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Koji Yashiki

Graduate School of Economics and Management, Tohoku University

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Discrimination against birth month in the hiring process? The case of Japanese professional baseball *

Koji Yashiki†

Abstract

This study examines wage discrimination by birth month, with a focus on the labor market of professional baseball leagues in Japan. The results show that even after controlling for performance, the younger players in a given cohort had lower incomes. This wage discrimination is caused by the undervaluation of them at enrollment. More specifically, the biased evaluation of teams in terms of a player's future success leads to the underpayment of the initial salary, which has a persistent impact on subsequent salaries. These findings suggest that improving the suboptimal hiring process can benefit teams and players.

JEL Classification: J24; J71; Z21

Keywords: discrimination; wage gap; birth month

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†Tohoku University, yashiki.koji.t6@dc.tohoku.ac.jp

1 Introduction

The "birth-month effect" describes how a person's birth month affects skill formation in childhood and subsequent wellbeing. During childhood, there is a maximum age difference of approximately one year within any given school cohort, and the absolute age difference negatively affects younger students' cognitive (Bedard and Dhuey, 2006), noncognitive (Yamaguchi et al., 2023), and physical skills (Helsen et al., 2005). Meanwhile, during adulthood, it is reasonable to expect that the birth-month effect is exacerbated in a self-fulfilling manner. Specifically, relatively younger individuals in a given cohort who have fewer initial skills are likely to acquire fewer subsequent skills than the others and perform poorly, providing the educational opportunities are selected based on the initial skill level. Hence, lower performance results in reduced outcomes, including income. There is evidence that birth month has an impact on income (Kawaguchi, 2011), business success (Du et al., 2012), and political positions (Muller and Page, 2016).

However, the question of whether the performance difference resulting from the educational process is the only factor in the income gap by birth month remains unanswered. Hence, this study investigates firm wage discrimination as a new factor in the described income gap. In the labor market, if the productivity of relatively younger individuals in a given cohort is underestimated, their compensation will be lower than that of the others. This situation, in which equally productive persons are treated unequally in a way related to an observable characteristic, is defined as "discrimination" in labor economics (List and Rasul, 2011). When testing for this phenomenon, we can consider discrimination as the residual difference when labor outcomes are compared between groups after controlling for productivity. However, for researchers, it is difficult to control for labor productivity when relying on contemporary wage data. As a result, official studies on wage discrimination by birth month are scant. Hence, this study examines the possibility that the given phenomenon may be caused by both firm labor discrimination and the educational system.

To overcome the lack of data, this study leverages professional sports data as the performance indicators are well tracked and curated. Specifically, this study leverages the data from the Japanese professional baseball labor market to identify wage discrimination by birth month after controlling for the performance indicators of athletes. The dataset used for this investigation includes all Japanese players enrolled in Nippon Professional Baseball (NPB) from 1994 to 2019. These data include both annual income and detailed performance statistics. Notably, the results of this study's evaluation indicate that the birth month effect on income in NPB remains, even after controlling for performance. That is, the players born from January to March have approximately 2% less income than the players born from April to June with identical performance. Hence, labor discrimination is found to be a factor in the income gap by birth month alongside the educational system.

To identify the mechanism of wage discrimination, this study applies causal mediation analysis (Imai et al., 2010) to the data, including the initial offer provided by an employer to a job candidate, finding that players with lower initial salaries tend to stagnate at a generally lower annual salary than other players with similar performance. Causal mediation analysis shows that a factor of discrimination is the underpayment of initial income. For relatively younger players in a given cohort, the initial income is 11% less because of their lower position in the draft. This underpayment stagnates subsequent income and explains most of the wage discrimination observed. This phenomenon is caused by the biased hiring processes of NPB teams, which overestimate players' skill levels at hiring rather than considering the growth rate of skills. On the evidence, relatively younger players in a given cohort have higher subsequent performance than others at the same draft position.

A few researchers have examined discrimination and the birth month effect, taking advantage of the unique characteristics of sports. For example, Gwartney and Haworth (1974), Price and Wolfers (2010), and Parsons et al. (2011) provided evidence of racial discrimination in sports markets, including Major League Baseball (MLB) and the National Basketball Association. Gibbs et al. (2012) and Sims and Addona (2016) examined the relationship between birth month and performance in the MLB and the National Hockey League, respectively. However, no sports economics study has examined discrimination alongside the birth-month effect.

The main contribution of this study is the identification of a new mechanistic channel for explaining the income gap by birth month. The literature has shown that the education system, or similar non-optimal strategies, generates income gaps by birth month (Kawaguchi, 2011; Yamaguchi et al., 2023)[1]. In addition to this consensus, this study provides new evidence that the income gap by birth month is caused by the discriminatory wage structure of firms.

According to conventional labor economics theory, discrimination is caused by the optimal decisions of economic actors (Becker, 1971; Phelps, 1972; Aigner and Cain, 1977). In contrast, recent research has proposed new mechanisms in which false beliefs (e.g., prejudice and heuristics) are systematically propagated, inducing suboptimal decision-making (Bohren et al., 2019, 2022, 2023). The findings of this study are consistent with recent research in that they show that biased evaluations at enrollment lead to negative effects on relatively younger players in a given cohort.

The remainder of this paper is organized as follows. Section 2 explains the datasets used and provides a description of the analytical construct of the research design. Section 3 describes the approach applied to identify wage discrimination by birth month and shows the results. Section 4 conducts further analysis to reveal the mechanism behind the focused discrimination in this study, and Section 5 makes discrimination reduction recommendations. Finally, Section 6 concludes the paper.

[1] Kawaguchi (2011) suggests that the birth month could have a lifetime impact on eventual educational attainment and labor market outcomes if the initial difference in performance has a causal impact on subsequent performance through feedback effects, such as stigmatization. Yamaguchi et al. (2023) suggest that compensatory skill investment in cognitive skills may be an optimal strategy in the short run, but may not maximize lifetime earnings by underinvesting in noncognitive skills.

2 Background and Data

2.1 Japanese education system and the NPB draft

In Japanese schools, there is a maximum age difference of approximately one year within a class due to the School Education Law, which requires parents to enroll children in elementary school if they turn age six years by April 1. It also permits delaying schooling or advancement, which is rare. Then, the cutoff for the school year is strictly set to April 2. As a result, children who turn six on April 2 or later enter elementary school up to a year late.

The draft is almost the only way for Japanese amateur players to become professional players in NPB. The NPB draft is held every October and is attended by representatives of all 12 teams. To qualify, players must have Japanese nationality or belong to a Japanese school or qualified organization. High-school students cannot contract with professional teams prior to graduation. College students are also required to have been in college for at least 4 years prior to competing. Other players have more flexibility. During the draft, team leaders elect candidate players until all teams are satisfied or the number of players picked exceeds 120.[2] Based on the nature of this process, the players judged as best are picked in the earliest rounds. Thus, through the round pick in the draft, each team implicitly predicts the future success of the players and returns on investment.

2.2 Data

Data were obtained from NPB official website and NikkanSportsAgency (1994-2019)[3]. The subject of this study is all Japanese players enrolled in 1994–2019. Players enrolled before 1994 and foreign players enrolled as free agents were excluded. As shown at the top of Table 1, the number of individual units was 2,210, of which 1,036 were fielders, and the others were pitchers. Of the 2,210, 864 were high-school graduates, and the rest were college

[2] This regulation has been in place since 2001. Before that, teams were limited to 8 players per team.

[3] The information about performance and profile is from the NPB official website <https://npb.jp/>. The information on the annual salary is published by each team and reported by the Nikkan Sports Agency, Inc.

Table 1: Descriptive statistics

	All	Fielder	Pitcher	HS grad	Not HS grad
Sample size					
Individuals	2,210	1,036	1,174	864	1,346
Num.Obs.	14,920	7,623	7,297	8,729	6,191
Mean of variables					
Annual income	29,062	29,121	28,999	22,766	33527
Game	26.5	38.7	13.8	22.3	29.5
Plate appearance	117.5	117.5	–	56.1	62.8
Inning	31.9	–	31.9	10.7	19.2

Source: Information about performance and profile is from the NPB official website.<https://npb.jp/>. The information on annual salary is published by each team and reported by NikkanSportsAgency (1994-2019) in the annual player directory.

Note: Annual income is given in units of 1,000 yen. The number of innings for fielders and the number of plate appearances for pitchers is observable but not used in the analysis.

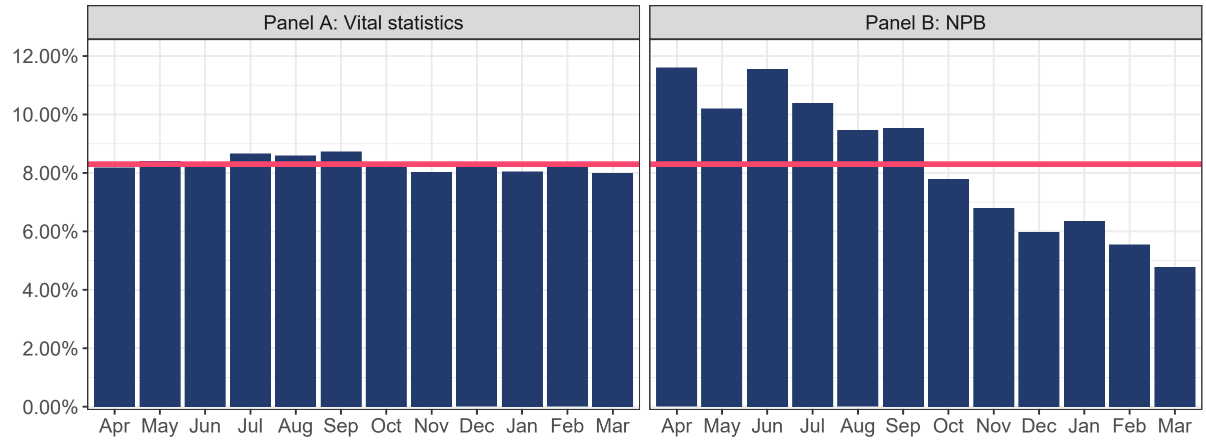
or other organizational accessions. This dataset included birth date, academic background, physical characteristics, and performance (e.g., number of games, plate appearances, and innings played). The means of some of these variables are reported at the bottom of Table 1.

2.3 Descriptive analysis

Disparities of birth month naturally exist in the NPB, as illustrated in Figure 1. The data were adjusted to normalize the otherwise unequal number of days per month. Panel A shows the share across all Japanese births. Note that the birth months are quite uniformly distributed at around 8.3%, which matches the relative frequency achieved when assuming random births. Panel B presents the share across the NPB, where a disparity is clarified. That is, relatively younger players hold a smaller share. In particular, March-born players number less than half the number of April-born players.

The deviation mechanism of the disparity illustrated in Figure 1 is explained by Figure 2, which shows the distribution of the skills of candidate players per cohort at the time of the draft. If a player's skill is x and is an increasing function of time from birth, then the distribution of all April-born players' skills is located to the right of that of all March-born

Figure 1: Distribution of birth month (adjusted for number of days)



Source: Information in Panel A was taken from vital statistics reported by the Ministry of Health, Labor, and Welfare <https://www.mhlw.go.jp/toukei/list/81-1a.html >. Information in Panel B was taken from the NPB official website. <https://npb.jp/> and the player directory published by NikkanSportsAgency (1994-2019).
Note: To match the birth years of NPB players in the sample, the vital statistics of 19952000 were used. For monthly comparisons, the relative frequency was calculated by dividing the number of births per month by the number of days per month. The horizontal bar was drawn at 8.3%, which mirrors the relative frequency, assuming random births.

players. Hence, if the cutoff for entering NPB is θ, the number of players in the NPB born in April is greater than that born in March. The average skills of NPB players by birth month are summarized as follows.

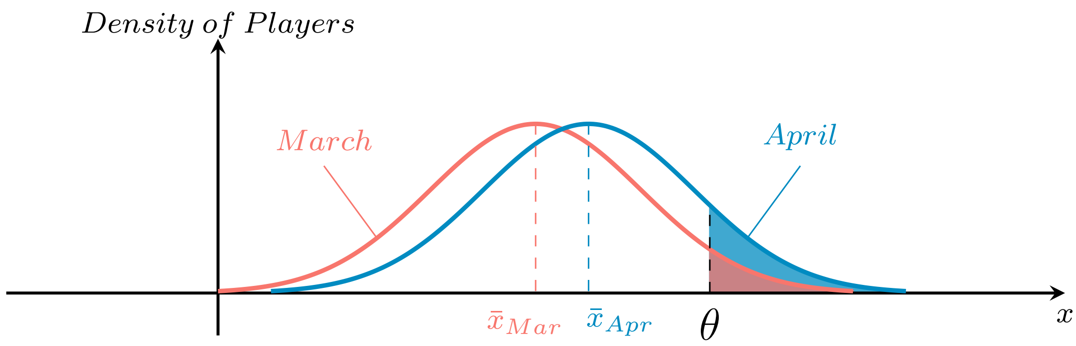
$$E[x|birthmonth = April, x > \theta] > E[x|birthmonth = March, x > \theta] \tag{1}$$

Comparing the average skill of players beyond the cutoff in each distribution, the average skill of April-born players is larger than that of March-born players[4].

Figure 3 provides supporting evidence for the discussion above. Panel A shows the first-year performance of high-school graduate players by birth month. The relatively younger players, who are likely to have fewer skills, perform poorly. Panel B shows that the weight distribution of April-born players is to the right of that of the March-born players, indicating that even by age of 19, birth month affects physical maturity. In sports, physical disadvan-

[4]Suppose that the skill distribution for players born in April is a rightward shift of the distribution for those born in March by δ. Further, assume that players' skills follow a normal distribution such that $x_{\text{March}} \sim \mathcal{N}(\mu, \sigma^2)$ and $x_{\text{April}} \sim \mathcal{N}(\mu + \delta, \sigma^2)$. Under these assumptions, we can show that Equation (1) holds.

Figure 2: Distribution of skills by birth month



tages directly affect March-born players' performance, as illustrated in Panel A and B. Then, as shown in Panel C, it is not surprising that the difference in performance affects players' income. These facts are consistent with the relationship between income and performance gaps due to birth month, which follows the literature. Section 3 shows that the income gap by birth month persists, even after controlling for various performance statistics.

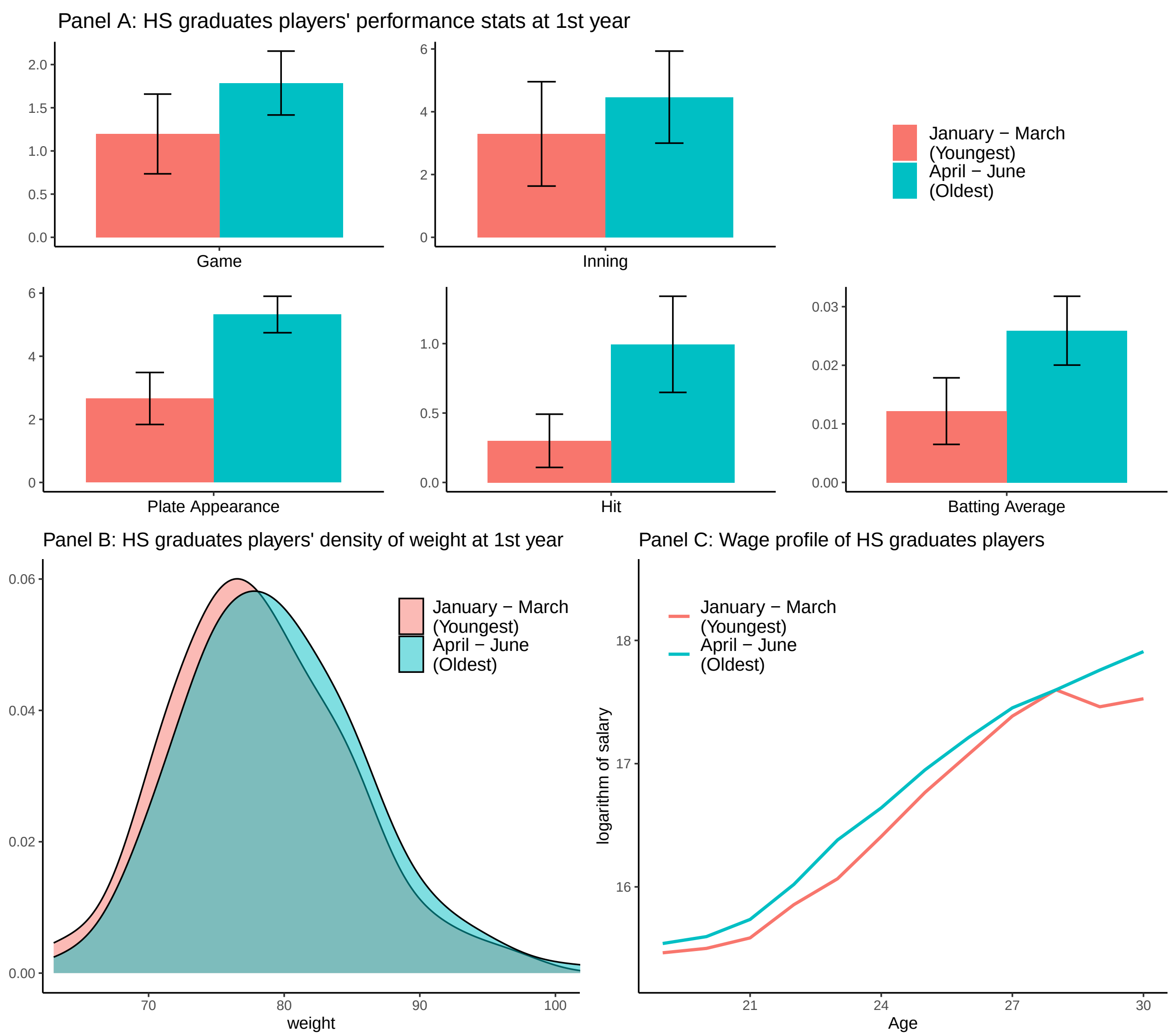
3 Income gap by birth month

3.1 Estimation strategy

This section estimates the effect of the birth month on income while controlling for performance to identify wage discrimination by birth month, as shown in Figure 4. The sample was divided into four groups based on the calendar quarter of birth: April–June, July–September, October–December, and January–March. Based on Higuchi (1993), the following equation is estimated:

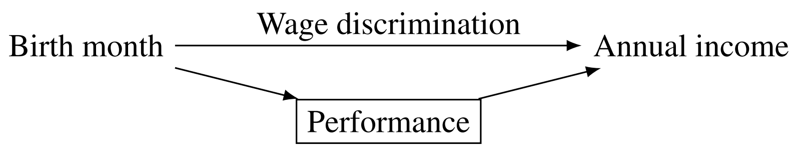
$$\begin{aligned} Y_{i,t} = \alpha_1 + &\sum_{q\in\{1,3,4\}} \beta_q T_i^q + \sum_{s=1}^{S} \zeta_s \mathbf{1}(exper_{i,t} = s) + \\ &\theta perf_{i,t-1} + \lambda\, cum\ perf_{i,t-2} + X'_{i,t}\xi_2 + u_{i,t} \end{aligned} \tag{2}$$

Figure 3: Comparison of players' JanuaryMarch and AprilJune birth months based on performance, weight, and annual income



Note: In Panel A, the mean number of games was calculated for all players, innings were tallied for pitchers, and plate appearances, hits, and batting averages were calculated for fielders. The error bars indicate one standard error from the mean. In Panel C, annual income after age 30 is not shown due to the small sample size.

Figure 4: Discrimination by birth month



where $Y_{i,t}$ is the logarithm of the annual income for player i in year t, adjusted by CPI. T_i^q is a dummy variable for the quarter of birth. The second quarter of birth was taken as the base group. $\mathbf{1}(exper_{i,t} = s)$ is a dummy variable that takes the value of one if the player's experience at $t = s$. $X'_{i,t}$ is the vector of other covariates including the pitcher dummy, team dummy, birth cohort dummy, and educational background dummy. $perf_{i,t-1}$ is performance statistics at $t-1$. In addition to the lagged performance, following (Higuchi, 1993), the cumulative performance was controlled as follows:

$$cum\ perf_{i,t-2} = \begin{cases} \dfrac{\sum_{s=1}^{t-2} perf_{i,t}}{t-2} & \text{if } t > 2, \\ 0 & \text{if } x = 2 \end{cases}$$

To control for performance, the following performance statistics were used as a proxy: the number of fielder plate appearances per game, pitcher innings played per game, and the number of games regardless of position. In the benchmark sample that includes both pitchers and fielders, the term used to control for performance is as follows:

$$perf_{i,t} = \text{performance}_{i,t} \times D_i^{pitcher} + \text{performance}_{i,t} \times (1 - D_i^{pitcher})$$

with $\text{performance}_{i,t}$ and $D_i^{pitcher}$ are defined as follows:

$$\text{performance}_{i,t} = \begin{cases} \text{\# of inning}_{i,t} & \text{If } i \text{ is pitcher,} \\ \text{\# of plate appearance}_{i,t} & \text{If } i \text{ is batter} \end{cases} \qquad D_i^{pitcher} = \begin{cases} 1 & \text{if } i \text{ is pitcher,} \\ 0 & \text{if } i \text{ is batter} \end{cases}$$

Because only one of the performance indicators can be normally observed for one player,

Table 2: Effects of birth month on annual income

Sample	(1) All	(2) Fielders	(3) Pitchers
July–September	-0.019**	-0.009	-0.043***
	(0.009)	(0.011)	(0.014)
October–December	-0.010	-0.028**	0.006
	(0.010)	(0.012)	(0.016)
January– March	-0.020*	-0.022*	-0.023
	(0.011)	(0.013)	(0.017)
Num.Obs.	12 710	6587	6122

Note: Income was deflated by CPI for all goods in the base year 2020. The sample was restricted to players with two or more years of experience. Column (1) uses the sample of all players, and Column (2) uses the sample of fielders. Column (3) uses the sample of pitchers, and each entry refers to the estimated coefficient on a given quarter dummy, which indicates a percentage income change from the April-June-born player. The full estimation results are reported in Appendix A. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

depending on the role, many values go missing when both indicators are included in the regression. However, the new performance variable enables the pitcher and fielder performance to be controlled simultaneously without losing values.

3.2 Results

Table 2 reports the effects of the birth month on income after controlling for players' performance. Each entry indicates a percentage income difference between April–June born players and other groups. Column (1) reports the benchmark results for all players with two or more years of experience. Columns (2) and (3) report the results for the subsamples of fielders and pitchers, respectively. Column (1) shows that all birth-month groups have lower incomes compared with the April–June born players, even after controlling for performance. Notably, the January–March born players had -2.0% income than the April–June born players. In Columns (2) and (3), the estimated coefficients were similar to the benchmark results. However, the coefficient for the June–March born players in Column (3) is not statistically significant due to difficulties controlling for pitcher performance. The number of

Table 3: Robustness check addressing survival bias and endogenous enrollment timing

	(1)	(2)	(3)
Sample	Experience ≤ 10	HS Graduates	Experience ≤ 10 HS Graduates
July–September	-0.018*	-0.037***	-0.032**
	(0.011)	(0.013)	(0.013)
October–December	-0.020	-0.053***	-0.039**
	(0.012)	(0.017)	(0.016)
January–March	-0.022*	-0.032*	-0.051***
	(0.013)	(0.019)	(0.018)
Num.Obs.	5471	3212	2584

Note: Income was standardized by CPI for all goods in base year 2020. Column (1) uses a sample of fielders with 10 or fewer years of experience. Column (2) uses a sample of high-school graduate fielders, and Column (3) uses the sample of high-school graduate fielders with 10 or fewer years of experience. The coefficient indicates the proportion of income difference between April-June and the others. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

games played and innings pitched depends on player roles as starters or relievers. Thus, the available performance statistics in the dataset may not have been fully controlled for pitcher performance.

Table 3 reports the results of the robustness checks used to address potential endogeneity issues. The analysis was restricted to fielders to better control for performance. First, survival bias was addressed. Due to the feature of the dataset, only continuing players' incomes were observed. If birth month and survival rate were to be correlated, the estimates would be biased. To avoid this issue, I restricted the sample to players with less than 10 years of experience. Column (1) reports the result, indicating that the average income of January–March born players was 2.2% less than that of the April–June born players, which agrees with the benchmark results. Second, endogenous enrollment timing was addressed. In a few cases, amateur players rejected team offers due to their personal evaluation of their skill levels and that of the team prospects. Hence, their enrollments were delayed. This endogenous adjustment would have biased the coefficients. Hence, to overcome this concern, a subsample of only high-school graduates was used. Column (2) reports the results, indicating that the average January–March players income was 3.2% less than that of the April–June play-

Table 4: Robustness check using narrower birth day window

Sample	(1) All	(2) Fielders	(3) Pitchers
March	-0.152***	-0.219*	-0.218*
	(0.056)	(0.122)	(0.123)
Num.Obs.	419	237	177

Note: Income was standardized by CPI for all goods in base year 2020. To narrow the birthday window, a subsample of players born around 7 days from 4/2 was used. Column (1) uses a sample of all players. Column (2) uses a sample of fielders, and Column (3) uses a sample of pitchers. The coefficient indicates the proportion of income differences between the April-June and the others. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ers, indicating a larger impact of the birth month than the benchmark.[5] Moreover, Column (3) shows the results considering both concerns, and the coefficients are consistent with the benchmark results.

Table 4 reports the results after controlling for unobserved heterogeneities caused by the manipulation of birth timing. To accommodate this, the birthday bandwidth of the sample was narrowed to equalize unobservable player characteristics. That is, the bandwidth was set 7 days before and after the cutoff, which would have been difficult to manipulate for birth timing. As a result, the coefficients were negatively significant and larger than those of the benchmark results.

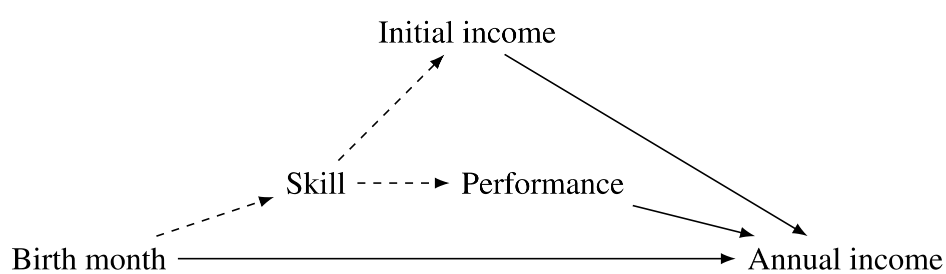
In summary, the wage gap by birth month after controlling for player performance has been shown to differ from that reported in the literature. That is, differences occur, even when individual performances are equal. Section 4 explores the mechanisms of perceived labor discrimination.

[5]Section 5 discusses why the point estimates are larger when the sample is restricted to high school graduates.

4 Mechanism

This section examines the discrimination mechanism by identifying the impact of birth month on initial income, as illustrated in Figure 5. Relatively younger players within a given cohort may experience lower initial incomes partially due to physical immaturity at the time of the draft, as discussed in Section 2. This initial disadvantage may result in stagnant subsequent income despite equivalent performance levels compared to their peers. Consequently, if wages are determined by wage history and performance, the birth month could influence subsequent wages through its effect on initial wages. Figure 5 presents a directed acyclic graph depicting the causal pathway from birth month to annual income, mediated by initial income. To verify this mediation effect, a causal mediation analysis was performed (Imai et al., 2010).

Figure 5: Mechanism of wage discrimination by birth month



Note: Nodes and edges represent random variables and causalities, respectively. The direction of the edge captures the direction of causality. The edges of unobserved confounder (Skill) are represented with dashed lines.

4.1 Empirical strategy

This section explains the decomposition of two effects on annual salary from birth month after controlling for performance. The first is the effect of birth month on annual income through initial income (i.e., the average causal mediation effect (ACME)). The second is the direct effect of the birth month on annual income (i.e., average direct effect (ADE)). In Figure 5, ACME is shown as the arrow from birth month to annual income via initial income, whereas ADE is shown as the arrow directly from birth month to annual income.

Nevertheless, it is anticipated that the ADE will be close to zero, given the absence of a theoretical foundation to support a direct effect from birth month to annual income.

Let τ, M_i, and Y_i denote treatment status, mediator, and outcome, respectively; treatment status is a binary variable, $\tau \in \{0, 1\}$, $M_i(\tau)$ is the potential mediator for individual i and treatment τ and $Y_i(\tau, M_i(\tau))$ is the potential outcome for i with τ and $M_i(\tau)$. Based on these notations, ACME is defined as follows:

$$ACME = E[Y_i(\tau, M_i(1)) - Y_i(\tau, M_i(0))]$$

The effect of the treatment on outcome by means other than mediation variables is the ADE, which is expressed as follows:

$$ADE = E[Y_i(1, M_i(\tau)) - Y_i(0, M_i(\tau))]$$

The sum of ACME and ADE is the Total Effect, which equals the average treatment effect (ATE).

$$Total\ Effect = ATE = ADE + ACME = E[Y_i(1, M_i(1)) - Y_i(0, M_i(0))]$$

Imai et al. (2010) showed that if the following sequential ignorability assumption are satisfied, ACME is nonparametrically identified:

$$\{Y_i(\tau', m), M_i(\tau)\} \perp T_i \mid X_i = x_i \tag{i}$$

$$Y_i(\tau', m) \perp M_i(\tau) \mid T_i = \tau, X_i = x_i \tag{ii}$$

Condition (i) claims that the assignment of the treatment is independent of potential outcome and mediator values condition on covariates X_i. This is satisfied if the birth month is randomly assigned to the players, which is the case in this study. Condition (ii) claims that the assignment of the mediator is independent of potential outcome, given covariates and treatment. It is satisfied if the confounders between annual salary and initial income are controlled. In this study, potential confounders that may violate condition (ii) are educational background, defense position, and team affiliation. Thus, these covariates are controlled. The educational background may be a post-treatment confounder, which should not be controlled (Imai et al., 2011). For robustness, the estimation results excluding educational background from covariates are presented in Appendix C. Furthermore, the subsample analysis that restricts the sample to high school graduates is presented in Table 7. Performance is not a confounder that violates the sequential ignorability assumption.[6] However, It is controlled for to focus on the discrimination part of the birth month effect.

On the basis of this framework, ACME and ADE were estimated using two regressions. The first employed a mediation equation, and the other employed an outcome equation. The mediation equation regresses the mediator on the treatment variable with covariates, and the outcome equation regresses the outcome on the treatment variable and the mediator with covariates. The estimation process then involves predicting the mediators for both treatment values $(M_i(1); M_i(0))$. Next, the outcome equation predicts outcome Y_i by $T_i = 1$ and $M_i = M_i(0)$, and then $T_i = 1$ and $M_i = M_i(1)$. Subsequently, from the two regressions, the average difference between the outcomes was computed to obtain a consistent estimate of ACME, and the standard error was bootstrapped for the estimation.

Hence, the following mediation equation is regressed:

$$M_i = \alpha_2 + \beta_1 T_i + X_i' \xi_1 + e_i \tag{3}$$

where M_i is the logarithm of initial income,[7] X_i is the vector of covariates, including the pitcher, team, school cohort, and educational background dummies, and T_i is a treatment dummy that takes the value of one if player i was born in January–March (zero otherwise).

[6] Even if initial income affects subsequent performance, the sequential ignorability assumption remains satisfied.

[7] The dependent variable (initial income) is the sum of the initial salary and the contract money.

The outcome equation is as follows:

$$
\begin{aligned}
Y_{i,t} = \alpha_3 + \beta_2 T_i + \sum_{s=1}^{S} \gamma_s (M_i \cdot \mathbf{1}(exper_{i,t} = s)) + \\
\sum_{s=1}^{S} \zeta_s \mathbf{1}(exper_{i,t} = s) + \theta perf_{i,t-1} + \lambda\, cum\ perf_{i,t-2} + X'_{i,t}\xi_2 + u_{i,t}
\end{aligned}
\tag{4}
$$

where $Y_{i,t}$ is the logarithm of annual income for player i in year t, adjusted by CPI. T_i is a treatment dummy, $M_i \cdot \mathbf{1}(exper_{i,t} = s)$ is the interaction term of the logarithm of initial income and experience dummies, and the other covariates are the same as in Eq. (2). Details of the derivation of Eq. (4) are provided in the Appendix B.

4.2 Result

To apply the analysis to the framework of causal mediation analysis, it was necessary to define the treatment and control. Hence, the sample was restricted to players born in April-June and January-March. Then, the treatment variable, T_i, was defined as follows:

$$
T_i = \begin{cases} 1 & \text{If } i \text{ is born in January-March,} \\ 0 & \text{If } i \text{ is born in April-June} \end{cases}
$$

This method makes the results comparable to the benchmark results. Previous studies have employed the same approach (Bedard and Dhuey, 2006; Kawaguchi, 2011; Yamaguchi et al., 2023).

Table 5 reports the results of the causal mediation analysis. In Panel (A), coefficient β_1 of Eq. (3) is presented. All coefficients were negative, and the first column shows that the January–March cohort had 11% less income than the April–June cohort. This result indicates a wage gap by birth month at enrollment.

In Panel (B), coefficient β_2 of Eq. (4) is presented. The coefficients are close to zero, indicating that there was almost no residual effect on income from birth month when controlling for initial income and performance. Coefficients γ_s of Eq. (4) are shown in Figure

6 in the order experience s. The impact of initial income on subsequent income was mostly positive, and the effect decayed with experience, but remained statistically significant for fielders with 10 years of experience and pitchers with six or fewer years of experience. This result shows that players with higher initial incomes are more likely to have higher subsequent incomes. In Panel (C), ACME, ADE, and ATE are reported. ACME was consistently significant, and negative with estimates of $-0.016 \sim -0.018$ across specifications. This result indicates that January–March–born players had $1.6\% \sim 1.8\%$ less annual income than April–June–born players based on their initial income, even after performance was controlled. ADE is equal to β_2 in Eq. (4), as reported in Panel (B): almost zero. The total effect was also negative and consistent with the results of Eq. (2) in Section 3. Additionally, the bottom of Panel (C) presents the results of sensitivity analysis recommended by Imai et al. (2010). ρ is the correlation coefficient between the explanatory variable and the unobserved covariates, indicating the degree of violation of the sequential ignorability assumption. The results report ρ that makes ACME zero, and, for Column (1), ACME is zero when the number of correlations between explanatory variables and unobserved covariates is 0.5.

The robustness check is presented in Table 7. As in Section 3, concerns about survival bias and endogenous enrollment timing were addressed via subsample analyses. For simplicity, only the ACME, ADE, and ATE are reported; however, the results show that the benchmark results presented in Table 5 are robust.

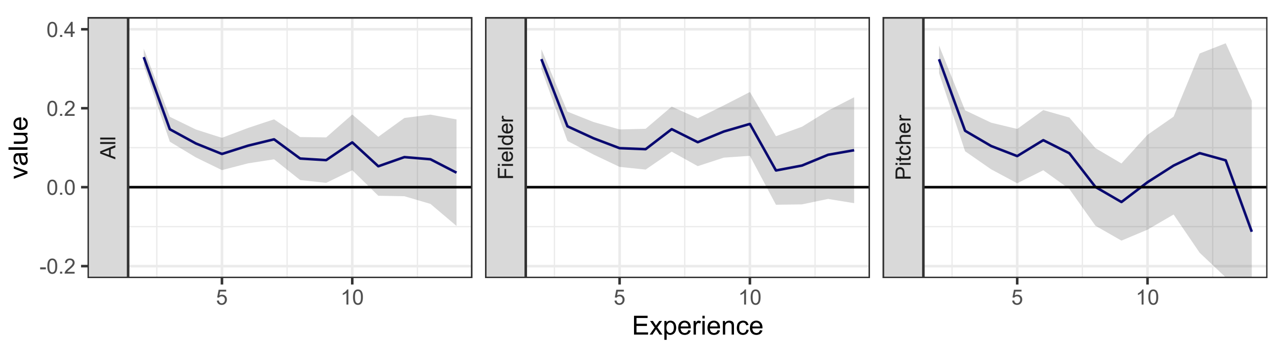
This section provides three lines of evidence on wage discrimination by birth month. First, relatively younger players in a given cohort have less initial income. Second, their initial income affects subsequent annual income, even after controlling for performance. Third, they inefficiently stagnate at a lower salary than relatively older players in a given cohort with similar performance due to lower initial incomes. These findings suggest that the evaluation of players at enrollment is the main factor of labor discrimination by birth month. Section 5 focuses on further interpretations and discusses the incentives for teams to eliminate discrimination.

Table 5: Mediation and direct effect of birth month on income

	(1) All	(2) Fielder	(3) Pitcher
(A) Mediation equation			
β_1	-0.113^{*}	-0.224^{***}	-0.032
	(0.058)	(0.086)	(0.082)
Num.Obs.	1085	539	546
(B) Outcome equation			
β_2	-0.006	-0.003	-0.016
	(0.013)	(0.012)	(0.018)
Num.Obs.	6196	3384	2810
(C) Causal mediation analysis			
ACME	-0.016^{***}	-0.018^{***}	-0.016^{***}
	(0.003)	(0.005)	(0.005)
ADE	-0.006	-0.003	-0.017
	(0.011)	(0.012)	(0.018)
Total Effect	-0.022^{**}	-0.022^{*}	-0.032^{*}
	(0.012)	(0.012)	(0.019)
ρ at ACME = 0	0.5	0.6	0.5
Num.Obs.	6196	3384	2810

Note: Income was standardized by CPI for all goods in the base year 2020. The coefficient indicates the proportion of income difference between April-June-born players and January-March-born players. Robust standard errors are reported in parentheses. ρ is the correlation coefficient between the explanatory variable and the unobserved covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 6: Impact of initial income on subsequent income (γ_s)



Note: γ_s is estimated up to s = 22 for fielders and s = 20 for pitchers, respectively, but for clarity values $s < 15$ are reported. The ribbon indicates the confidence interval (90% CI).

Table 6: Robustness check addressing survival bias and endogenous enrollment timing

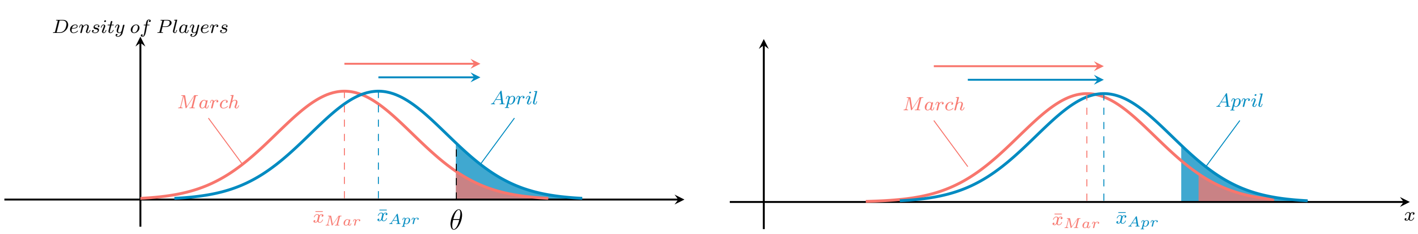
Sample	(1) Experience ≤ 10	(2) HS Graduates	(3) Experience ≤ 10 HS Graduates
Causal mediation analysis			
ACME	-0.026***	-0.028***	-0.038***
	(0.006)	(0.007)	(0.009)
ADE	0.005	-0.006	-0.018
	(0.011)	(0.019)	(0.016)
Total Effect	-0.022**	-0.034*	-0.056**
	(0.013)	(0.020)	(0.018)
Num.Obs.	2822	1704	1405

Note:Income was standardized by CPI for all goods in the base year 2020. The coefficient indicates the proportion of income difference between April-June-born players and January-March-born players. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Disucussion

To further explore the structure behind discrimination, this section focuses on catching up on skills and selection through a draft system. The key points include a shift and heterogeneity of the distribution of skills based on birth month, as shown in Figure 7. As discussed in Section 2, Panel A shows the distribution of skills and cutoff θ for enrollment. First, the rightward shift of both distributions is noncontroversial. Second, as suggested by the literature, a reduction in the effect of birth month is needed with age (Kawaguchi, 2011; Ya-

Figure 7: The distribution of skill by birth month



Panel A: At enrollment

Panel B: After enrollment

maguchi et al., 2023; Larsen and Solli, 2017). The size of the shifts is assumed to be greater for March players than for April players. Hence, the two distributions should grow closer after enrollment, as shown in Panel B. That is, if a player born in April and a player born in March have the same skill level at enrollment, the player born in March is expected to have a slightly higher skill level. Therefore, for optimizing roasters, teams must hire and set wages based on not only the skill level but also the potential growth rate of the players.

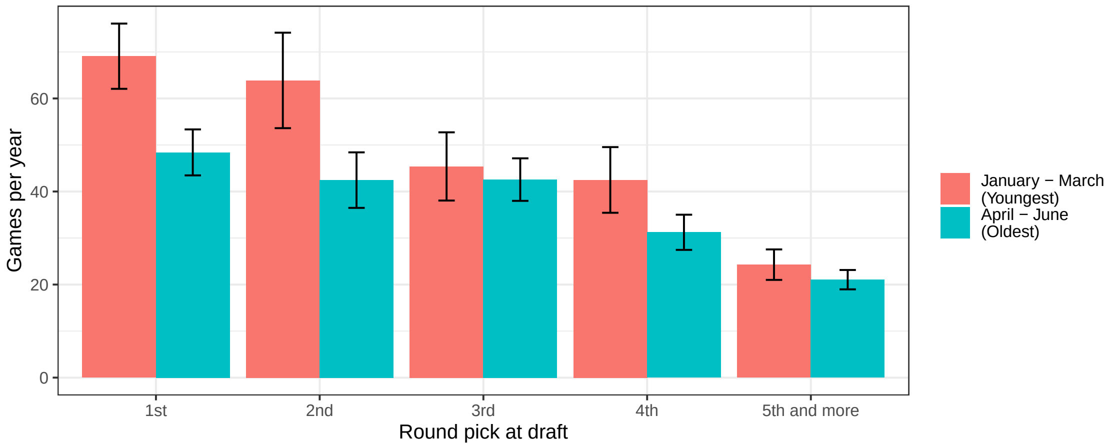
In an efficient market with rational expectations, agents and team leaders are assumed to make unbiased predictions about the future, and individual expectations are aggregated into unbiased estimates of fundamental value. Moreover, in the NPB, the evaluation aggregated to each team should be consistent with the players' subsequent performance.

However, there seems to be a discrepancy between the evaluation and performance. Figure 8 shows the number of games per year by birth month and round pick in the draft. As suggested by reason, players drafted in earlier rounds perform better, but the predictions are biased by birth month. In every round, March players consistently perform better than April players. This fact is similar to reports in several pieces of literature (Gibbs et al., 2012; Sims and Addona, 2016). Moreover, in some rounds, the number of games played by March players is greater than that of April players picked in earlier rounds. Notably, for an April player picked in the first round and a March player picked in the second round, the average difference is 15.47 games per year, which is statistically significant ($p = 0.008$).

The potential inefficiency between evaluation and performance may be caused by ignoring the heterogeneity of growth rate by birth month, as illustrated in Figure 7. The disregard for the relatively high growth rate of March players leads to their undervaluation of the draft; hence, their initial income is lower. As discussed in Section 4, a lower initial income causes subsequent wage discrimination. Moreover, this implication can explain the larger estimates of wage discrimination in the subsample of only high-school graduates, whose skill gaps per birth month are larger.

This discrimination is largely caused by stereotypes, heuristics, and other inaccurate beliefs (Bohren et al., 2023). In the typical hypothesis of conventional labor economics,

Figure 8: Annual average the number of games played by birth month and round pick at the draft



Note: The sample is for fielders only. The error bars indicate confidence interval (90%Cl) of mean.

discrimination is caused by the optimal decisions of economic actors (Becker, 1971; Phelps, 1972; Aigner and Cain, 1977). In contrast, if discrimination is caused by inaccurate beliefs, then hiring and promotion decisions based on these previous evaluations are flawed (Bohren et al., 2019). From the perspective of the NPB, it is reasonable to consider that the heuristic over evaluation of skill levels while ignoring growth rate leads to potential inefficiencies, as shown in Figure 8. Moreover, these suboptimal decisions cause wage discrimination for relatively younger players in each cohort. Therefore, correcting beliefs about players' skills will benefit not only the players but also the teams.

6 Conclusion

This study examined wage discrimination by birth month using data from labor market in NPB, which included player salaries, profiles, and performance statistics. This unique feature allowed for the accurate estimation of the wage function when controlling for worker productivity. The results show that, even after controlling for performance, a statistically and economically significant difference in income by birth month was found. This evidence of labor discrimination provides a new channel for understanding the effect of birth month on income.

Further analyses shed light on the mechanisms behind the observed discrimination. The relatively younger players in a given cohort tend to have lower skills at enrollment; however, it is noteworthy that their skills catch up quickly, and the performance gap decreases. However, teams do not accurately predict this heterogeneity, which leads to an underestimation of the future success of January–March-born players at enrollment. As a result, teams set their initial salaries that were lower than appropriate. Because this wage discrimination in early players' careers is not eliminated by promotion rules based on wage history and performance, it is pervasive.

Inaccurate statistical discrimination can lead to suboptimal hiring and promotion decisions. Hence, the discrepancy between evaluation and performance, as indicated by the research, suggests a potential opportunity loss for teams. If this mechanism of discrimination is not sport-specific, the recruitment process in the general labor market may increase the income gap by birth month as well. The findings of this study suggest that to correct for the birth month effect, it is necessary to investigate firm recruitment processes, as well as the policies set forth by the Japanese educational system.

Furthermore, the finding of a greater income gap in the subsample of high-school graduates suggests that, in junior age groups, the disparity caused by selection, which ignores heterogeneity in growth rates by birth month, is more severe. According to the literature, this type of discrimination can be corrected by providing the correct information during the hiring process. This study should help the industry in this regard.

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A Full estimation result of benchmark

This table reports all estimates of the benchmark results estimated by Eq. (2).

	(1) All	(2) Fielder	(3) Pitcher
game	0.008***	0.008***	0.021***
	(0.000)	(0.000)	(0.000)
game (cumulative)	0.009***	0.009***	0.027***
	(0.000)	(0.000)	(0.001)
performance	0.137***		
	(0.006)		
performance (cumulative)	0.075***		
	(0.006)		
plate appearance / game		0.141***	
		(0.006)	
plate appearance / game (cumulative)		0.072***	
		(0.006)	
inning / game			0.153***
			(0.004)
inning / game (cumulative)			0.092***
			(0.005)
pitcher	−0.020*		
	(0.011)		
pitcher × game	0.013***		
	(0.000)		
pitcher × game (cumulative)	0.017***		
	(0.001)		
pitcher × performance	0.019***		
	(0.007)		
pitcher × performance (cumulative)	0.013*		
	(0.007)		
High-school graduates	−0.067***	−0.038***	−0.104***
	(0.009)	(0.010)	(0.014)
Num.Obs.	12 710	6587	6122

Note: Income is standardized by CPI for all goods in the base year 2020. Column (1) uses the sample of all players with two or more years of experience. Column (2) uses the sample of fielders with two or more years of experience. Column (3) uses the sample of pitchers with two or more years of experience. The coefficient indicates the proportion of income difference between April-June born player and each group. Robust standard errors are reported in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Derivation of the outcome equation

The outcome function is set up based on a wage function with the concept that income in year t is determined by performance and income in year $t-1$ respectively. The equation can be transformed as a nested equation as follows:

$$\begin{aligned}
\underbrace{y_{i,t}}_{\text{Income}} &= \gamma y_{t-1} + \theta \underbrace{perf_{t-1}}_{\text{Performance}} + \mu_i + \epsilon_{i,t} \\
&= \gamma(\gamma y_{t-2} + \theta perf_{t-2}) + \theta perf_{t-1} + \mu_i + \epsilon_{i,t} \\
&\qquad\qquad \vdots \\
&= \gamma^{t-1} y_{i,1} + \theta perf_{i,t-1} + \gamma\theta perf_{i,t-2} + \gamma^2 \theta perf_{i,t-3} + \cdots + \gamma^{t-1}\theta perf_{i,1} + \mu_i + \epsilon_{i,t} \\
&= \underbrace{\gamma^{t-1} y_{i,1}}_{\text{initial income}} + \theta perf_{i,t-1} + \underbrace{\gamma\theta \sum_{s=2}^{t} \gamma^{s-2} perf_{t-s}}_{\text{Cumulative performance}} + \mu_i + \epsilon_{i,t}
\end{aligned} \tag{5}$$

Finally, wage becomes a function of initial income weighted by year, performance at $t-1$, weighted cumulative performance weighted by year, and fixed effect.

To perform a regression analysis, adjust the Eq (5). First, to generate the term of cumulative performance, γ must be estimated by system GMM. However, the short panel prevents accurate estimation of γ. Therefore, for estimation purposes, the term of cumulative performance is substituted by the following proxy:

$$cum\ perf_{i,t-2} = \begin{cases} \dfrac{\sum_{s=1}^{t-2} perf_{i,t}}{t-2} & \text{if } t > 2, \\ 0 & \text{if } x = 2 \end{cases}$$

Second, I attempt to substitute fixed effects with an indicator of player attributes such as educational background, role of player, affiliated team, and birth cohort, since the regression cannot include both fixed effects and birth month variables. Based on the above, I estimate

Eq. (6):

$$Y_{i,t_i^0+s} = \alpha_2 + \beta_2 T_i + \sum_{s=1}^{S} \gamma_s (M_i \cdot \mathbf{1}(exper_{i,t_i^0+s} = s)) + \sum_{s=1}^{S} \zeta_s \mathbf{1}(exper_{i,t_i^0+s} = s) +$$
$$\theta perf_{i,t_i^0+s-1} + \lambda\, cum\ perf_{i,t_i^0+s-2} + X'_{i,t_i^0+s}\xi_2 + u_{i,t_i^0+s} \tag{6}$$

C Address the possibility of post-treatment confounder

It is possible that an individual's educational background may be influenced by the month of their birth, and this could act as a post-treatment confounder. In that case, educational background should not be included as a control variable (Imai et al., 2011). To address potential concerns, this table presents the results of the benchmark causal mediation analysis, in which educational background is excluded from the control variables.

Table 7: Mediation and direct effect of birth month on income (Excluding educatinal background from control variables)

	(1) All	(2) Fielder	(3) Pitcher
Causal mediation analysis			
ACME	−0.014***	−0.018***	−0.011**
	(0.003)	(0.004)	(0.005)
ADE	0.003	0.000	0.006
	(0.010)	(0.012)	(0.018)
Total Effect	−0.011	−0.018	−0.005
	(0.011)	(0.013)	(0.019)
Num.Obs.	6196	3384	2810

Note:Income was standardized by CPI for all goods in the base year 2020. The coefficient indicates the proportion of income difference between April-June-born players and January-March-born players. Robust standard errors are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01