These factors, as well as the skewed distributions of salary and contract length, highlight the sensitivity of the predictions to outliers with higher value. This is especially relevant when evaluating the risks of shirking behavior, where players may underperform relative to contract expectations in the first year, particularly if increased financial security impacts motivation to maintain peak performance.

Discussion/Conclusion

The results of this study provide a comprehensive understanding of the factors influencing player performance changes in the context of shirking behavior post-contract signing. Using advanced statistical models such as Generalized Additive Models (GAMs), we explored the relationship between player performance and contract characteristics, and used the findings to make predictions for the 2025 free-agent class.

The findings from the WAR change model strongly support the hypothesis of shirking behavior. Both salary change and contract length were significant predictors of performance decline between the contract year and first year post-signing. The negative coefficient for salary change indicates that players receiving greater salary increases tend to experience greater drops in WAR. This trend may reflect reduced motivation after securing financial stability or the pressures of meeting elevated expectations tied to high-value contracts. Similarly, longer contracts are associated with greater performance declines, reinforcing the idea that the increased job security provided by long-term deals might reduce a player's drive to maintain peak performance, highlighting the risks teams face when committing to long contracts. Market size was not a significant predictor of WAR changes challenging the assumption that players in large markets face greater performance pressure due to heightened media presence or fan expectations. International status was also insignificant, suggesting a player's socioeconomic background does not significantly influence post-contract performance. The impact of signing with a new team varied by position as it was significant for pitchers but not for hitters. This could mean pitchers may benefit from changes in coaching strategies or team alignment with their strengths, while hitters may not experience comparable advantages.

The RMSE analysis for the WAR change models confirmed that including salary change and contract length as predictors significantly improved the model's predictive accuracy in explaining change in WAR. The full models outperformed reduced versions without these predictors, showing the importance of contract terms in explaining post-signing performance trends. However, biases were observed for high-earning players due to the statistical nature of WAR. Elite players start from higher performance levels, and have greater room to decline compared to replacement-level players, who may see smaller drops or even improvements motivated by modest contract gains.

This pattern results in high-end players being more likely to experience largers performance declines, though these drops are often smaller relative to their historical value. While these biases do not undermine the findings of the mode, the emphasize the need to interpret predictions within the context of player quality. Incorporating contract data after the offseason is over and every free agent signs could mitigate some of the biases shown in the predictions.

The evidence of shirking behavior has critical implications for team navigating free agency. To mitigate the risks of performance decline, teams could re-evaluate contract structures for higher-salary players by offering shorter deals or including performance incentives to sustain motivation. However, this approach is often impractical, as securing high-end free agents in competitive markets typically require long-term guaranteed contracts. Players may also be reluctant to sign with teams that impose performance-based conditions or offer fewer years. For lower-tier players, smaller financial incentives or shorter contracts can act at motivators, encouraging more consistent performance.

While the findings are robust, several limitations must be considered. External factors such as off-field issues, team dynamics and player personality traits are challenging to model and can significantly influence performance. Additionally, this study only focused on the first year, leaving room for analysis to examine performance trends over the full contract duration. Extending the analysis could reveal patterns where players "coast" during their contracts before experiencing a performance surge in the contract year as they seek a more lucrative deal.

This study highlights the critical role of contract terms, such as salary change contract length, in influencing player performance changes post-contract signing. These findings provide strong evidence of shirking behavior in MLB for both pitchers and hitters, with high-performing players showing greater statistical dropoff due to their elevated starting point and natural regression. Contrastly, lower-tier players appear more resilient, with smaller financial incentives serving as motivators for most consistent performance. Both these trends were also apparent when making predictions for next season's performance for the current 2025 free-agent class. These findings offer actionable insights for teams navigating free agency, emphasizing the potential hazards of signing players to large contracts, as well as the need to tailor contract strategies to balance financial incentives with performance incentives. As the models are applied to the 2025 free agents, incorporating their contract details once all the players sign may enhance prediction accuracy as some of the salary and contract length predictions for high-end players may be inaccurate due to the skewness of the two variables. This can help ensure teams optimize their player investments while accounting for the inherent risks of shirking behavior brought on from large contracts.

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