Analyzing the Value of Consistency Among NHL Players, Offensively & Defensively

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December 12, 2025

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Abstract

This paper investigates whether consistency in player performance influences salary determination in the National Hockey League (NHL). Using publicly available data from the 2015-2016 through 2024-2025 seasons, the study constructs standardized per 60-minute performance metrics and develops offensive and defensive consistency indices using weighted variance change (WVC). Linear regression models controlling for age and time on ice show that offensive performance, experience, and usage are the strongest predictors of cap hit, while defensive performance plays a smaller role. Consistency does not meaningfully predict salary; in several cases, greater inconsistency is associated with higher pay, suggesting that teams prioritize players with high offensive ceilings even if their output fluctuates across seasons. This is surprising, however, because most people think that consistent output would lead to higher pay. These findings indicate that NHL teams reward peak performance rather than stable year-to-year contributions, contributing to broader discussions on how analytics inform valuation in professional sports.

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Introduction

Consistency among players' performance has been linked to winning more games, so it would be in a team's best interest to create a consistent team by signing and drafting consistent players (Hwang, 2020). It isn't simply "star players" helping generate wins for teams, it is everyone working together to win games (Mukherjee, 2018). Creating metrics within ice hockey has continued to evolve since the creation of sports analytics (Nandakumar, 2018). However, there is not one method or metric that is claimed to be the standard for quantifying anything from performance to, more relevantly, consistency in ice hockey or other sports. There is short-term volatility, environmental consistency in the form of home and away games, and adaptability measures to maintain performance (Vapnek, 2024).

This paper will aim to define a single consistency metric that quantifies the consistency at which NHL players perform, both offensively and defensively. Then, analyze the connection, if any, that consistency relates to salary. My research question is: *Do NHL teams value consistent players?* Understanding if teams value consistent players will allow us to know if it is better to be a high performing player, whether that's in scoring or preventing goals, or a consistent player that continually provides value to the team.

Literature Review

The value of human capital in professional sports is a complex and important business domain. It is situated at the intersection of rigorous sports evaluations, economic theory, and shifting market dynamics. A precise financial assessment is crucial to strategic team management since it establishes a professional athlete's worth to a club and the price a club should pay for them (Gulbrandsen & Gulbrandsen, 2011). Accurately determining a player's actual financial and competitive value is essential for organizational success in contemporary team sports leagues. The corpus of research on this subject has expanded, incorporating formal economic frameworks and data-driven analytical models in addition to more conventional, subjective scouting techniques.

The research on the fundamental accounting and economic ideas that characterize a player as a revenue-generating asset, the development of advanced analytics to measure a player's actual performance value, the empirical data on contracts, market power, and the factors influencing the final negotiated price, and the new conceptual frameworks that integrate value and price determination are all critically synthesized in this review of the literature. This synthesis's main goal is to chart the intellectual evolution from basic performance metrics to comprehensive valuation models, clearly identifying the variables that influence a player's inherent value as well as the negotiated market outcome.

Economic Foundations and Valuation Challenges. Defining a professional athlete as a quantifiable financial asset is complicated by the high uncertainty and legal structure of employment contracts. From an accounting perspective, Financial Reporting Standards (FRS 10) require investments in football player contracts to be capitalized as intangible assets (Amir & Livne, 2005). However, Amir and Livne (2005) contests that weak, short-term association between the initial investment and future economic benefits challenges the underlying asset capitalization criteria. They point out that the "investment's" economic life is frequently shorter than the normal amortization term. This demonstrates how strict accounting procedures and the erratic nature of athletic careers are not related.

A player's worth in terms of money must be based on their proven ability to bring in more money for the team, which can come from performance on the field (Gulbrandsen &

Gulbrandsen, 2011). Accordingly, a transfer is only logical if the anticipated rise in revenue outweighs the selling club's financial obligations and perceived value loss (Gulbrandsen & Gulbrandsen, 2011). This "value" then determines the market price cap.

The market mechanisms governing price determination were established through models that treated the transfer fee as a “hedonic price”, a value determined by the quantifiable attributes of the player (Carmichael, Forrest, & Simmons, 1999). However, the estimation of this price contains selection bias as only the small sample of players who change teams possess an observed price. To address this challenge, it requires complicated econometric techniques, such as the Heckman procedure, used to model the probability of a player entering the market, thus creating the technical basis for understanding market price (Carmichael et al., 1999).

Shift to Advanced Analytics and Consistency, Quantifying Value. The analytical revolution in sports has continually improved for how to measure what the value a player adds by moving beyond “biased” traditional statistics to metrics that capture the reliability and quality of performance. The integration of advanced data technologies (like Sabermetrics and Statcast) with machine learning (ML) algorithms marks the intellectual turning point in accurately forecasting value (Franco, 2024).

Consistency, an aspect of sports analytics that was previously unmeasured, is a major focus. According to Vapnek (2024), consistency can be defined in three main ways: environmental consistency, in-season adaptability, and short-term volatility. When traditional performance is considered, these variables have statistically substantial explanatory power for arbitration salaries (Vapnek, 2024). The cost of inconsistent performance or large output variance serves as the foundation for the economic case for rewarding consistency (Bodvarsson & Brastow, 1998). High-variant workers are penalized by receiving lower compensation since it takes them longer and more effort to precisely predict their true projected Marginal Revenue Product (MRP). Thus, supporting the idea that trustworthy contributions should be specifically rewarded by employers (Bodvarsson & Brastow, 1998).

Contracts, Market Power, and Compensation. While advanced analytics determine the basis of a player's value, the final negotiated price (salary and transfer fee) is governed by market constraints, competitive dynamics, and individual player behavior. The transfer price itself is mostly determined by empirical factors. According to Carmichael et al. (1999), the ultimate negotiated fee is significantly influenced by a player's career experience and goal totals when examining the transfer market. Market structure, which usually resembles a monopsony or oligopsony, plays a significant role in mediating this process (Carmichael et al., 1999). Particularly in competitive bidding circumstances for great players, this setting enables the selling club to demand monopoly rents from purchasing clubs.

Consequently, the amount paid was more than the selling club's technical floor value (Frick, 2011). Furthermore, the duration of the contract introduces behavioral variables affecting the need for compensation. Frick (2011) provides evidence for the moral hazard hypothesis in professional sports, demonstrating that players in the German Bundesliga, the top German soccer league, exhibited significantly increased performance as their contract approached its expiration date (in advance of renegotiation). This suggests that high salaries and job security, while satisfying the player, reduce the incentive to maximize effort over the life of a contract. Therefore, it forces clubs to build compensation strategies that factor in the risk of shirking (Frick, 2011). This notion directly informs how much a club should pay as a long-term contract may require a premium to mitigate the behavioral risk.

Holistic Value, Price, and Marketability. Modern models use non-athletic contributions to appropriately reflect a player's worth. Fan appeal has been demonstrated to be essential to a player's value addition since it has a direct impact on non-performance revenue streams such as merchandise sales, sponsorship deals, and broadcasting rights (Gulbrandsen & Gulbrandsen, 2011). To forecast transfer fees, Aydemir, Taskaya, and Temizel (2022) created a comprehensive "Probabilistic/ML Assembling model" that successfully integrated in-game performance data with player popularity metrics, like Google Search Trends. This showed how empirical machine learning research may successfully model this external value. The effectiveness of this model shows that both indisputable commercial outreach and athletic output affect a player's current value (Aydemir et al., 2022).

More conceptual frameworks have been developed because of this complexity. Option valuation (suitable for simulating uncertain futures, such as injury recovery), probabilistic (ML-driven prediction), relative (comparables), and intrinsic (discounted cash flow/marginal revenue product) are the four categories into which Hill et al. (2025) classified valuation methodologies. The Option Pricing Framework is a useful theoretical tool for forecasting trajectory and recovery, and it helps create a scientifically based pricing baseline (Gulbrandsen & Gulbrandsen, 2011).

Conclusion. The literature has definitively moved the analysis of player economics beyond subjective scouting and simple linear regressions. Research now confirms that determining a player’s worth relies on accurately quantifying value through objective, complex performance metrics (like consistency and low volatility) and non-athletic marketability (fan appeal), while setting the price requires understanding empirical contract behavior and prevailing market power.

Despite the analytical success in quantifying individual variables, a singular, empirically validated framework that seamlessly integrates every dimension, from the monitoring costs associated with consistency to the probabilistic revenue stream derived from fan appeal, into a single intrinsic valuation model and negotiation strategy remains elusive. The clear intellectual gap is centered on the methodology required to unify these modern analytical dimensions to provide both a comprehensive determination of a player's actual value and a precise, optimized strategy for determining how much to pay.

Ethical Considerations

This research involves the use of publicly available NHL performance and salary data, which minimizes concerns related to privacy or the handling of personally sensitive information. All data were collected from open, reputable sources that already publish player statistics, contracts, and season-by-season outcomes for public consumption. Because of this, there are no human subjects, and no personally identifiable information is used beyond what is already made public by the league, teams, and media outlets.

However, several ethical considerations still arise in conducting and interpreting this type of analysis. First, quantitative player evaluation has the potential to influence perceptions of player value and performance in ways that may overlook contextual factors, such as injuries, coaching decisions, role changes, or team-specific strategies. Reducing players to a set of metrics, particularly those that emphasize volatility or “inconsistency”, can present an incomplete or potentially misleading representation of their contributions. Acknowledging this limitation helps avoid overstating the precision or generalizability of the models.

Second, ethical care must be taken to avoid reinforcing biases that already exist within professional sports labor markets. If a model disproportionately prioritizes offensive output, for example, it may unintentionally reproduce the same undervaluation of defensive or non-scoring roles that the NHL labor market already displays. For this reason, the interpretation of findings is limited to identifying statistical associations rather than prescribing how players should be valued.

Finally, transparency in data processing and model development is essential. All transformations including standardization to per-60-minute rates, construction of performance composites, and calculation of weighted variance change are clearly documented to allow for reproducibility and to prevent misleading conclusions drawn from opaque analytical choices. The goal is to contribute to the broader understanding of player valuation rather than produce tools that can be misused or misinterpreted without context.

Data & Methods

Data

The data was collected from two online sources. The seasonal player performance data was collected from Hockey-Reference (2025) by web scraping the data in comma-separated format. The salary data was collected from CapWages (2025) also by web scraping the data, which is in a table format. Then, everything was exported into an Excel spreadsheet and turned it into a csv. The player performance data is divided into several categories based on the type of metrics that are measured: The basic data includes goals, assists, points, etc. The advanced(adv) data includes Corsi for, Corsi against, etc. And the miscellaneous(misc) data includes total goals scored for while on the ice, total goals scored against while on the ice, offensive point shares, defensive point shares, etc. (Hockey-Reference, 2025). Further information of variables from the data collected can be found in Appendix B and the codebook in the documentation folder. For both performance data and salary data, the data was collected from the 2015-2016 season to

2024-2025 season. First, all the player performance tables are merged. Later, the combined player performance data is merged with the salary data for convenient analysis. In total, there are 9400 observations in the combined dataset of both performance and salary, before any filtering. For the analysis, the important variables are:

Variable	**Data Type**
Games Played	Discrete
Goals	Discrete
Assists	Discrete
Blocks	Discrete
Corsi For	Discrete
Corsi Against	Discrete
Goals for while on ice	Discrete
Goals against while on ice	Discrete
Offensive point shares	Continuous
Defensive point shares	Continuous
Salary	Continuous

The data needed to be wrangled before any form of analysis. First, all the variables of interest were standardized to a per 60-minute metric because not every player plays the same amount of time on the ice nor do they play the same number of games. This is a simple calculation by taking the metric, dividing it by the players total time on ice, and then multiplying it by 60. Then, new variables are derived to measure offensive performance, defensive performance, and, overall, consistency both offensively and defensively using the standardized metrics. Offensive and defensive performance are derived by weighting each metric, that is used to measure offense and defense respectively, by the estimated coefficients in a multiple linear regression model. Once these are created, weighted variance change (WVC) is used to calculate the consistency in both offense and defense for each player (Popovic, 2013). WVC is taking the variance of a metric for each time-period and weighting it on some factor for each time-period. The equation for calculating the WVC can be seen in equation (1). The variable *w* in the equation is the weights, and specifically to the research question, the weights are the number of games played in a season. Games played is used as weights since players should be weighed less if they played fewer games versus more games. The variable x represents the metric that is being used to calculate the inconsistency in from season to season. Offensive performance and defensive performance are the metrics that we are interested in analyzing a player's consistency in. This is then taken and standardized into z-scores for easier interpretations of comparing players. Below are two visualizations on the distribution of the consistency metrics created using weighted variance change and then standardized into z-scores, Figure 1 for offensive inconsistency and Figure 2 for defensive inconsistency.

$$(1)\ WVC = \frac{\sum_i w_i(x_i - \bar{x}_i)^2}{\sum_i w_i}$$

Figure 1. Distribution of offensive inconsistency index calculated from WVC

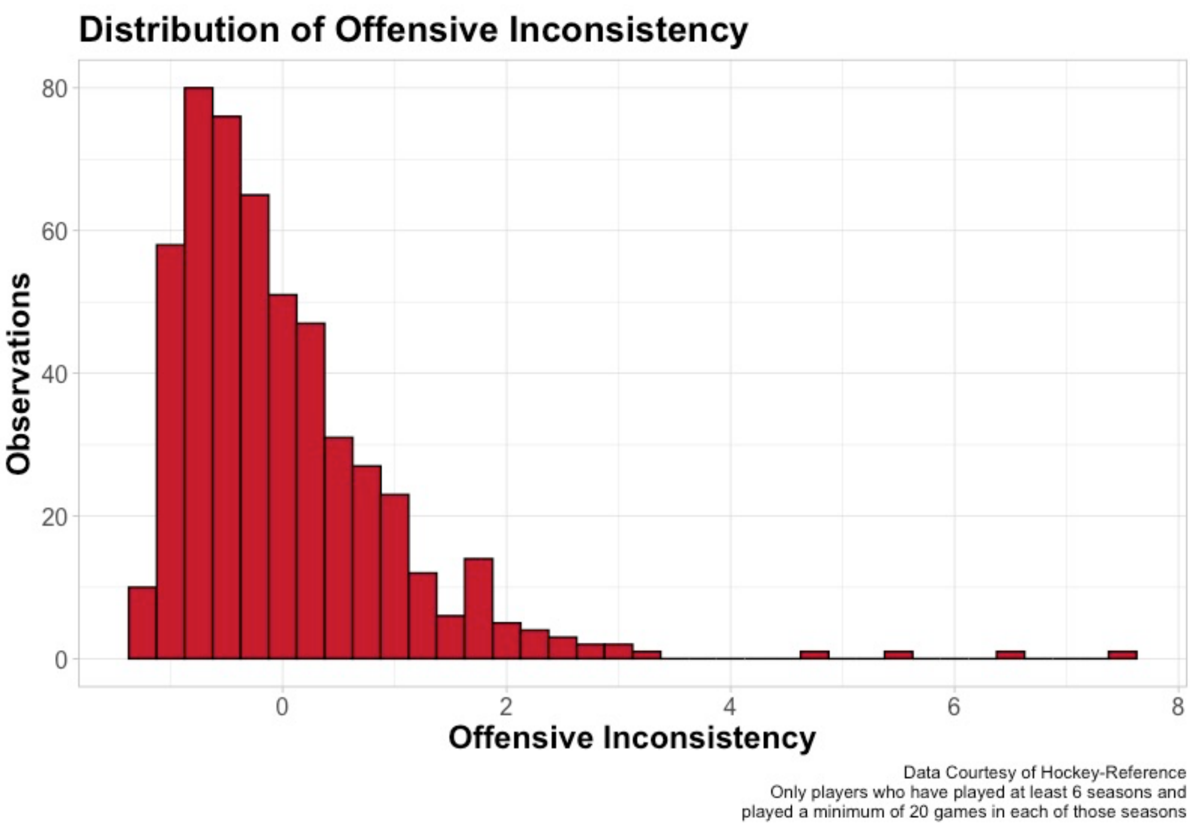
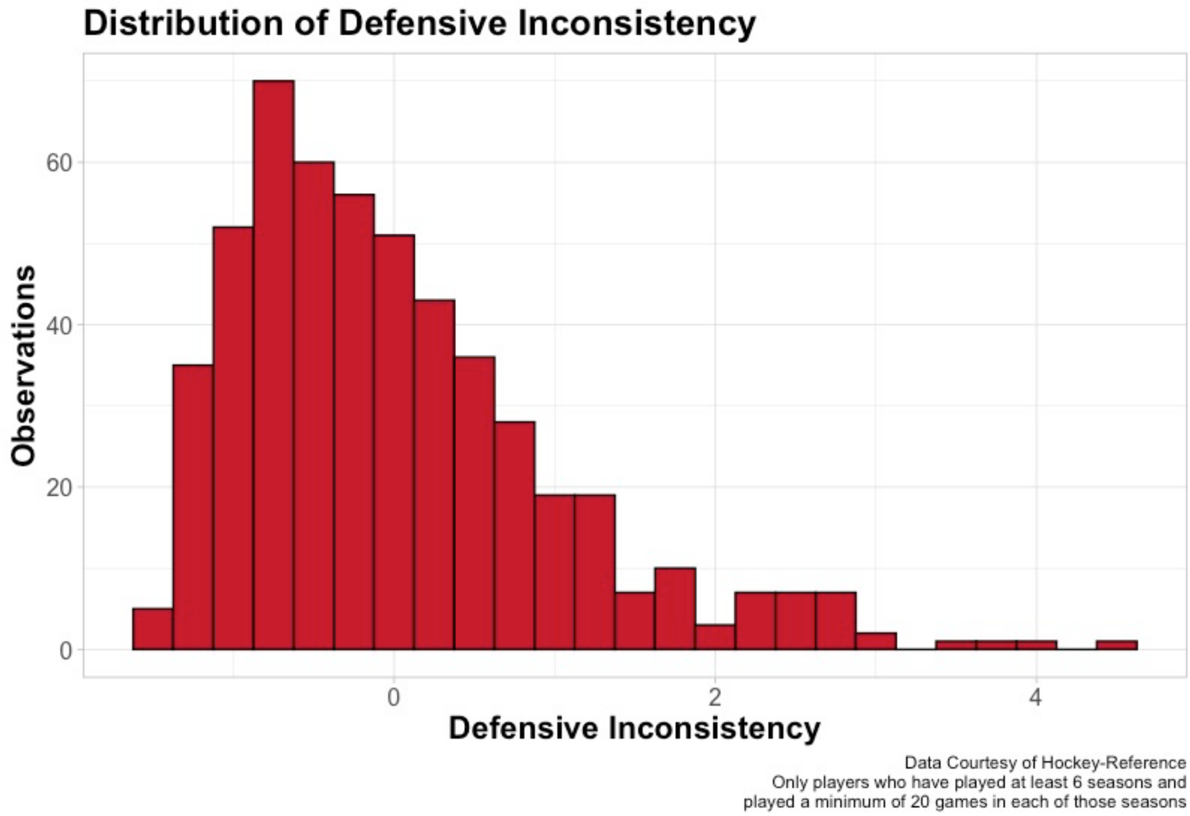


Figure 2. Distribution of defensive inconsistency index calculated from WVC



The data includes time information where every row contains the metrics for one player for one season (year). The structure of the data is that of panel data where every observation will include the player's metrics for a certain season, or year more simply. There are generalized assumptions that will need to be made and filtering for the best interpretation of results. Therefore, the exclusion criteria will include players that didn't play in at least 6 of the 10 possible seasons and any players that didn't play in at least 20 games in any given season. This is because we could get some very consistent or inconsistent players that only played for a few seasons or for very few games in a season, but they wouldn't offer much insight if their consistent play led them to getting paid more than previously. Hence, the analysis should include players who played for several seasons and more than a quarter of the season to identify the relationship between consistency and players' salaries.

Methods

The statistical and analytical design of the study will mainly compose of linear regression and correlation testing to see if there is a strong relationship between a player's consistency and their salary. Additionally, offensive performance and defensive performance are added into the linear regression analysis to test if they are better predictors of a player's salary (Equations 2, 3, and 4). These tests are used because the research question is set up as an econometrics question to see if consistency affects a player's salary, or if there is some other factor(s) that are a better predictor or indicator of a player's salary (Lewis, 1979). The key input variables are offensive performance, defensive performance, consistency score, and salary, also referred to as cap hit, while controlling for age and time on-ice per 60 minutes.

$$(2)\ \ Caphit_i = \beta_0 + \beta_1 offensive\ performance_i + \beta_2 defensive\ performance_i + \beta_3 offensive\ consistency_i + \beta_4 defensive\ consistency_i + \beta_5 age_i + \beta_6 time\ on\ ice_i$$

$$(3)\ \ Caphit_i = \beta_0 + \beta_1 offensive\ performance_i + \beta_2 offensive\ consistency_i + \beta_3 age_i + \beta_4 time\ on\ ice_i$$

$$(4)\ \ Caphit_i = \beta_0 + \beta_1 defensive\ performance_i + \beta_2 defensive\ consistency_i + \beta_3 age_i + \beta_4 time\ on\ ice_i$$

The key outputs are the estimated coefficients for each variable, the p-values of each variable, and the R^2 value from the linear regression analysis output. These tests will help to answer the research question because each will help understand how those variables impact a player's salary, offensively, defensively, and consistency score, and their significance in their prediction of a player's salary. The statistical analyses and model choices are validated by first analyzing the data appropriately before the statistical tests and modeling to ensure it doesn't violate any key assumptions of those tests or models such as a mean around zero and multicollinearity amongst variables in the models. There are enough data points to ensure precision as there are over 500 players that have a played a minimum of 20 games in each season and a minimum of 6 seasons from the 2015-2016 season to the 2024-2025 season (Hockey-Reference, 2025; CapWages, 2025).

Results

After performing the first linear regression (2), most of the variables are statistically significant for predicting a player's cap hit (in millions of dollars) at a 99.9% confidence level (p-value < 0.01). The variables that aren't statistically significant at the 99.9% confidence level and are not statistically significant at all are defensive performance, defensive consistency, and the interaction between defensive performance and defensive consistency which can be seen in Table 1. The R2 value for this regression is reported at 0.530, meaning the model accounts for 53.0 percent of the variance. Offensive performance, offensive consistency, age, and time on-ice per 60 minutes were the only predictors with a positive coefficient and displays the largest effects on cap hit. This means that an increase in these variables lead to a general increase in a player's salary. The defensive consistency variables are going in the direction that was expected, the more inconsistent a player is, the less money they make. However, the offensive consistency coefficient is positive, implying that the more inconsistent a player is, the more money they make. This goes against the intuition that a player who consistently produces earns more money. Plus, it has a small effect size for predicting a player's salary compared to that of offensive performance. The defensive performance coefficient is negative, which was not expected and could just be masked by the larger effect offensive performance has on cap hit. The interaction terms seem to be significant with a player performing better and being more inconstant being paid less, which conforms to the expectations.

Table 1. Linear Regression Outputs of Three Models on Cap Hit

	Combined Model	Offensive Model	Defensive Model
(Intercept)	−7.957***	−8.024***	−8.425***
	(0.246)	(0.243)	(0.262)
Offensive Performance	1.292***	1.220***	
	(0.058)	(0.040)	
Defensive Performance	−0.105		1.111***
	(0.068)		(0.050)
Offensive Inconsistency	0.270***	0.273***	
	(0.042)	(0.040)	
Defensive Inconsistency	0.008		0.122***
	(0.035)		(0.036)
Age	0.209***	0.210***	0.209***
	(0.007)	(0.007)	(0.008)
Avg. Time on Ice	0.328***	0.329***	0.361***
	(0.008)	(0.008)	(0.009)
Off. Performance X Off. Inconsistency	−0.169***	−0.170***	
	(0.030)	(0.028)	
Def. Performance X Def. Inconsistency	−0.043		−0.256***
	(0.039)		(0.040)
Number Observations	4031	4031	4031
R2	0.530	0.529	0.453

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Moreover, the first regression is split into strictly looking at the effect of offense (Offensive Model), using equation (3), and defense (Defensive Model), using equation (4), have on cap hit respectively. Starting with the offensive performance and inconsistency on cap hit, all the variables were statistically significant at the 99.9% confidence level (p-value < 0.001). The R2 value for this regression came out to 0.529, meaning the model could explain for 52.9 percent of the variance within the data. The direction of the coefficients, positive or negative, are going in the direction that was to be expected, except for offensive consistency. The estimated coefficient for offensive inconsistency (0.273) is positive meaning that the more inconsistent a player is, the more money they make. This is surprising as it goes against the logic that a player who is less consistent in their production would be paid less. However, the interaction term of offensive performance and offensive consistency (-0.170) is negative, meaning a player who is both high performing and inconsistent gets paid less holding all other variables constant and when assuming offensive performance or consistency is non-zero. Offensive performance (1.220) and offensive inconsistency (0.273) have a positive effect on cap hit holding all other variables constant. Thus, the better a player performs, the higher their salary will be, and the more inconsistent a player is, the higher their salary will be.

Next, the defensive performance regressing on cap hit is captured at the 99.9% confidence level. All other variables share the same 99.9% confidence level. The R2 value of this regression is 0.453, hence the model can account for 45.3 percent of the variance within the data. This is marginally lower than the offensive performance and inconsistency regression. Thus, defensive performance and inconsistency don’t do a great job at capturing a player’s cap hit. The sign of the coefficient is expected with defensive performance (1.111) having a positive effect on cap hit. However, defensive consistency (0.122) is also positive, meaning that a player who is more inconsistent defensively is paid more which goes against common intuition that someone who is more consistent should be rewarded. The interaction term between defensive performance and defensive consistency (-0.256) has a negative sign, thus a player who is both high performing and inconsistent is paid less, holding all other variables constant and when assuming defensive performance or consistency is non-zero.

To visualize these effects, figures 3 and 4 display the linear relationship between offensive performance and cap hit and between offensive inconsistency and cap hit.

Figure 3. Linear trend of offensive performance vs. cap hit

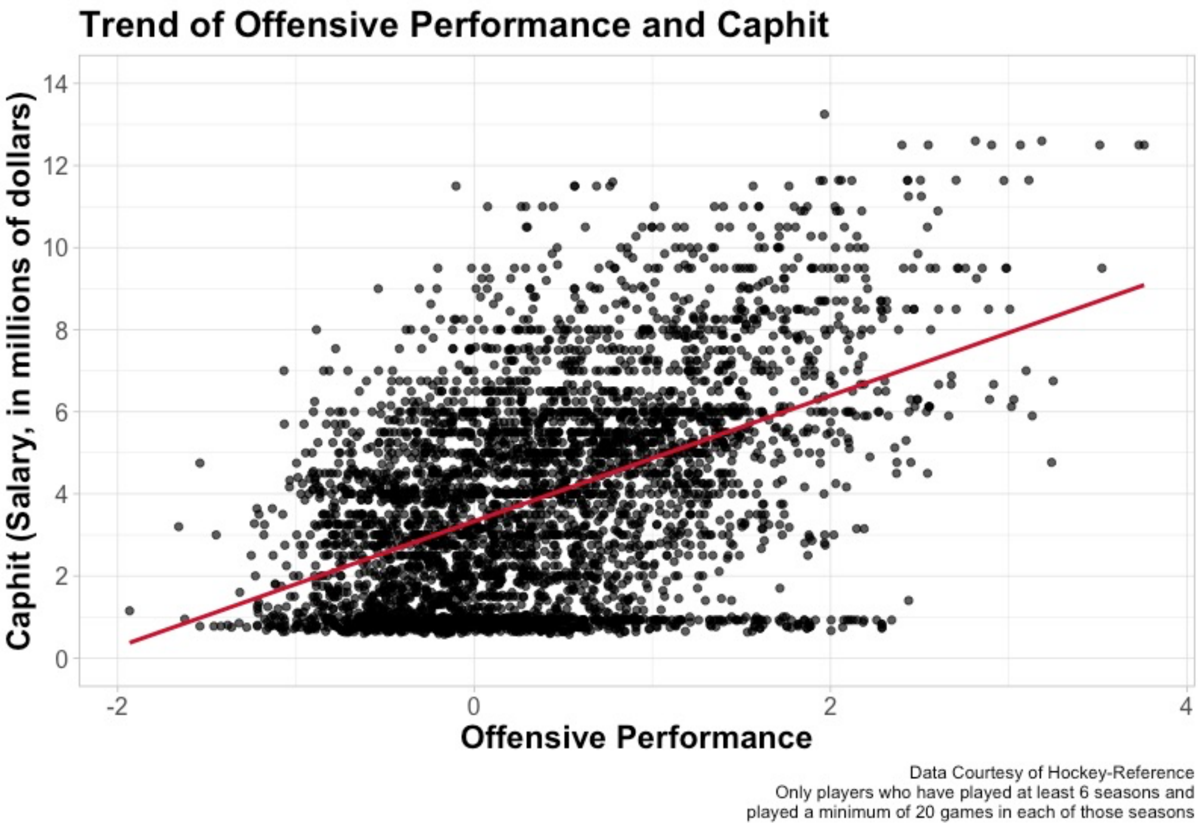
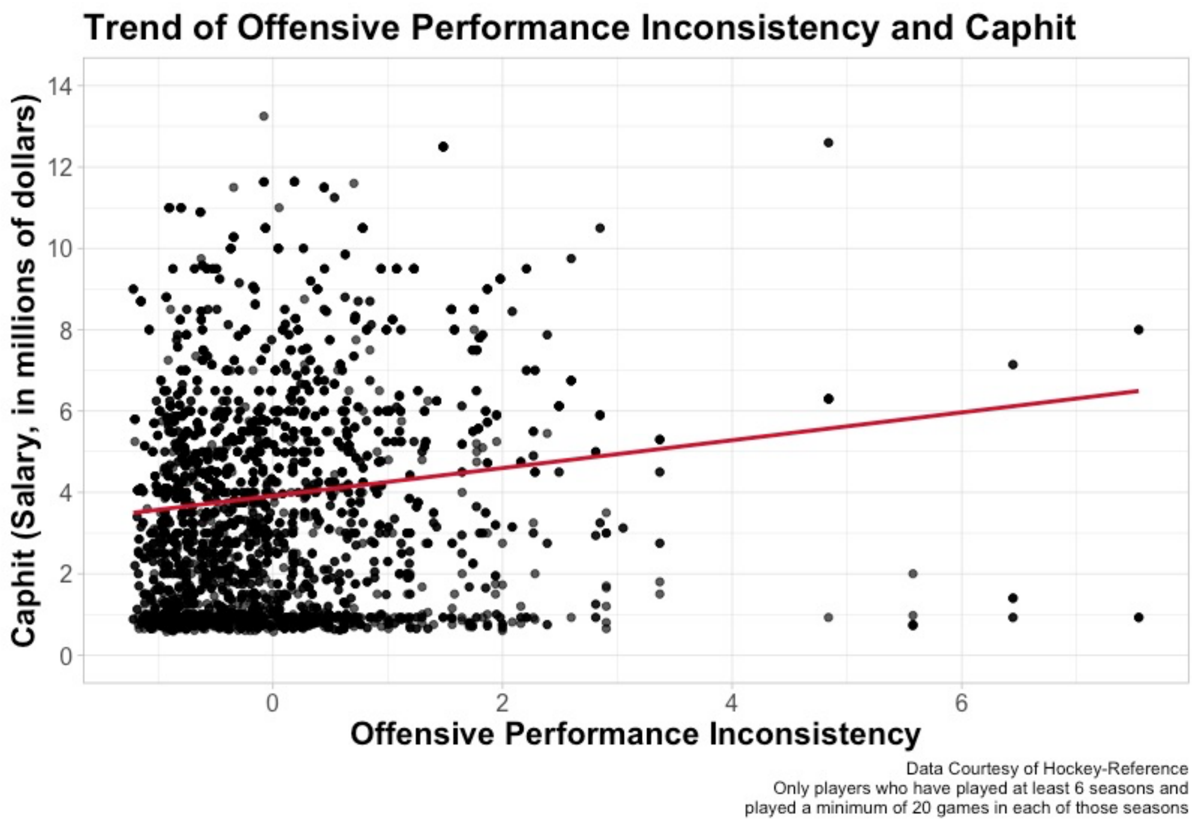


Figure 4. Linear trend of offensive inconsistency vs. cap hit



There is a much stronger relationship between offensive performance and a player’s salary than offensive inconsistency and a player’s salary. There seems to be no visible trend, linear or otherwise, in offensive inconsistency and cap hit, suggesting that consistency itself is not a good indicator of a player’s salary, and, therefore, teams seem to value higher performing players more than consistent players. Defensive performance and inconsistency follow very similar trends to that of offensive performance and inconsistency allowing for the same interpretation and can be seen in Figures 5 and 6 in Appendix C.

Since there are control variables within each model, each control variable is tested against each explanatory variable for potential multicollinearity and could be proxying the effect of the explanatory variable on a player’s salary. This is accomplished by establishing a correlation test for the control variables of average time on ice (ATOI) and age against each of the explanatory variables including offensive performance, defensive performance, offensive consistency, and defensive consistency. There is no significant correlation between any of the variables, but it is relative to know that the direction of each correlation coefficient, positive or negative, lines up with what we would expect. An older player would tend to have a decrease in offensive and defensive performance and in offensive and defensive consistency. And a player with a higher average time on ice typically leads to higher offensive and defensive performance and offensive and defensive consistency.

Discussion and Interpretation

The results from each of the regression equations provide a clearer understanding of how NHL teams value performance and consistency, and how these factors translate into player compensation. Overall, the findings indicate that teams place substantially more weight on how well a player performs rather than how consistently they perform, like Vapnek's (2024) findings of performance having substantial explanatory power for salaries. This trend appears strongly in both the combined regression and the models that isolate offense and defense.

Beginning with the full model, offensive performance, age, and time on ice per 60 minutes emerge as the strongest predictors of cap hit, all carrying large and statistically significant coefficients. These results align with prior research emphasizing that teams reward observable contributions that are easily tied to scoring and winning (Gulbrandsen & Gulbrandsen, 2011). In contrast, defensive performance is not statistically significant in the combined model, suggesting that offensive output continues to dominate market valuation in the NHL.

One of the more unexpected findings concerns the role of consistency. Both offensive and defensive inconsistency show positive signs in several models, meaning that players who are more inconsistent tend to earn higher salaries. This contradicts the theoretical expectation that high-variance players should be penalized due to the uncertainty they introduce (Bodvarsson & Brastow, 1998). Instead, the positive coefficient for offensive inconsistency may reflect that players with high offensive variance also tend to be players with high upside, athletes capable of producing large scoring spikes even if that output is not steady across seasons. Teams may view this volatility as an acceptable trade-off for the potential of game-changing performances.

The interaction terms provide important nuance. In both offensive and defensive regressions, the interaction between performance and inconsistency is negative and significant, indicating that a player who is simultaneously high performing and highly inconsistent may be penalized relative to a similarly high-performing but steadier player. This suggests that inconsistency alone is not rewarded. Rather, the market rewards players whose inconsistency accompanies high offensive peaks, but not those whose overall output becomes difficult to interpret when volatility becomes extreme.

The defensive-only regression highlights another notable pattern: the explanatory power of the defensive model is weaker than that of the offensive model (R2 of 0.453 vs. 0.529). This implies that defensive contributions remain harder to translate into salary negotiations, even when measured through advanced metrics. While defensive performance does show a significant positive effect on salary, its market importance appears secondary to offense, mirroring broader trends in hockey analytics and player valuation.

Finally, the visualization of offensive and defensive inconsistency against cap hit helps clarify these findings. Whereas offensive and defensive performance both show clear positive linear relationships with salary, the inconsistency trends display no obvious linear form. This reinforces that consistency, as measured through weighted variance change, is not an important determinant of pay in current NHL markets. Teams appear far more willing to pay for peak output and role importance than for steady, predictable performance across seasons.

Taken together, these results suggest that NHL teams do not rely heavily on consistency when determining salary. Instead, compensation appears driven by a combination of offensive productivity, accumulated experience (age), and established responsibility (time on ice). The evidence points to a market structure in which potential upside and offensive impact overshadow the economic benefits of stable, low-variance performance. This reflects the broader valuation patterns identified in the literature, where high-impact players command premium prices even when their contributions are uneven across time.

Conclusion

The purpose of this study was to examine whether consistency, measured through weighted variance change in offensive and defensive performance, plays a meaningful role in determining NHL player salaries. By constructing standardized performance metrics, developing offensive and defensive consistency indices, and applying linear regression models that controlled for age and time on ice, the analysis provides clear evidence on how teams value players within the current labor market.

Across all models, performance level consistently emerges as the dominant predictor of player salary. Offensive output offers the strongest explanatory power for cap hit, reflecting the long-standing tendency of NHL salary structures to reward scoring, point production, and offensive play-driving more heavily than defensive contributions. Defensive performance, while still valued, appears less influential in determining compensation and is captured by a model with weaker predictive power.

The findings regarding consistency are especially noteworthy. Neither offensive nor defensive consistency serves as a significant driver of salary, and in several models, inconsistency itself shows a positive effect. This suggests that NHL teams do not systematically reward players for stable output across seasons. Instead, the market appears to value players with high offensive ceilings, even if their performance fluctuates, more than predictable but lower-impact contributors. This pattern aligns with the broader economic literature that documents how sports labor markets often reward peak performance and perceived upside over predictability.

Ultimately, the results indicate that consistency, at least as measured through variance-based metrics, is not a critical factor in NHL compensation decisions. Instead, teams continue to prioritize offensive productivity, established usage, and accumulated experience. These findings contribute to the broader discussion about how advanced analytics intersect with labor valuation in professional sports. They also highlight the ongoing need for models that more accurately incorporate the full spectrum of player contributions, particularly those that are defensive, intangible, or difficult to quantify through traditional statistics.

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Appendix A

Github Repository

https://github.com/colesheegs/Analyzing-Value-of-Consistency-Among-NHL-Players

The repository includes the data collected and used in the analyses for answering the research question, the Quarto Markdown file including the data cleaning, transformation, analyses, and data visualization creation. Other documentation including a codebook and this paper is included in the Documentation folder. The README file explains what the analysis is and how to navigate the repository.

Appendix B

Variable Descriptions

Table 2. Variables from data collected and respective descriptions

Variables (Bolded means variable of interest)	Description
Player	Name of the player
Age	Age of the player as of Jan. 31 of the season in question
Pos	Position the player plays in
GP	Number of Games Played
G	Number of Goals
A	Number Assists
PTS	Number Points (goals + assists)
+/	Plus/Minus, the difference in the number of times a player was on the ice when a goaled was scored for or against while at even strength (same number of players on the ice for both teams)
PIM	Penalties in Minutes
EVG	Even Strength Goals
PPG	Power Play (the team has more players on the ice than the opposing team; the opposing team took a penalty) Goals
SHG	Short-Handed (the team has fewer players on the ice than the opposing team; the player's team took a penalty) Goals
GWG	Game-Winning Goals
EV	Even Strength Assists
PP	Power Play Assists
SH	Shorthanded Assists
SOG	Shots on Goal
SPCT	Shooting Percentage (G / SOG)
TSA	Total Shots Attempted
TOI	Time on Ice (in minutes)

ATOI	Average Time on Ice per game
FOW	Faceoff Wins
FOL	Faceoff Losses
FO%	Faceoff Percentage
BLK	Blocked shots
HIT	Hits
TAKE	Takeaways
GIVE	Giveaways
CF	Corsi For at Even Strength (Shots + Blocks + Misses)
CA	Corsi Against at Even Strength (Shots + Blocks + Misses)
CF%	Corsi For % at Even Strength (CF / (CF + CA)); Above 50% means the team was controlling the puck often with this player on the ice
CF% rel	Relative Corsi For % at Even Strength (On-Ice Corsi For % - Off-Ice Corsi For %)
TOI(EV)	TOI/60 at Even Strength (Time on Ice per 60 minutes)
Thru%	Percentage of shots taken that go on net
TGF	Total Goals On-Ice For
PGF	Power play goals for while the player was on the ice
TGA	Total Goals On-Ice Against
PGA	Power play goals against while the player was on the ice
OPS	Offensive Point Shares; an estimate of the number of points contributed by a player due to his offense.
DPS	Defensive Point Shares; an estimate of the number of points contributed by a player due to his defense.
PS	Point Shares; an estimate of the number of points contributed by a player.
Att	Shootout attempts
Made	Shootout shots made
Miss	Shootout shots missed

Pct	Percentage of shootout attempts converted
xGF	'Expected Goals For' given where shots came from, for and against, while this player was on the ice at even strength.
xGA	'Expected Goals Against' given where shots came from, for and against, while this player was on the ice at even strength.
E+/	'Expected +/-' given where shots came from, for and against, while this player was on the ice at even strength.
Offensive Performance	Z-score of offensive performance calculated by combining several "offensive" variables of interest into an index
Defensive Performance	Z-score of defensive performance calculated by combining several "defensive" variables of interest into an index
Consistency Index	Calculated by using weighted variance change across seasons and standardized on a scale from 0 to 100, 0 being very consistent and 100 being very inconsistent

Appendix C

Trends of Defensive Performance and Inconsistency

Figure 5. Linear trend of defensive performance vs. cap hit

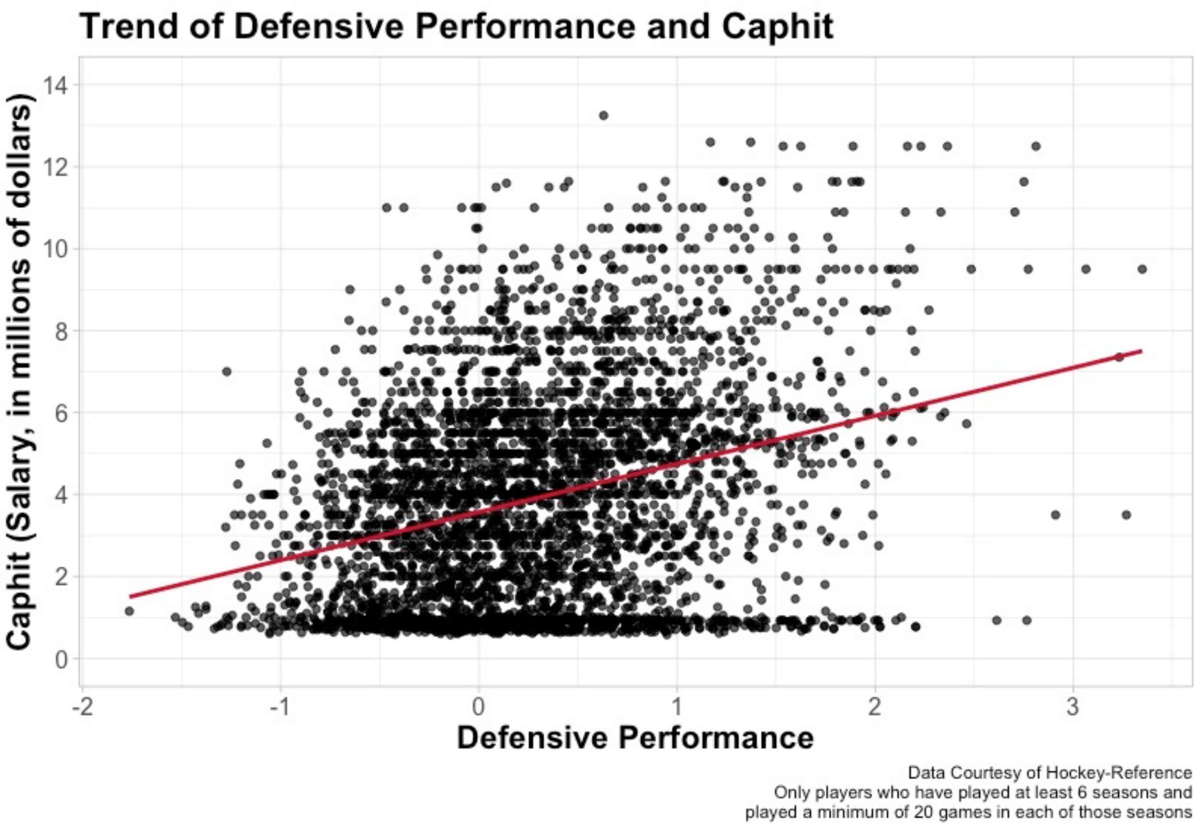

Figure 6. Linear trend of offensive inconsistency vs. cap hit