Cross-League Equivalencies: Using Former MLB Player Data to Evaluate NPB Transfers

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Abstract. Major League Baseball's posting market for Japanese pitchers has grown into a billion-dollar pricing problem, but the public sports-economics literature offers no transparent benchmark for valuing posted pitchers. This paper develops and validates a two-stage framework for predicting MLB contract value from Nippon Professional Baseball (NPB) performance. The first stage estimates a cross-league performance translation factor from 193 paired observations of pitchers with experience in both leagues. The second stage estimates a log-linear salary regression on 279 MLB starting-pitcher free-agent signings (2014–2024). The headline finding is that the cross-league skill gap is far smaller than raw statistics suggest: in raw xFIP units the conversion factor is 1.307, but it is 1.096 (95% CI $[1.067, 1.126]$) in league-normalized xFIP− units, indicating that approximately two-thirds of the apparent gap reflects league-level run environment rather than pitcher skill. The salary regression robustly prices xFIP− across four model specifications. Out-of-sample validation against 11 historical NPB-to-MLB transitions produces a 24–26% median absolute error for starting pitchers. Applied to the current NPB pitcher pool, the framework identifies a structured set of high-value posting candidates (Hiroya Miyagi, Shoki Murakami, Foster Griffin, Raidel Martínez).

1. Introduction

The 2024 free-agent signing of Yoshinobu Yamamoto by the Los Angeles Dodgers at twelve years, \$325 million surprised the industry. Not only did it set a new record as the largest pitcher contract in Major League Baseball (MLB) history, but it was also unprecedented in bringing an unproven international talent at this scale. While Yamamoto's performance at Orix Buffaloes within Japan's Nippon Professional Baseball (NPB) league was nothing short of extraordinary (164 IP, 1.21 ERA, 1.72 FIP, 0.884 WHIP, 169 K), fans were worried whether he would continue his dominant performance in the MLB and whether his contract value would be justified.

Along with Yamamoto, there has been a recent influx of Japanese-born talent transitioning into the United States such as Rōki Sasaki and Shota Imanaga, raising the concern that the posting market for NPB pitchers has grown into a multi-billion-dollar pricing problem. Yet, despite this scale, the public sports-economics literature offers no transparent benchmark for valuing posted pitchers. Published academic frameworks either rely on raw cross-league comparisons that conflate skill with run environment or attempt to translate NPB performance directly into MLB performance using extremely small samples of historical postings (Audet 2009).

This analysis aims to analyze the true fair market value of NPB players by building a framework for pricing posted NPB pitchers in MLB free-agent dollars. The framework rests on two estimation steps. First, we recover a cross-league performance translation factor between NPB and the MLB system using the same-pitcher windows for the 730 pitchers in our crossover sample who have played in both leagues. Second, we apply that factor to an MLB free-agent salary regression to predict annual contract value (AAV) for any current NPB pitcher.

We restrict the analysis to pitchers, not hitters, for a methodological reason. Hitter value in MLB depends heavily on defensive position: a shortstop and a first baseman with identical batting lines are not interchangeable assets, because positional scarcity drives a substantial component of player value (Baumer, Jensen, and Matthews 2015). Modeling cross-league hitter translation, therefore, requires modeling positional adjustment simultaneously with offensive translation, a distinct problem we leave to future work. Pitcher value, by contrast, depends primarily on observable run-prevention performance, making the cross-league translation cleaner.

We also reverse the direction of estimation relative to most prior work. The NPB-to-MLB sample of posted pitchers is small (only 43 pitchers in our crossover data first played in NPB and then signed in the American system; only 11 of these have contracts in the post-2014 Spotrac data), and prior econometric attempts have explicitly flagged this constraint (Audet 2009). The crossover population of pitchers who moved in the opposite direction, from the MLB system into NPB, is far larger and more statistically tractable for estimating the translation factor (Petriello 2012). We exploit this asymmetry.

2. Literature Review

The 2024 free-agent signing of Yamamoto sits at the intersection of three threads in the sports-economics literature: cross-league performance translation, MLB salary regression, and the empirical study of NPB-to-MLB player transitions. We review each thread and then situate this paper's contribution.

Cross-league performance translation. The methodological problem of converting one league's statistics into another's was first developed by James (1985), who introduced Major League Equivalencies (MLEs) for translating minor-league hitting statistics to MLB-equivalent levels. Davenport (1996) refined this framework into the Davenport Translations published by Baseball Prospectus, extending the methodology to pitchers and explicitly to multiple levels of professional play. Davenport's framework adjusts statistics for league offensive level, park, and competition quality, holding the player's underlying performance constant across contexts. Subsequent work has applied translation factors to cross-league questions, though most has used raw counting statistics rather than run-environment-normalized metrics. The limitation of raw-statistic translation is that it conflates pitcher skill differences with league-level run-environment differences.

MLB salary regression. The application of regression analysis to MLB salaries traces to Scully (1974), who pioneered the use of performance-to-salary models to estimate monopsony rents under the reserve clause. Bradbury (2007) extended this framework to free-agent pitchers, showing that defense-independent performance statistics (DIPS) — strikeouts, walks, and home runs — predict pitcher salaries more reliably than earned run average, and that the labor market already prices these defense-independent signals correctly. Krautmann, Gustafson, and Hadley (2003) tested the structural stability of salary equations across pitcher roles, finding meaningful differences between pitcher roles in how performance translates to salary, and concluding that aggregating all pitchers into a single equation is inappropriate. The literature established two patterns this paper relies on: $\log(\text{salary})$ is the appropriate functional form for the dependent variable, and performance, age, and contract length are the core covariates.

NPB-to-MLB transitions. The dedicated academic literature on Japanese players in MLB is small. Audet (2009) provides the most direct precedent: an econometric study of labor-market outcomes for Japanese players in MLB from 1995 to 2007. Audet finds evidence of pay discrimination against Japanese pitchers but not against Japanese batters, and explicitly notes that "there have been remarkably few studies focusing on Japanese players in MLB" and that the small sample of Japanese-player observations limits the precision of his estimates (1). Beyond this academic precedent, there have been attempts on industry blogs to grapple with the same data scarcity. One such analysis, published at FanGraphs, observed that the most reliable comparative analysis would come from the inverse direction (American pitchers transitioning into NPB) because the reverse population provides larger, cleaner samples (Petriello 2012). The present paper operationalizes this suggestion.

Contribution. This paper extends the salary-regression tradition of Scully, Bradbury, and Krautmann et al. by applying it to the NPB-to-MLB pricing problem, while addressing the small-sample constraint identified by Audet through inverse-direction estimation. The methodological contribution is the use of run-environment-normalized performance (xFIP−) rather than raw statistics.

3. Data

3.1. Data Sources

This study draws on four primary data sources. The Chadwick Bureau player ID register provides the cross-reference between MLB, NPB, and Baseball Reference identifiers used to identify pitchers with experience in both league systems. Baseball Reference provides individual career files for these crossover pitchers as well as a separate cohort of MLB pitcher seasons used for the salary regression. They are also used to compute league-aggregate season totals used to find the per-league-year FIP constants. NPB league-aggregate stats (Central and Pacific Leagues), MLB league-year aggregates (1986–2026), and 60 NPB league-year aggregates (1997–2026, 30 per league) all come from Baseball Reference. Spotrac provides MLB free-agent contract data covering the 2014–2024 signing-year cohorts, the earliest period for which detailed contract terms are publicly available. All contract values are deflated to 2024 dollars using the BLS CPI-U index.

3.2. Data Cleaning and Filtering

The cross-league translation step proceeds in chronological stages. We begin with the 3,194 players in the Chadwick Bureau register with any NPB affiliation. After verifying MLB and minor-league status through the MLB Stats API, we identify 730 pitchers with experience in both the NPB and the American system (573 MLB-level, 157 minor-league only). Career data is then collected from Baseball Reference for 407 of these 730 crossover pitchers; the remaining 323 have no usable Baseball Reference career records.

For each of the 407 pitchers, we construct paired performance observations capturing each transition between the American system and NPB. A pitcher with a single America-to-NPB transition contributes one observation. Pitchers whose careers include NPB-to-America-to-NPB sequences also contribute one observation per NPB stint. Pitchers with America-to-NPB-to-America-to-NPB sequences contribute two distinct observations. We restrict the analysis to NPB stints that began in 2000 or later to maintain comparability with the modern offensive era.

This procedure yields 363 paired observations across 353 unique pitchers, with 10 pitchers contributing two observations each from non-overlapping stints. We then apply an innings-pitched eligibility filter requiring at least 50 IP per side, within 3 season windows, leaving 193 paired observations as the sample used to estimate the cross-league translation factor. Figure 1 illustrates how this sample size varies across alternative window-size and IP-threshold specifications.

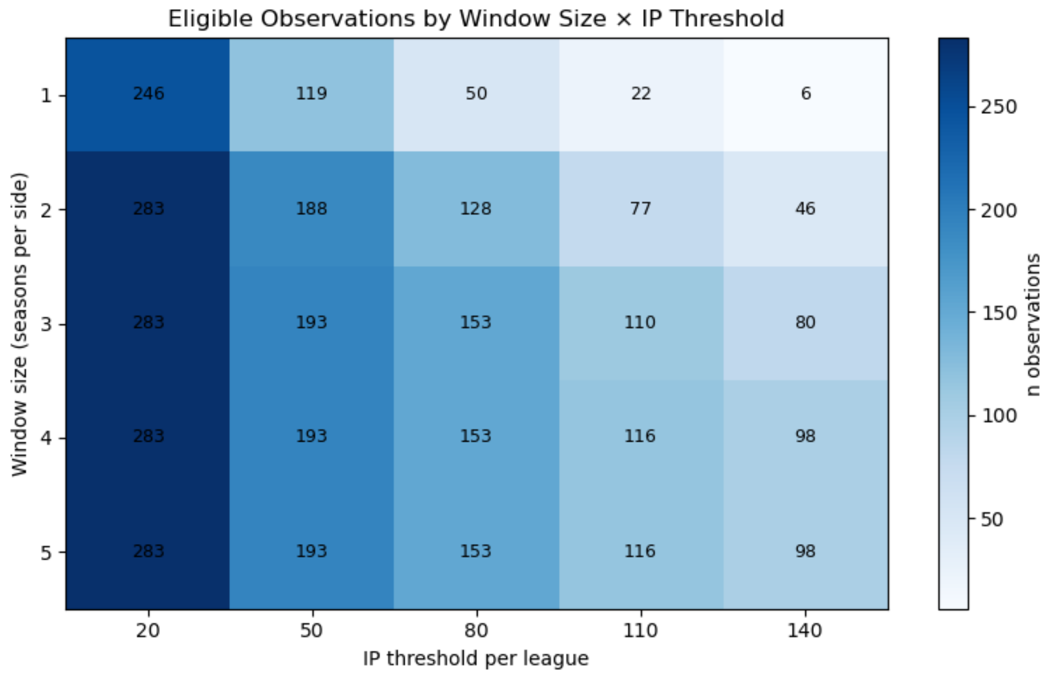

Figure 1. Eligible paired observations by window size and IP threshold. The preferred specification (3-season windows, 50 IP per side) yields 193 observations.

For the salary regression, MLB free-agent contracts begin at 1,606 raw rows. After dropping non-MLB rows, $0 and −$1 AAV rows, and 20 posted foreign-league pitchers (the prediction target, excluded from training data to avoid contamination), 1,423 contracts remain. After classifying by role, the pitcher sample comprises 298 starting pitchers and 505 relievers, for 803 total pitcher signings.

4. Methods

4.1. Core Methodology

The pipeline has two analytical stages as shown in Figure 2. In the first stage, we estimate a cross-league performance translation factor between NPB and the American system using paired observations from the 407 crossover pitchers. In the second stage, we estimate a log-linear MLB free-agent salary regression on contracts from 2014–2024. Predictions for current NPB pitchers are then generated by applying the translation factor to their NPB performance to obtain a predicted MLB performance level, then plugging this into the salary regression along with the pitcher's age and contract terms.

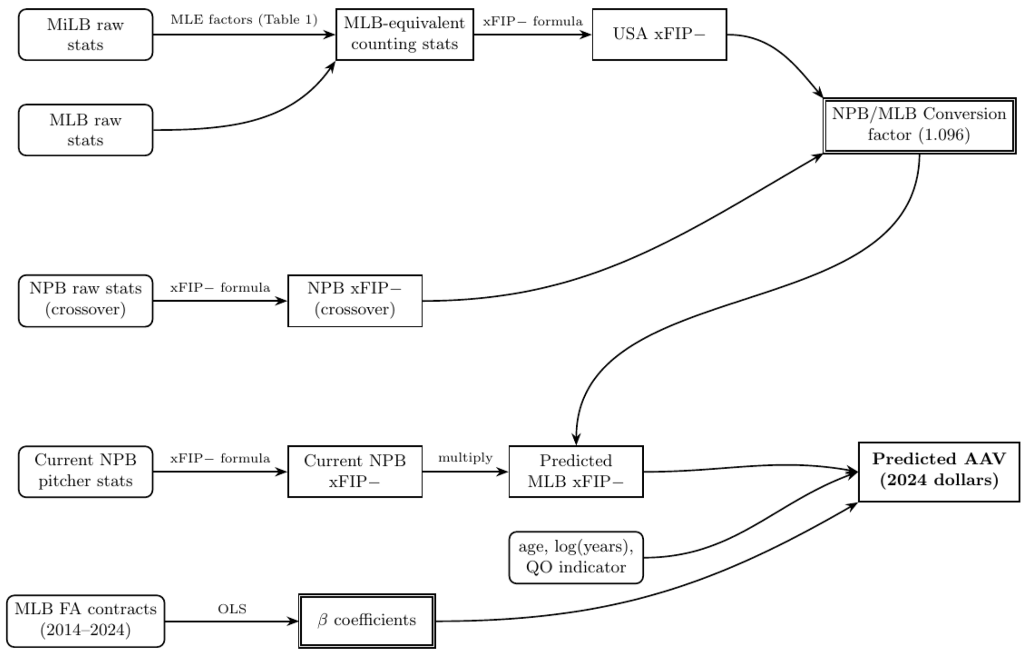

Figure 2. Path model linking NPB performance to predicted MLB contract value via the cross-league translation factor and salary regression. Round borders indicate data inputs, double borders indicate secondary findings, and bolded text indicates primary findings.

4.2. Performance Metric

We use Expected Fielding Independent Pitching (xFIP), normalized to league average (xFIP−), as the primary performance metric. xFIP is a defense-independent estimator of pitcher run prevention computed from strikeouts, walks, hit-by-pitch, and a league-average home-run rate applied to batters faced:

$$\text{xFIP} = \frac{13 \cdot xHR + 3 \cdot (BB + HBP) - 2 \cdot SO}{IP} + c_{FIP} \tag{1}$$

where xHR is the league-average home-run-per-batter-faced rate multiplied by the pitcher's batters faced, and c_{FIP} is the league-year constant calibrated so that the league-wide average xFIP equals the league-wide average ERA. Dividing xFIP by the league-average ERA in the same year and multiplying by 100 produces xFIP−, a unit-free scale on which 100 is league average and lower values are better.

The xFIP− transformation is the methodological core of the cross-league comparison. Each league has minor but different characteristics in play-style, field characteristics, and strike zones. Comparing raw xFIP across leagues would conflate these run-environment effects with pitcher skill. Dividing each pitcher's xFIP by his contemporaneous league's average ERA strips out the run-environment component, leaving a measure that compares each pitcher to his league peers in his own season.

4.3. Cross-League Translation: Minor League to MLB

USA-side performance windows for the crossover pitchers frequently include minor-league seasons at various levels. To make these comparable to MLB-level performance, we apply level-specific Major League Equivalency (MLE) factors to counting statistics following the framework of James (1985) and Davenport (1996). The factor schedule is shown in Table 1.

Table 1. MLE conversion factors applied to counting statistics by level.

Level	SO	BB	HR	HBP
Major (Maj)	1.00	1.00	1.00	1.00
Triple-A (AAA)	0.90	1.10	1.15	1.10
Double-A (AA)	0.82	1.18	1.25	1.18
High-A (A+)	0.75	1.25	1.35	1.25
Single-A (A)	0.68	1.33	1.45	1.33
Short-A (A−)	0.62	1.40	1.55	1.40
Rookie (Rk)	0.55	1.50	1.70	1.50

A pitcher's strikeouts at AAA are multiplied by 0.90 (because strikeout rates are typically harder to sustain at the higher level); his walks, home runs, and hit-batsmen are inflated proportionally. Each level moves further from MLB-equivalent, with Rookie ball receiving the largest discount on strikeouts and the largest inflation on negative events. After adjustment, multi-level seasons are aggregated into a single row per player-year before xFIP− is computed. This conversion metric needs to be further proven in the future.

4.4. Cross-League Translation: MLB to NPB

For each of the 193 eligible paired observations, we compute the conversion factor as the ratio of the USA-side window xFIP− to the NPB-side window xFIP−, averaged across observations using IP weights. Bootstrap resampling with 1,000 replications produces a 95 percent confidence interval. To assess robustness, we recompute the factor across a grid of 5x5 (both raw xFIP and xFIP−) and three alternative MLE schedules. Figure 3 shows the conversion factor across the sensitivity grid for both IP-weighted and equal-weighted averaging.

4.5. Salary Regression

We model MLB free-agent salary as a log-linear function of pre-signing performance and contract terms. For each of the 803 pitchers in the cleaned contract sample, we compute an IP-weighted xFIP− over the pitcher's three pre-signing MLB seasons (cumulative window of at least 100 IP). After joining to performance windows, 700 pitcher signings survive across the SP-and-RP pooled sample. Of the 298 starting pitchers, 279 join successfully to a performance window; the primary regression is estimated on these 279 signings:

$$\log(\mathrm{AAV}_{2024}) = \beta_0 + \beta_1 \cdot \text{xFIP-} + \beta_2 \cdot \text{age} + \beta_3 \cdot \log(\text{years}) + \beta_4 \cdot \text{QO} + \varepsilon \tag{2}$$

where age is age at signing, $\log(\text{years})$ is the natural log of contract length, and QO indicates whether the pitcher received a qualifying offer. We use $\log(\text{years})$ rather than linear years to allow

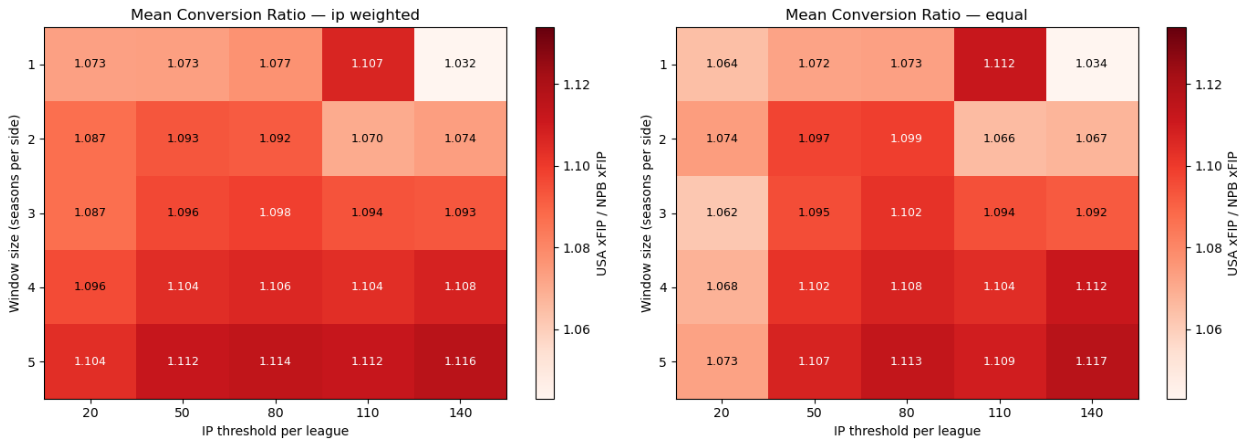

Figure 3. Mean conversion ratio (USA xFIP− / NPB xFIP−) across the sensitivity grid. Left: IP-weighted averaging. Right: equal weighting. The factor is stable in the range [1.03, 1.12] across all 25 specification cells, with the preferred 3-season × 50-IP cell at 1.096.

diminishing returns at long contract durations. Four model specifications are estimated to test robustness: the primary specification just described; a restricted sample of multi-year SP contracts only (n = 103); a pooled SP and RP sample of 700 signings with a reliever role dummy; and a no-QO sensitivity test that drops the qualifying-offer covariate to assess whether selection on QO recipients biases the headline performance coefficient.

4.6. Validation

The translation factor and salary regression are validated against 11 historical NPB-to-MLB pitcher signings in the post-2014 Spotrac data. For each pitcher, predicted MLB xFIP− is computed by multiplying his pre-signing NPB xFIP− by the conversion factor, and predicted AAV is computed by plugging this performance estimate, along with the pitcher's actual age and contract length, into the salary regression. Predictions are reported under two specifications: at the pitcher's actual contract length, and with contract length capped at the training-data 95th percentile (7 years) to avoid out-of-sample extrapolation for unusually long contracts.

5. Results

5.1. Cross-League Translation Factor

The estimated conversion factor between NPB and MLB performance is **1.096** in xFIP− units, with a 95 percent bootstrap confidence interval of [1.067, 1.126] across 193 paired observations. Substantively, this means a pitcher's xFIP− worsens by approximately 9.6 percent when moving from NPB to the American system, after controlling for league-level run environment.

The contrast with the same calculation in raw xFIP is large and informative. Using raw xFIP rather than xFIP−, the conversion factor is **1.307** with a 95 percent CI of [1.270, 1.344]. The 21-percentage-point gap between the raw-xFIP factor and the xFIP− factor is attributable to league-level run-environment differences. Figure 4 documents these differences: MLB's league-average xFIP has run 0.3 to 1.0 runs above the two NPB leagues across the 2000–2026 period. Approximately two-thirds of the apparent performance gap is run environment rather than pitcher skill.

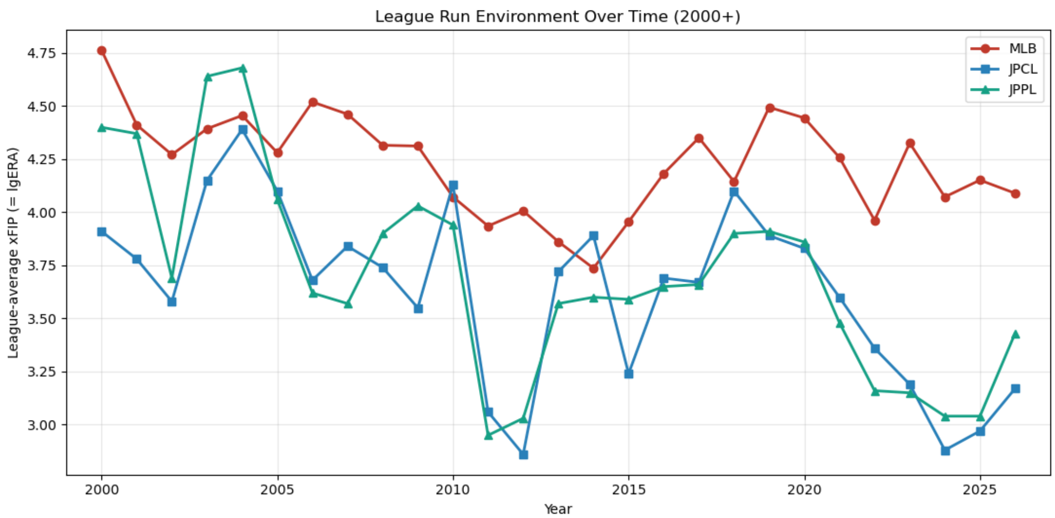

Figure 4. League-average xFIP (equivalent to league-average ERA) over time for MLB, NPB Central League (JPCL), and NPB Pacific League (JPPL). MLB consistently runs above both NPB leagues.

The conversion factor is stable across alternative specifications. Across the 25 cells of the window-size and IP-threshold sensitivity grid shown in Figure 3, the factor stays in the range $[1.03, 1.12]$. Across alternative MLE translation schedules, the factor ranges from 1.064 $[1.037, 1.091]$ under a lenient schedule (50 percent of the baseline level penalty) to 1.128 $[1.097, 1.159]$ under a conservative schedule (150 percent of the baseline penalty). The baseline estimate of 1.096 sits in the middle of this range, and all three bootstrap intervals overlap.

The factor is also stable over time. Figure 5 shows a rolling estimate computed within ±3-year windows from 2004 to 2024 (earlier years are dropped due to sample-size constraints). The rolling estimate ranges from approximately 1.06 in 2011 to approximately 1.13 in 2017–2018, with the 95 percent bootstrap CI overlapping the full-sample mean of 1.096 in nearly every reliable year. There is no era in the modern period for which the conversion factor diverges materially from the headline estimate.

However, the cross-league factor is a population-level translator, not an individual-level predictor. The R^2 for predicting USA-side xFIP− from NPB-side xFIP− in the eligible sample is 0.034. The conversion factor accurately calibrates how the *distribution* of NPB pitchers translates into MLB-equivalent terms, but individual prediction requires additional signal beyond NPB performance alone.

5.2. Salary Regression

Table 2 reports the salary regression results across four specifications. xFIP− is statistically significant and negative in all four (better performance is associated with higher AAV), with coefficients ranging from −0.0095 to −0.0288. Age, contract length (log-transformed), and the qualifying-offer indicator are positive and significant in every specification where they appear. R^2 ranges from 0.491 to 0.586.

The β(xFIP-) shifts by 16 percent between the primary and no-QO specifications (−0.0249 to −0.0288), and the qualifying-offer indicator carries a counterintuitive positive sign across specifications. The QO is a known selection effect: qualifying offers are extended only to high-

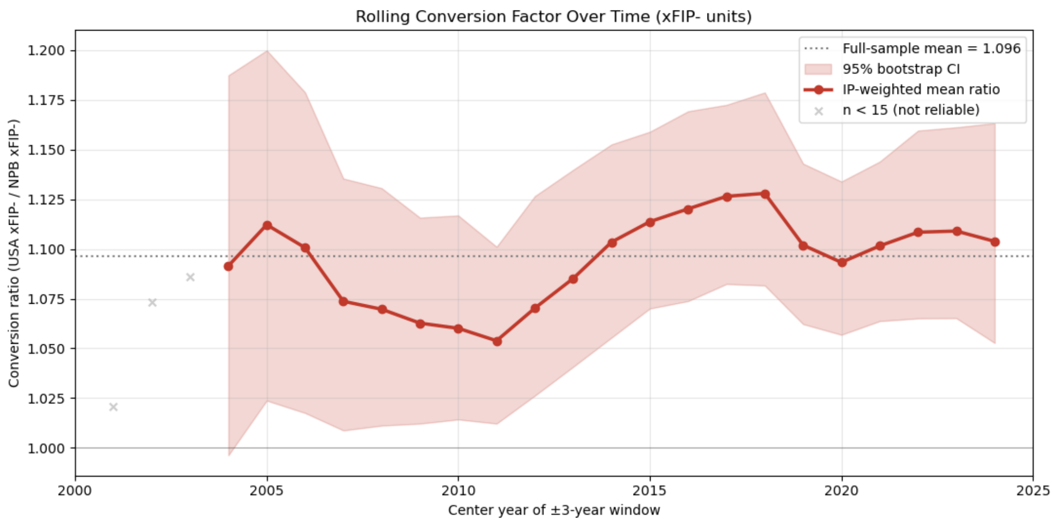

Figure 5. Rolling conversion factor in xFIP− units, computed within ±3-year windows centered on each year from 2004 to 2024. The dotted horizontal line marks the full-sample mean of 1.096. Pink band: 95 percent bootstrap CI. Gray X markers indicate years with insufficient sample size ($n < 15$).

Table 2. Salary regression: xFIP− significantly priced into AAV across four specifications. Dependent variable: log(AAV in 2024 dollars). MLB SP free-agent signings, 2014–2024.

Specification	n	β(xFIP-)	β(age)	β(log yrs)	β(QO)	β(RP)	R^2
Primary	279	-0.0249^{***}	$+0.041^{***}$	$+0.725^{***}$	$+0.613^{***}$	—	0.528
Robust A	103	-0.0095^{*}	$+0.049^{***}$	$+0.651^{***}$	$+0.332^{***}$	—	0.586
Robust B	700	-0.0139^{***}	$+0.029^{***}$	$+0.946^{***}$	$+0.573^{***}$	-0.579^{***}	0.516
Robust C	279	-0.0288^{***}	$+0.038^{**}$	$+0.852^{***}$	—	—	0.491

Primary: all SP, with QO. Robust A: multi-year SP only. Robust B: SP + RP with role dummy. Robust C: all SP, no QO.
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

quality free agents whose unobserved star quality is captured by the QO indicator rather than by xFIP− alone. The small shift in β(xFIP-) when QO is dropped indicates that this selection effect does not materially bias the headline performance coefficient. The role dummy in Robustness B carries the expected negative sign: relievers earn approximately $\exp(-0.579) \approx 0.56$ times what comparable starters earn at the same xFIP−, age, and contract length.

5.3. Validation and Forward Predictions

We validate the framework against 11 historical NPB-to-MLB pitcher signings between 2014 and 2024. For each, predicted MLB xFIP− is computed by multiplying the pitcher's pre-signing NPB xFIP− by the conversion factor. Predicted AAV is then computed by plugging this performance estimate into the primary salary regression along with the pitcher's actual age and contract length.

Across the 11 validation pitchers, the **median absolute percentage error is 36 percent** under the capped-years specification and 46 percent at actual contract length. The **mean absolute percentage error is 69 percent** capped and 74 percent at actual length. Figure 6 plots predicted against actual AAV under both specifications, with pitchers labeled by signing era. Broken out by role, errors for starting pitchers in the 2016–2020 cohort are 26 percent and in the 2021–2025 cohort are 24 percent: stable across both eras. Reliever errors are larger in percentage terms (146 percent in 2016–2020, 86 percent in 2021–2025) but reflect the small-denominator problem in sub-\$3M reliever pillow deals, where a \$4M dollar error translates to a 200 percent percentage error.

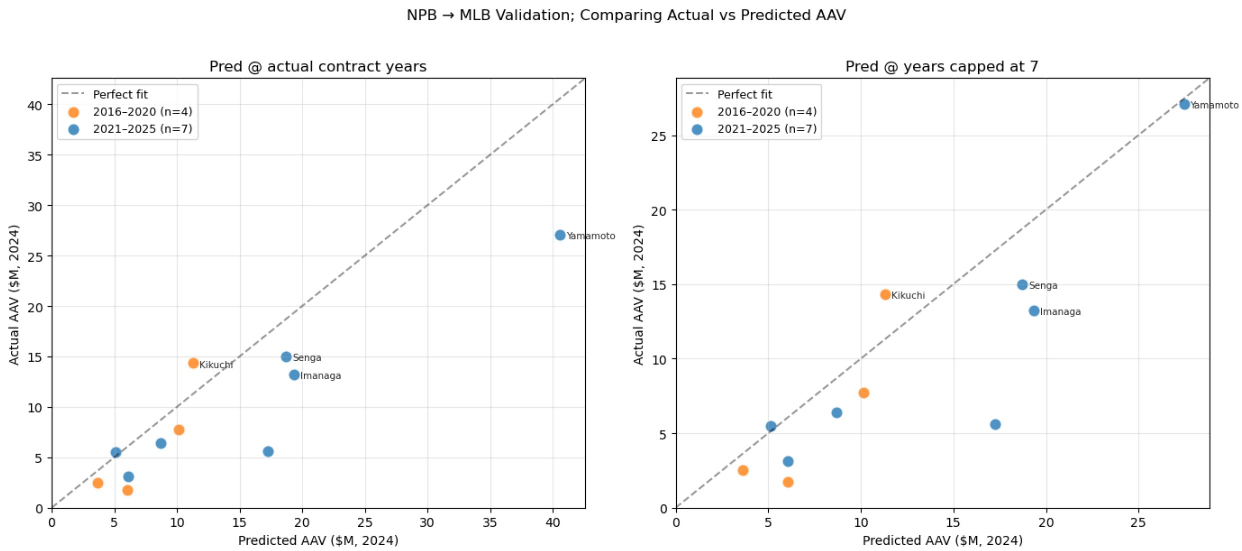

Figure 6. NPB-to-MLB validation. Predicted AAV (x-axis) vs. actual AAV (y-axis) for 11 historical NPB-to-MLB pitcher signings, 2014–2024. Left panel: predictions at the pitcher's actual contract length. Right panel: predictions with contract length capped at 7 years (training-data 95th percentile). Dashed line: perfect prediction.

The headline validation case is Yoshinobu Yamamoto, who signed a 12-year contract for the largest pitcher AAV in MLB history. The salary regression's $\beta(\log \text{years})$ is calibrated to a training distribution where 95 percent of contracts are 7 years or shorter; only three starting-pitcher signings in training exceeded 9 years. Capping contract length at the training-data 95th percentile (7 years) to avoid out-of-sample extrapolation, the model predicts an AAV of **\$27.4M for Yamamoto against an actual AAV of \$27.1M, an error of approximately 1 percent**. Without the cap, the model predicts \$40.6M, an error of 50 percent. The visual contrast between the two panels in Figure 6 illustrates this directly: Yamamoto sits far below the 45-degree line at actual contract length and essentially on the line under the capped specification.

Applying the framework to the 132 currently active NPB pitchers in the prediction pool, Table 3 reports the top 10 predicted MLB AAVs among realistic candidates (age 33 or under). Predicted values assume a five-year contract length. Three young Japanese starters with sub-80 NPB xFIP– (Miyagi at age 24, Inoue at age 25, Murakami at age 28) headline the list at \$15–\$18M AAV. Foreign-born NPB pitchers also appear prominently: Foster Griffin (a former MLB pitcher who returned back to the MLB) at \$19.5M, and Cuban-born reliever Raidel Martínez at \$15.3M among RP candidates.

Table 3. Top 10 NPB pitchers age ≤ 33 by predicted MLB AAV (5-year contract assumption).

Pitcher	Role	Age	NPB xFIP−	Pred. MLB xFIP−	Pred. AAV
Haruto Takahashi	SP	30	77.6	85.0	$20.8M
Foster Griffin	SP	29	78.5	86.0	$19.5M
Shoki Murakami	SP	28	79.5	87.2	$18.1M
Katsuki Azuma	SP	30	83.9	92.0	$17.5M
Haruto Inoue	SP	25	79.3	87.0	$16.1M
Takahisa Hayakawa	SP	27	83.9	92.0	$15.5M
Chihiro Sumida	SP	26	82.7	90.7	$15.3M
Raidel Martínez	RP	29	68.5	75.1	$15.3M
Hiroya Miyagi	SP	24	80.0	87.6	$15.2M
Kohei Arihara	SP	33	94.0	103.1	$15.0M

6. Discussion

6.1. Interpretation

The most consequential finding is that the apparent gap between NPB and MLB pitcher performance is much smaller than raw statistics suggest. The raw-xFIP conversion factor of 1.307 implies a 31 percent skill gap, while the league-normalized xFIP− factor of 1.096 implies only about 10 percent. Roughly two-thirds of the apparent gap is attributable to league-level run-environment differences, not to pitcher skill. Once run environment is properly controlled for, NPB and MLB pitchers are far more comparable than what the common sentiment has typically suggested.

The salary regression demonstrates that this corrected performance signal translates cleanly into market dollars. xFIP− is significantly priced into AAV across all four model specifications, with the headline coefficient shifting by only 16 percent when the QO covariate is dropped, indicating that QO selection does not materially bias the performance coefficient. The model's headline validation prediction (Yamamoto's $27.4M AAV against an actual $27.1M) provides external evidence that the integrated framework can price unprecedented contracts within the support of the training data.

6.2. Limitations

Four limitations qualify these findings. First, the cross-league translation operates at the population level. The R^2 for predicting individual USA-side xFIP− from NPB-side xFIP− is only 0.034, meaning that any single pitcher's translation carries substantial unexplained variance. The salary regression compensates for this by adding age, contract length, and role as additional signal, but the underlying noise in cross-league individual prediction remains a real constraint.

Second, the salary regression extrapolates poorly to contracts longer than seven years. Only three starting-pitcher signings in the training data exceeded nine years. Predictions for contracts beyond this range require the years-cap mechanism we apply for Yamamoto's twelve-year deal. This cap is a transparency choice, not a model improvement: the model genuinely has no evidence for the linear-in-log relationship at such extreme contract lengths.

Third, the validation sample is small (11 pitchers) and skewed toward relievers in sub $3M pillow deals where percentage errors blow up. The 24–26 percent median absolute error among starting pitchers is a more reliable accuracy benchmark than the headline 36 percent median across all roles.

Fourth, the MLB free-agent population is systematically older than the typical posted NPB pitcher. The regression captures pricing at MLB free agency, not market value at all career stages, and predictions for posted pitchers assume this pricing regime applies to them.

6.3. High-Value NPB Targets Identified by the Model

The Top 10 predictions in Table 3 reveal three distinct categories of candidates that the framework identifies as undervalued or unrecognized in current market discourse. The first category is young Japanese starting pitchers with sub-80 xFIP−: Hiroya Miyagi (age 24, predicted \$15.2M AAV), Haruto Inoue (25, \$16.1M), and Shoki Murakami (28, \$18.1M). These are pitchers with established multi-year NPB track records who would translate to above-MLB-average performance under the conversion factor, and who fall well within the prime age range for MLB front offices to pursue.

The second category is foreign-born pitchers in NPB. Foster Griffin, a former MLB pitcher who returned to MLB, ranks second on the list at \$19.5M predicted AAV. Cuban-born reliever Raidel Martínez ranks ninth at \$15.3M, driven by his exceptional 68.5 NPB xFIP−, which more than compensates for the reliever role discount that the salary regression's β(reliever) coefficient applies.

The third category is established veteran Japanese starters at the upper end of the age filter: Haruto Takahashi (30, leading the list at \$20.8M), Katsuki Azuma (30, \$17.5M), and Kohei Arihara (33, \$15.0M). These pitchers carry both the NPB credentials and the age-experience premium that the salary regression rewards.

7. Conclusion

This paper develops and validates a framework for valuing posted Nippon Professional Baseball pitchers in MLB free-agent dollars. The framework comprises two estimation stages: a cross-league performance translation factor recovered from 193 paired observations of crossover pitchers, and a salary regression fit on 279 MLB starting-pitcher free-agent signings between 2014 and 2024. Predictions are generated by applying the translation factor to a target pitcher's NPB performance and plugging the result into the salary regression with the pitcher's age and contract terms.

Two primary findings emerge. First, the cross-league translation factor in run-environment-normalized units is 1.096 with a 95 percent bootstrap CI of $[1.067, 1.126]$, indicating that NPB pitchers' xFIP− worsens by approximately 10 percent when they transition to the American system. This is far smaller than the apparent 31 percent gap suggested by raw statistics: approximately two-thirds of that gap is run environment, not skill. Second, the salary regression captures meaningful pricing structure, with xFIP− significant across all four model specifications and the headline performance coefficient stable across robustness tests.

Two natural extensions follow. A hitter version of this framework would require modeling the cross-league translation factor simultaneously with MLB's positional value adjustment, since hitter value depends heavily on defensive position. The same translation methodology could also be applied to other leagues (KBO, the Cuban Serie Nacional, the Mexican League) to provide a unified cross-league valuation framework for the increasingly international MLB free-agent market.

The contribution of this paper is to demonstrate that the cross-league gap is much smaller than common scouting wisdom suggests, and that once the gap is correctly measured, MLB free-agent market pricing translates accurately into transparent dollar predictions for posted pitchers.

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