Hiring Decisions under Productivity Uncertainty: Risk Preferences and Inaccurate Statistical Discrimination in NHL Entry Drafts

Chengyuan Hua[1] and Brad R. Humphreys[1]

[1]West Virginia University

March 13, 2025

Abstract

This paper analyzes firm hiring decisions under uncertainty about worker productivity utilizing quasi-experimental variation generated by age requirements with specified cutoff dates. We exploit an exogenous September 15 cutoff date in the National Hockey League entry draft to estimate a sharp RDD and find evidence of risk aversion by teams when drafting players. Specifically, teams appear risk averse in early rounds, but risk neutral in later rounds, supporting predictions made by models in the literature. Additional evidence from a triple difference-in-differences model shows relative-age-based statistical discrimination in the draft, providing implications for firm hiring strategies. We also find suggestive evidence that this discrimination is partly driven by experience, and more accurate statistical discrimination is associated with greater team success.

Key Words: Hiring Decisions, Risk Preferences, Statistical Discrimination, National Hockey League, Entry Drafts, Relative Age

JEL Codes: J23, J24, J71, M51, Z22

1 Introduction

While economists understand the fundamental problem firms face when hiring workers, the strategies firms employ to address hiring problems require further investigation (Oyer and Schaefer, 2011). Hiring decisions are inherently risky because worker productivity is not fully observable ex

ante, making it difficult for firms to distinguish between candidates with similar credentials but different underlying abilities. How firms make hiring decisions under such uncertainty represents one of the most important tasks in personnel management, as hiring mistakes can be costly due to training investments, turnover, and productivity mismatches. In this paper, we investigate two research questions regarding such hiring decisions. First, are firms risk-averse or risk-seeking? In other words, do they tend to choose workers with less uncertain productivity or take risks in pursuit of the potential upside offered by risky workers? Second, is there statistical discrimination in these hiring decisions, and if there is, is it accurate or exaggerated?

As noted by Kahn (2000), professional sports provide unique opportunities for labor market research. In the context of entry drafts in professional sports leagues, team draft decisions are analogous to firm hiring decisions, the process of a new player making the team roster at the start of the season parallels the probationary period in many jobs where firms evaluate new employees and determine if they are suitable, and the player performance after making the team roster represents worker realized productivity. Recent research (Ahmadi et al., 2025) uses data from the Major League Baseball entry draft to investigate the impact of discrimination on firm hiring decisions. We analyze outcomes from the National Hockey Association (NHL) entry draft to gain new insight into hiring decisions in labor markets, including the the presence of risk aversion and statistical discrimination in firm hiring decisions.

The NHL draft features a novel age cutoff for player eligibility. Starting in 1980, only players at least 18 years old on or before September 15 of the draft year were eligible for the annual NHL entry draft. Exploiting this exogenous cutoff date in a sharp RDD approach, we find evidence that teams are risk averse in drafting players in the early rounds of the draft but risk neutral in later rounds, supporting the option value predictions in the model of firm hiring decisions developed by Lazear (1998).

NHL rules also specify an upper age limit for North-American players in the draft. A North-American player is no longer eligible for the entry draft if he is over 20 years of age on December 31 of the draft year. A recent line of research analyzes hiring decisions in the context of accurate and inaccurate statistical discrimination, an important distinction for understanding sources of discrimination (Bohren et al., 2023). We exploit this calendar year cutoff in a triple difference-in-differences model to investigate the presence of statistical discrimination based on date-of-birth of

players in the NHL draft. We find evidence of statistical discrimination against players born in the last quarter of the year (hereafter Q4) compared to players born in the first quarter (hereafter Q1).

Under the assumption that draft position reflects team beliefs about a player's future productivity, significant coefficients on the Q4 birth indicator variable in regression models explaining post-draft outcomes conditioning on draft position indicate the presence of inaccurate statistical discrimination. The presence of statistical discrimination implies that NHL teams undervalue Q4 players and teams can benefit from drafting more Q4 players or drafting them earlier, which improves market efficiency. We also find evidence that the NHL upper age limit reduces this discrimination, and that this discrimination is partly driven by previous team drafting experience.

Finally, we investigate the extent to which risk preferences and relative-age-based statistical discrimination explains firm performance. We find that less risk aversion and larger statistical discrimination against Q4 players are associated with increased variance in team performance over time. In addition, less successful teams are less risk averse, while more successful teams are better capable of predicting future player productivity. Finally, teams with more accurate statistical discrimination are more successful.

The closest paper to ours, Hendricks et al. (2003), analyzed data from National Football League (NFL) drafts to test Lazear (1998)'s model of how uncertainty about productivity affects firm hiring decisions. In NFL drafts, teams select eligible players from college teams with heterogeneous quality. Hendricks et al. (2003) used this distinction to proxy for risk preferences under the assumption that players from lower quality college teams will not have faced strong competition in college, providing professional teams with limited information about their future productivity. The authors found that, conditional on being selected in an early round of the NFL draft, players from lower quality college teams tended to have more successful careers; the reverse was true in later rounds of the draft. These results suggest that teams place a higher value on productivity uncertainty in later rounds, supporting the predictions in the model developed by Lazear (1998).

Two recent papers looking at the Major League Baseball drafts both closely relate to our paper (Ahmadi et al., 2022, 2025). Both papers find evidence of biased drafting decisions, in terms of maximizing the team's interest, in later rounds of the Major League Baseball (MLB) draft, either driven by racial discrimination (Ahmadi et al., 2025) or spatial proximity (Ahmadi et al., 2022). Their explanation is that, in later draft rounds, the opportunity cost of making a mistake is lower,

so there is less scrutiny from the organization and hiring managers have greater latitude, thus leading to biased hiring decisions.

In another theoretically related paper, (Lepage, 2024) showed that, in the context of a majority/minority group distinction with information asymmetries, even in the absence of negative prior beliefs about the minority group, employers still exhibit persistent inaccurate statistical discrimination against the minority group. A follow-up empirical paper, Benson and Lepage (2024), confirms the presence of experience-based discrimination in hiring decisions made by a large national US retailer. We apply the empirical methods used in this paper to our setting and find similar results about experience and statistical discrimination.

Previous research also documented the presence of relative age effects (RAE) and RAE reversal in the NHL draft. RAE represents statistical discrimination based on date of birth. Teams that lack player productivity information may rely on relative age as a productivity signal, and could make draft decisions with statistical discrimination against Q4 players. (Deaner et al., 2013; Fumarco et al., 2017) document the presence of more Q1 players on NHL team rosters and that Q4 players appear in more games, score more goals, and command higher salaries. In junior hockey, because of the size and maturity advantage for children born in Q1, these players likely receive more exposure to better competition than Q4 players. Such exposure contributes to development of their abilities and better reflects their productivity.

The accuracy of firms beliefs about worker productivity matters. If firms hold accurate beliefs about group differences in productivity, then statistical discrimination can be thought of as "efficient" in that it represents the optimal response to a signal-extraction problem (Aiger and Cain, 1977; Schwab, 1986). Alternatively, if discrimination reflects inaccurate beliefs or stereotypes, Q4 players are likely to be put at a disadvantage (Pallais, 2014; Bordalo et al., 2016; Bohren et al., 2023). Many studies develop evidence of statistical discrimination in labor markets, for example Agan and Starr (2018) and Doleac and Hansen (2020), but not many assess the accuracy of this statistical discrimination (Agan and Starr, 2018; Bohren et al., 2023). This setting allows for an assessment of the accuracy of firms beliefs.

This paper makes two main contributions to the literature. First, Hendricks et al. (2003) generated variation in uncertainty about worker productivity based on the level of competition players experienced while playing college football, assuming that players competing at the highest

level, NCAA Division I-A, generated less uncertainty about future productivity than players from all other levels of college football. We exploit an exogenous cutoff date to generate variation in uncertainty about worker productivity, so our results represent more credibly causal estimates than others in the literature investigating firm risk preferences in hiring decisions. Second, we contribute to the literature on statistical discrimination by being the first to investigate statistical discrimination based on relative age in professional sports labor markets and the first to assess the accuracy of this form of discrimination.

2 Context: NHL Drafts and Age Requirements

Like other professional sports leagues in North America, the NHL conducts an annual entry draft where teams select eligible players in a predetermined order based on team performance in the previous season. Typically, this sequence reflects a reverse order of the previous season's standings to promote parity in the league.

The draft awards one pick per round to each team. The number of teams in the league determines the number of picks per round. This changed over the sample period due to league expansion from 21 teams in 1980-1990, to 22 teams in 1992, 24 teams in 1993, 26 teams in 1994-1997, 27 teams in 1998, 28 teams in 1999, 30 teams in 2000-2016, 31 teams in 2017-2020, and 32 teams from 2021 to the present. The number of rounds in each draft also changed from 10 rounds in 1980, to 11 rounds in 1981, 12 rounds in 1982-1991, 11 rounds in 1992-1994, 9 rounds in 1995-2004, and 7 rounds from 2005 to the present. This drafting process explicitly implies teams' preferences for players, making it an ideal setting to study organizational hiring decisions.

The NHL draft features age requirements and associated cut-off dates for draft eligibility. In general, 18 to 20 year old hockey players are eligible for the entry draft. Starting in 1980, to be eligible for the annual NHL entry draft, a North-American player must have been at least 18 years old on or before September 15 and younger than 21 on December 31 of the draft year. Non-North-American players over the age of 20 on December 31 of the draft are eligible. September 15 represents a threshold date for other NHL events. For example Recent NHL/NHLPA CBAs always expire on September 15.

Based on NHL draft age eligibility requirements, North-American players born between January

1 and September 15 gain an advantage because they are eligible for three NHL entry drafts, while players born between September 16 and December 31 are eligible for only two. The youngest age at which players born just after September 15 can enter the NHL draft is just below 19 years of age, roughly one year later than players born just before or on September 15. One related concern is the compliance of this requirement, and according to our dataset, only 3 were drafted under 18[1]. Therefore, we tend to believe that these requirements are well enforced.

To illustrate the impact of age requirements on draft eligibility, Figure 1 shows the NHL draft eligibility of different cohorts of players born in 2020 and 2021 in North America based on date of birth. From Figure 1, players born between 1 January and 15 September in both 2000 and 2001 were eligible for three drafts, while those born between 16 September and 31 December were only eligible for two, and entered the draft roughly one year later than the 1 January to 15 September cohorts. Note that European players born in 2000 were eligible for the 2021 NHL draft and later drafts.

In addition to the annual entry draft, the NHL created a Supplemental Draft for undrafted college players who were at least 21 years old, beginning in 1986. The creation of this supplemental draft was prompted by Canadian born hockey player Adam Oates (dob 27 August 1962). While initially eligible for the 1981 NHL draft, Oates was not drafted in any NHL entry draft. Instead, he played college hockey at RPI in the US. After his team won the NCAA Ice Hockey Championship in 1985, Oates was a hot commodity as a free agent player and was able to command a salary much higher than most NHL rookies. This situation prompted the creation of the Supplemental Draft.

This draft allowed NHL teams to acquire any good talent that they missed out on in the annual entry draft while still limiting rookie salaries. NHL Supplemental Drafts were held annually from 1986 until 1994. They were discontinued in the 1995 NHL/NHLPA Collective Bargaining Agreement. On average, about 20 college players were drafted per year in these drafts and about 4 players per draft cohort eventually played in the NHL.

Lower level hockey leagues, collectively called junior hockey, also use cutoff dates for age classifications. These leagues are called junior hockey and not amateur hockey because some, for example the CHL in Canada, are semi-professional. The cutoff dates in junior hockey vary across areas and

[1]Joe Larson drafted in 1989, Ryan Pisiak drafted in 1992, and Peter Smith drafted in 1982. Joe Larson was born on 01/22/1987 and drafted in 1989, which should be a measurement error. We tried to verify birth information of these 3 players by other sources, but didn't find anything useful.

over time. Calendar year cutoffs at 31 December represent the most commonly used age threshold in junior hockey. Calendar year cutoffs group players born in the same calendar year into separate groups. The presence of these calendar year thresholds makes identification of age effects in the NHL using the 31 December NHL draft threshold problematic.

Other cutoff dates exist in junior hockey. For example, in Minnesota, the original cutoff date for participating in junior hockey was 1 September, mirroring the Minnesota school age eligibility threshold. When USA Hockey moved its eligibility threshold to 1 July during the 1990's, Minnesota Hockey adjusted it's cutoff to 1 July 1 to align with the national classification cutoffs.

USA Hockey later reverted to using a calendar year cutoff for eligibility, but Minnesota chose to keep the July 1 cutoff as it accommodated players with birthdays in August and July who generally start kindergarten a year later. Minnesota moved the cutoff date to 1 June in 2020, arguing that 1 June represent a more natural cutoff because a significant fraction of students with June birthdays start kindergarten at age six, like those with July and August birthdays, while very few students with May birth dates start school at age six[2].

Our empirical analysis exploits both the 15 September and December 31 NHL draft eligibility thresholds. Using the September 15 cutoff, we compare the NHL performance of drafted players who were 18 years of age or older to drafted players who were just under 19 years of age. Both groups are eligible for the same annual draft, but the second group is nearly one year older than the first group and has one additional year of junior hockey experience when drafted. Using the December 31 cutoff, we investigate whether statistical discrimination against players born in Q4 is accurate, and team drafting decisions on players are eligible for the last time.

3 Data

Our data come from Elite Prospects, a hockey data resource that provides detailed information on hockey players worldwide, including nationality, date of birth, position, NHL draft pick, and game stats from the NHL and other hockey leagues. Our sample includes all players in the 1980-2023 NHL entry drafts, a total of 10,467 drafted players.

Figure 2 shows the distribution of birth months in the sample. The number of drafted NHL

[2]Source: www.minnesotahockey.org/news_article/show/1113441

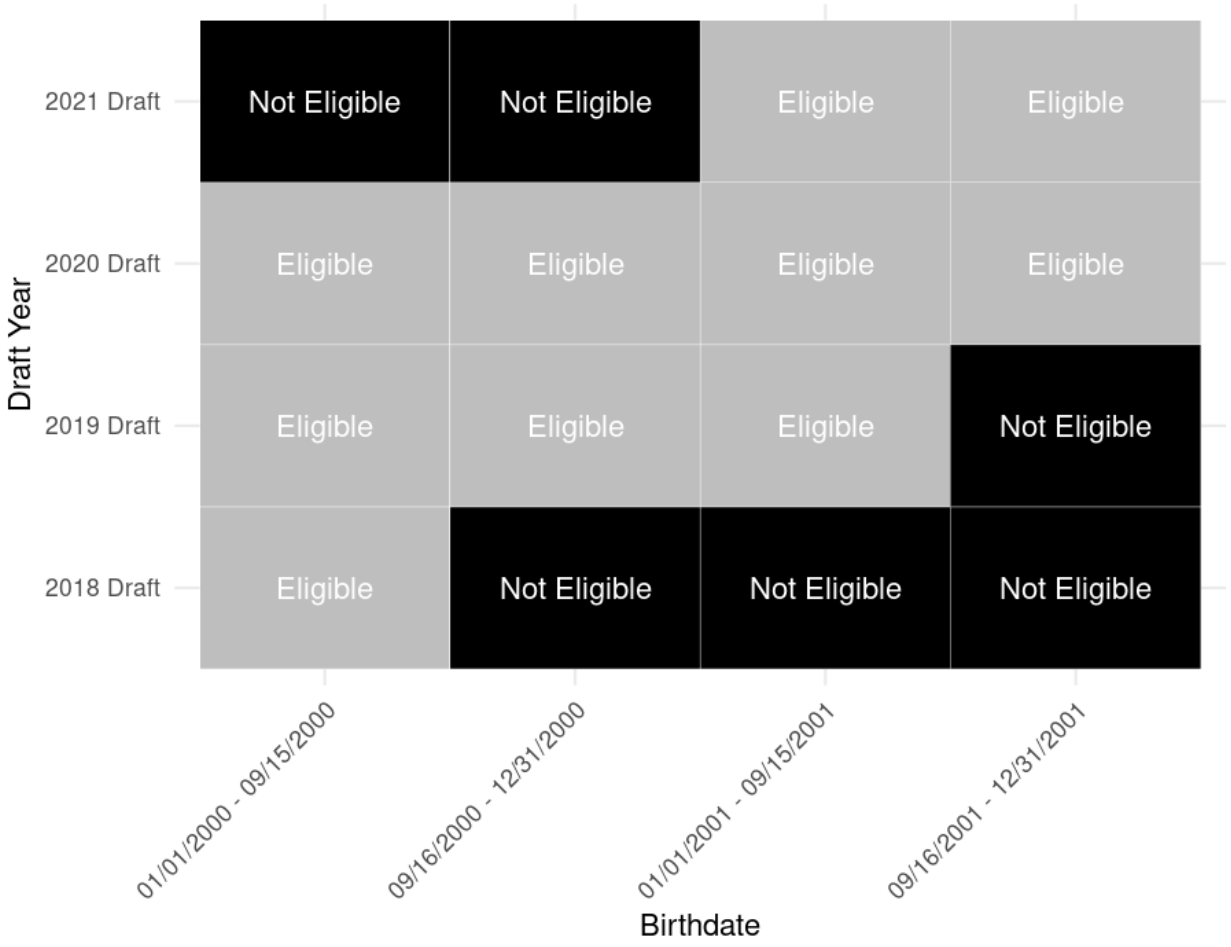


Figure 1: Draft Eligibility for North-American Players Born in 2000 and 2001
Notes: This figure shows NHL entry draft eligibility for North-American hockey players born in 2000 and 2001.

players declines monotonically with birth month, whether the player is from North-America or elsewhere. This stylized fact is consistent with previous research (Fumarco et al., 2017; Deaner et al., 2013) and indicates the presence of statistical discrimination based on relative age in NHL using a larger sample of players than in previous research.

Based on the two types of cutoff dates and date of birth, we construct two variables of age for each player, which would be running variables in the later RDD analysis after recentering. The first is the age on September 15 of the draft year and the second is the age on December 31 of the draft year.

Figure 3 presents the raw data plots at the cutoff date of 15 September, and provides preliminary evidence on the variance effect. Compared to players in the 19- group, who received an additional year of training in junior hockey relative to players in the 18+ group, 18+ group players were generally selected with later draft picks and experienced worse professional labor market outcomes. The discontinuity at the cutoff is especially pronounced for the player's draft pick position. There are jumps for whether a player makes the team roster and All-star appearances as well. In addition, there is little difference in career length, although 18+ entered the league one year earlier and their average career length was supposed to be a year longer ceteris paribus.

Figure 4 presents the raw data plot at the cutoff date of December 31. Notably, this figure only considers North-American players as only them are subjected to this upper limit of age. The left panel compares players just above and just below 19 on December 31 of the draft year, and outcomes seem continuous at the cutoff. The right panel compares players just above and just below 20, and players just above 20 demonstrate relatively better labor market outcomes.

4 Risk Preferences and Firm Hiring Decisions

4.1 Conceptual Framework

Lazear (1998) argued that potential employees vary in ability, described by the first moment of the distribution of employee productivity, and in the degree to which the future productivity of the employee is risky, described by the second moment of the employee productivity distribution. Lazear (1998) developed a model where potential employees vary in terms of their riskiness. If firms can easily terminate risky workers whose productivity turns out to be low and earn rents on

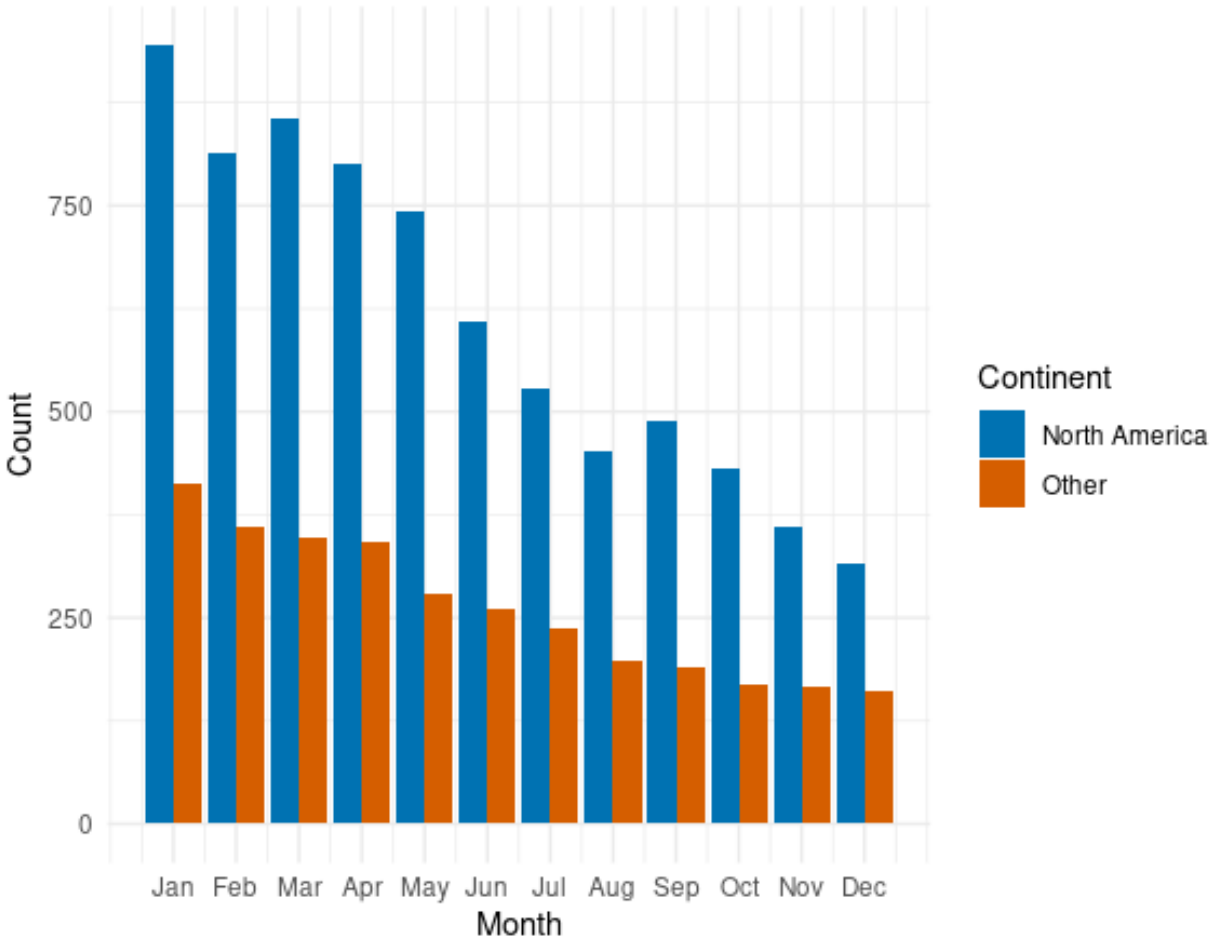


Figure 2: Distribution of birth months

Notes: This figure presents the distribution of birth month. Blue bars denote North-American players, while orange bars denote players from other continents.

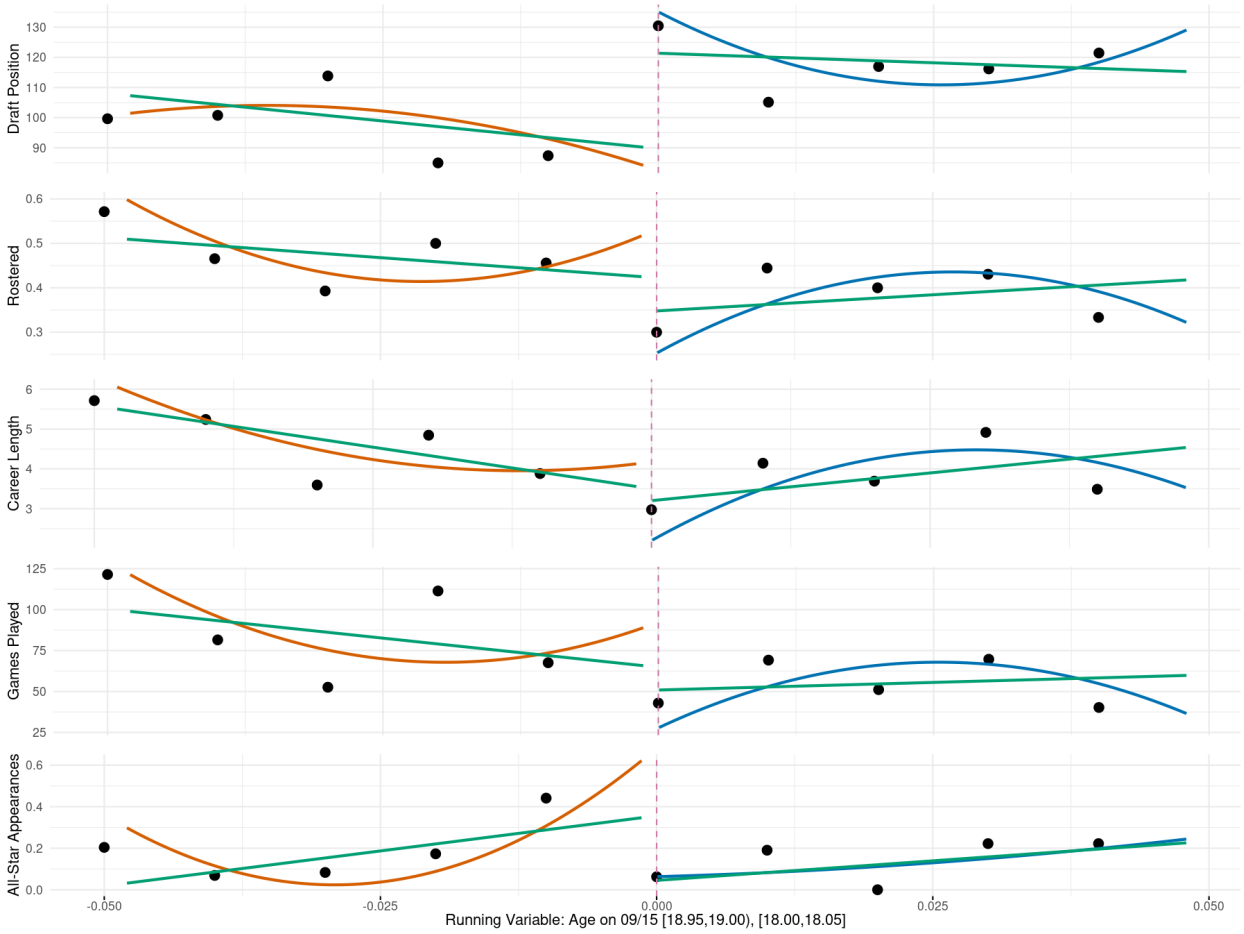


Figure 3: Raw data plot of 19- and 18+

Notes: This figure presents the raw data plot of labor market outcomes at the cutoff date of September 15. Each point is the average of the bin with a width of 0.01 year (3.65 days). Orange lines are local linear fits while blue/green lines are local quadratic fits.

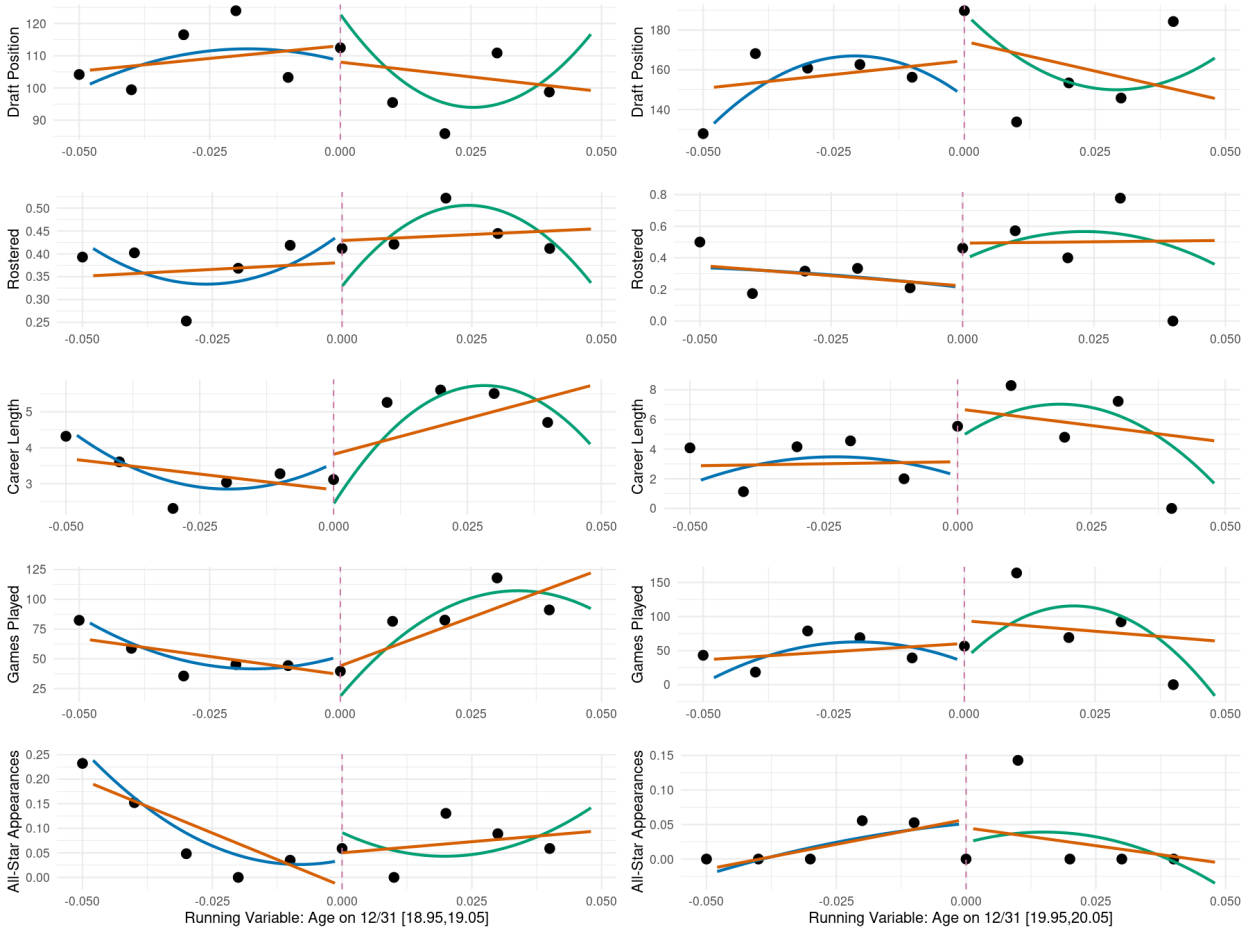


Figure 4: Raw data plot at the cutoff date of December 31

Notes: This figure presents the raw data plot of labor market outcomes at the cutoff date of December 31. Each point is the average of the bin with a width of 0.01 year. Orange lines are local linear fits while blue/green lines are local quadratic fits. The left panel compares North-American players just below and just above 19, while the right panel compares North-American players just below just above 20.

those with high realized productivity due to barriers to worker mobility, then hiring a risky worker who has a high option value might be profitable. On the other hand, risk-averse firms will prefer to hire potential employees with less productivity uncertainty (Hendricks et al., 2003).

Lazear (1998) posited that younger workers might have larger option values for two reasons. First, younger workers have less prior labor market experience, leading to greater uncertainty about their future productivity. Second, younger workers have longer remaining careers, increasing the option value of hiring them (Bollinger and Hotchkiss, 2003). We exploit information about the age of players drafted in the NHL and rules governing how old a player must be to qualify for the NHL draft to identify systematic differences in expected player productivity.

The following conceptual framework formally links these concepts to our empirical analysis and informs our research question: does uncertainty about player productivity affect NHL team drafting decisions? Assume that the position a team selects a player in the entry draft depends on both expected productivity and the variance of productivity conditioned on a pre-draft signal. Formally

$$DraftPosition_i = a\mathbb{E}(y_i|x_i) + b\mathbb{V}(y_i|x_i), \tag{1}$$

where $DraftPosition_i$ is the position that player i gets selected by a team. y_i represents the productivity of player i selected in draft d and x_i player i's pre-draft productivity signal. $\mathbb{E}[\cdot]$ is the expected value of player i given the distribution of player productivity in a draft. The parameter a reflects the impact of expected player ability on draft position. a should be negative as higher expected ability conditional on the pre-draft signal should lead to a player getting drafted earlier.

$\mathbb{V}(\cdot)$ represents the variance of the distribution of player productivity. The parameter b, which reflects the impact of variance in player ability on draft position, represents the parameter of interest. The sign of b reflects the risk preferences of teams in the draft. If teams are risk-averse and avoid uncertainty in terms of the variance of player ability, $b > 0$ because larger variance in player ability causes teams to draft risky players later in the draft. However, if teams draft decisions reflect risk neutral or risk seeking preferences, then teams take into account the upside, the large option value of risky draft picks, and draft risky players in early rounds, so $b < 0$.

We exploit the NHL draft age eligibility requirements described above to identify separate groups of drafted players with different option values, based on age. The two groups of players are

identified as 19- and 18+. The 19- group contains players who were just below 19 years of age on 15 September of each draft year and the 18+ group contains players who were 18 years of age and above on 15 September. Both groups are eligible for the same annual draft. To account for the impact of player age on option values, we first assume that

$$\mathbb{E}(y|19-) = \mathbb{E}(y|18+), \tag{2}$$

which simply assumes an equal average mean productivity level in each group. Hendricks et al. (2003) also use this identical mean productivity assumption in their theoretical model. Second, we assume that

$$\mathbb{E}[V(y|x, 19-)] < \mathbb{E}[V(y|x, 18+)], \tag{3}$$

Equation 3 means that the conditional expected variance in productivity in the 19- group is smaller than that of the 18+ group. This difference comes from the fact that the 19- group has one more year of junior hockey experience and information about their performance than the 18+ group. This leads to systematically less uncertainty about the expected performance in the older, more experienced 19- group. This exactly matches the assumptions made in the model developed by Lazear (1998).

Again, we argue that 15 September represents an exogenous cutoff threshold because that threshold only applies to players entering the NHL draft. Junior hockey leagues extensively use 31 December cutoff dates for many eligibility requirements, which weakens the exogeneity of the 31 December cutoff date in the NHL draft. Because of the unique nature of the 15 September cutoff date, there should be no significant differences between NHL draft eligible players born just before and after 15 September.

Next, we calculate the difference between the expected draft position for the 18+ group and

the 19- group

$$\begin{aligned}\mathbb{E}(DraftPosition|18+) - \mathbb{E}(DraftPosition|19-) &= a\mathbb{E}[\mathbb{E}(y|x,18+)] + b\mathbb{E}[\mathbb{V}(y|x,18+)] \\ &\quad - a\mathbb{E}[\mathbb{E}(y|x,19-)] - b\mathbb{E}[\mathbb{V}(y|x,19+)] \\ &= a[\mathbb{E}(y|18+) - \mathbb{E}(y|19-)] \\ &\quad + b(\mathbb{E}[\mathbb{V}(y|x,18+)] - \mathbb{E}[\mathbb{V}(y|x,19+)]) \\ &= \gamma b,\end{aligned} \tag{4}$$

where $\gamma = \mathbb{E}[\mathbb{V}(y|x,18+)] - \mathbb{E}[\mathbb{V}(y|x,19+)] > 0$ reflects the assumption used in Equation 3. Then, by testing the sign of $\mathbb{E}(DraftPosition|18+) - \mathbb{E}(DraftPosition|19-)$, we are able to tell team risk preferences in drafting players.

An alternative is to follow the practice of Hendricks et al. (2003), namely using draft positions as signal and other measures of productivity as outcomes, to test the sign of b. But we prefer to employ the above framework, because compared to other measures like whether a player actually played in the league or whether he showed up in an all-star game, drafting decisions are much more like hiring decisions for firms.

Teams might act differently in response to the uncertainty about player's productivity in different draft rounds. They could be risk-averse in early rounds due to large costs of mistakes in these rounds, but value uncertainty in late rounds due to the upside potential of risky players (Hendricks et al., 2003). We can easily extend our framework to test for the presence of such heterogeneity in draft decisions by estimating separate empirical models for draft rounds, although we need stronger versions of Equation 2 and Equation 3, in that they need to reflect that they still hold separately for players drafted in different rounds.

4.2 Identification Strategy

September 15 represents a unique cutoff date in hockey rarely used outside of the NHL draft, strengthening its exogeneity. Therefore, this cutoff provides quasi-experimental variation that randomly assigns players born just after September 15 to one more year in junior hockey before entering the NHL than players in the 18+ group. This random assignment allows us to causally estimate the effect of uncertainty about productivity on draft outcomes, providing new insights into firm

hiring decisions. We employ a sharp RDD to identify the variance effect using the September 15 cutoff date. Specifically, we estimate the following local linear regressions:

$$\begin{aligned} DraftPosition_i = \alpha + Risky_i\tau + X_i\beta_- + Risky_{id}X_i\beta_+ + \\ DraftYear_d + Position_i + Nationality_i + \varepsilon_{1i}, \end{aligned} \tag{5}$$

where X_{id} is the running variable, defined as player i's age recentered on age on September 15 of draft year d. A local linear triangular kernel estimator is used to estimate β_- and β_+ because of its good performance at the boundary (Fan and Gijbels, 1992; Cattaneo et al., 2019). $Risky_{id}$ is an indicator variable equal to 1 if player i in draft d was born on or just before 15 September, in other words members of the 18+ group. $DraftYear_d$, $Position_{id}$, and $Nationality_{id}$ are vectors of draft year fixed effects, position fixed effects, and nationality fixed effects. τ, the parameter of interest, represents the impact of variance in expected player productivity on team draft decisions.

$$\begin{aligned} Y_i = \alpha + Risky_i\tau + X_i\beta_- + Risky_iX_i\beta_+ + \theta DraftPosition_i + \\ DraftYear_i + Position_i + Nationality_i + \varepsilon_{2i}, \end{aligned} \tag{6}$$

where Y_i represents career labor market outcomes for drafted players, including an indicator equal to one if player i ever makes the team roster, NHL career length in seasons, career NHL games played, and NHL All-star appearances by player i. For drafted players never rostered in NHL, we assign a zero value to the rest outcomes, to increase sample size and statistical power. $DraftPosition_i$ is the draft position of player i. Equation 6 conditions on the draft position of player i, replicating the approach used by Hendricks et al. (2003).

We recognize that Y_i, exhibit both left and right censoring like the data analyzed by Hendricks et al. (2003). The data are left censored because the zeros in these outcomes have considerable heterogeneity in the quality of players, especially for NHL career length in seasons, career NHL games played, and NHL All-star appearances. The data are right censored because they include players whose career is still ongoing. We can only avoid this data limitation by using draft position as the outcome variable, which is another reason why Equation 5 is our preferred specification.

Bandwidth selection is the key of the RDD analysis based on local polynomial regressions, and the common practice is to use a data-driven bandwidth selection process, which minimizes mean

squared errors (MSE). In addition to this approach, we employ another bandwidth selection based on institutional knowledge. As mentioned in the previous section, September 1 was once used for age classifications in junior hockey in the US, so including players born before September 1 may introduce bias to our estimates. As a result, our primary approach is to select 15 days as the bandwidth. In another word, we select only players born in September into our analysis sample. This would add credibility to our estimates if results are robust to the bandwidth selection process.

We identify local average treatment effects (LATEs) that should be interpreted with caution (Calonico et al., 2019; Cattaneo et al., 2019; Cattaneo and Titiunik, 2022). These LATEs are identified based on players who are drafted as soon as they are eligible and thus relatively more talented, or of higher productivity. In this sense, the above results cannot be extrapolated to a player who has lower productivity and is drafted on his second or third attempt.

4.3 Baseline Results

Table 1 presents RDD estimates using different bandwidths, and both sets of results are similar in direction and statistical significance. In Panel A, with our preferred bandwidth, compared to 19-, 18+ were approximately selected 44 positions later and 20 p.p. less likely to make the roster. These results indicate that generally, teams dislike uncertainty about player productivity and act in a risk-averse manner when drafting and tenuring players.

The identical mean productivity assumption itself predicts null effects on players' subsequent career outcomes, but we find 18+ have worse career outcomes. In Table 1, although the difference in career length does not significantly differ from 0, it is significantly smaller than 1, which is the theoretical difference if we assume 18+ and 19- retire at the same age. 19- also demonstrate better outcomes in games played and All-star game appearances. Statistical discrimination might be able to explain this phenomenon (Hendricks et al., 2003). Draft position itself is a signal as well and thus can be used for statistical discrimination, in such a way that teams tend to favor players with earlier draft positions by offering them more opportunities and resources, specifically more playing time and more attention from managing and coaching staff. As a result, there will be more improvement in these players' productivity, reinforcing the team's initial choice.

Column 2-5 in table 2 present RDD results conditioning on draft position. This is a replication of Hendricks et al. (2003) and shows a null effect, which essentially means teams are generally

risk-neutral. These results are somewhat different from theirs, perhaps for the following reasons. First, here we look at team general risk preferences, while they look at risk preferences at different segments respectively. To make results more comparable, we will also examine risk preferences at different segments in the upcoming analysis. Second, the sports and study period are different. Third, although we are both looking at the effect of variance in productivity, the way we identify the risky group is different. They define risky players as players from a less visible football program (not NCAA Division IA).

In Appendix B.1 and B.2, we check the continuity of covariates at the September 15 cutoff date, and perform placebo tests using August 15 and October 15 as placebo cutoff dates. Results show that covariates are balanced at the September 15 cutoff date, and there is no discontinuity in draft position at placebo cutoff dates, lending credibility to our RDD analysis.

Table 1: RDD estimates not conditioning on draft position

	Draft position (1)	Rostered (2)	Career length (3)	Games played (4)	All-star (5)
Panel A: Using Bandwidth of 15 Days					
Risky	44.46***	−0.20**	−1.35	−42.74*	−1.76*
	(12.88)	(0.09)	(0.96)	(22.29)	(0.27)
Bandwidth			0.04		
Obs			262 19- and 280 18+		
Panel B: Using MSE-optimal Bandwidths					
Risky	23.07***	−0.10**	−0.86*	−27.32**	−1.77*
	(6.58)	(0.04)	(0.51)	(12.42)	(0.08)
Bandwidth	0.16	0.19	0.18	0.16	0.22
Obs	920+1067	1068+1284	975+1155	896+1035	1200+1506

Notes: This table presents RDD estimates using different bandwidths. All regressions control for draft year, position, and nationality fixed effects. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

4.4 Heterogeneity in Draft Round

Hendricks et al. (2003) find that NFL teams are risk-averse in the early rounds, but tend to favor risky players from the last rounds of the draft. This motivates us to investigate whether such heterogeneity exists in NHL drafts as well. Table 3 shows RDD results consistent with Hendricks et al. (2003), supporting Lazear (1998)'s option value predictions.

Table 2: RDD estimates conditioning on draft position

	Draft position (1)	Rostered (2)	Career length (3)	Games played (4)	All-star (5)
Panel A: Using Bandwidth of 15 Days					
Risky	44.46***	−0.05	0.28	−8.13	−0.35
	(12.88)	(0.08)	(0.81)	(19.22)	(0.26)
Bandwidth			0.04		
Obs			262 19- and 280 18+		
Panel B: Using MSE-optimal Bandwidths					
Risky	23.07***	−0.03	−0.06	−7.60	−0.09
	(6.58)	(0.03)	(0.42)	(10.79)	(0.09)
Bandwidth	0.16	0.25	0.20	0.18	0.19
Obs	920+1067	1314+1750	1098+1339	975+1155	1039+1249

Notes: This table presents RDD estimates using different bandwidths. Draft year, position, and nationality fixed effects are included. In addition, column 2-5 control for draft position. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

Firstly, there is a big difference in the number of drafted players. In the first 3 rounds, there are more 19- players drafted than 18+ (risky) players; while in the last 3 rounds, there are more risky players drafted. This divergence clearly shows that teams are more risk-averse in the early rounds than late rounds. In addition, in column 1, where the subsample is players drafted in the first 3 rounds, risky players are drafted in later positions, indicating risk aversion again. In column 2, where the subsample is players drafted in the last 3 rounds, there are no significant differences in average draft position between 19- and 18+, indicating less risk aversion or risk neutrality in pursuit of option values.

These results are also consistent with Ahmadi et al. (2022, 2025). In the early rounds where the opportunity cost of making a mistake is high and there is intensive supervision from the organization, managers tend to be risk averse. In contrast, in the later rounds, managers tend to be risk neutral, and other biases they have, such as homophily and spatial proximity examined in these two papers, are more likely to take effect.

Table 3: Heterogeneity in draft round

	First 3 rounds (1)	Last 3 rounds (2)
Risky	13.40**	17.95
	(6.79)	(11.71)
Obs	127+108	69+94

Notes: This table presents RDD results on heterogeneity in draft rounds using September sample. The dependent variable is draft position. All regressions control for draft year, position, and nationality fixed effects. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

4.5 Heterogeneity in Player Position

Since different positions play different roles in games, teams may have heterogeneous risk preferences for forwards, defensemen, and goaltenders. We explore this heterogeneity and presents results in table 4. Results show that teams are risk-averse when selecting forwards and defensemen, but risk-neutral when selecting goaltenders. This difference between skaters (forwards and defensemen) and goaltenders is consistent with Allen (2021), who reported systematic differences between goaltenders and other hockey players in terms of training.

Table 4: Heterogeneity in player position

	Forward (1)	Defenseman (2)	Goaltender (3)
Risky	44.94**	55.71**	17.42
	(17.81)	(24.20)	(34.74)
Obs	146+166	85+89	31+25

Notes: This table presents RDD results on heterogeneity in player positions using September sample. The dependent variable is draft position. All regressions control for draft year and nationality fixed effects. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

5 Relative-age-based Statistical Discrimination

5.1 Identification Strategy

The sharp RDD cannot be used to make causal inference at calendar year cutoffs for two reasons. First, NHL Supplemental Drafts conducted in 1986-1994 weakened the sharpness of these cutoffs, requiring a fuzzy design instead if we want to keep entry drafts in these years in the sample and continue to use RDD (Cattaneo et al., 2024). Second, calendar year cutoffs are frequently used in junior hockey to classify players into different groups. This leads to different development paths, which makes these cutoffs endogenous. Therefore, even if we adopt a fuzzy RDD design, we are unable to interpret the estimates as causal.

To address these concerns, we employ the triple differences-in-differences (DDD) approach to disentangle the effects of relative age and the effects of NHL upper age limits. Specifically, we compare players from different continents (North America or not), born in different quarters (Q1 versus Q4), and drafted at different attempts (first eligible attempt versus second). Non-North-American players are not subject to the upper age limit, so they are unaffected by this policy and represent the control group, while North-American players represent the treatment group. Moreover, Q4 North-American players, who lose one more eligible draft than Q1 players due to this policy, represent a more intensely treated group. The DDD model specifications are as follows:

$$\begin{aligned} DraftPosition_i = \sigma_0 Last_i + \sigma_1 NA * Q4_i + \sigma_2 Q4 * 2nd_i + \sigma_3 NA * 2nd_i + \sigma_4 Q4_i + \sigma_5 2nd_i \\ + DraftYear_i + Position_i + Nationality_i + \varepsilon_{3i}, \end{aligned} \tag{7}$$

$$\begin{aligned} Y_i = \sigma_0 Last_i + \sigma_1 NA * Q4_i + \sigma_2 Q4 * 2nd_i + \sigma_3 NA * 2nd_i + \sigma_4 Q4_i + \sigma_5 2nd_i \\ + DraftPosition_i + DraftYear_i + Position_i + Nationality_i + \varepsilon_{4i}, \end{aligned} \tag{8}$$

where $Q4_i$ is an indicator variable equal to 1 if player i is born in the fourth quarter. NA_i is an indicator variable equal to 1 if player i is an North American. $2nd_i$ is an indicator equal to 1 if player i is drafted in his second eligible draft. $Last_i$ represents the three-way interaction of NA_i, $Q4_i$, and $2nd_i$, equal to 1 if player i is drafted in his last eligible draft.

Note that this sample only contains players selected in their first two eligible drafts and born

in Q1 or Q4. In another word, players born in Q2 and Q3, as well as players drafted in their third attempt are excluded in from the data used in these DDD regression models. Draft year, player position, and nationality fixed effects are included in both equation (7) and (8), and player draft position is included in equation (8). Equation (7) and (8) do not include NA_i because it is collinear with the nationality fixed effects.

σ_0 and σ_4 are the parameters of interest. σ_0 reflects the causal effect of the NHL upper age limit on Q4 North-American players drafted in their second (and final) eligible draft. Under the assumption that $DraftPosition_i$ represents team beliefs about player i's future productivity, σ_4 in equation (8), which controls for draft position, should be statistically indistinguishable from zero if relative-age-based statistical discrimination is accurate. Otherwise, a positive σ_4 indicates inaccurate beliefs and excess statistical discrimination against Q4 players.

Again, among the outcome variables, *Rostered*, suffers from right censoring, while the rest suffer from both left and right censoring. The direction of the bias in σ_4 caused by right censoring is expected to be negative, because there is likely positive selection in Q4 players, which makes them more likely to have better outcomes in the early stage of their careers. In this sense, our estimates of σ_4 are conservative. The impact of left censoring in outcomes is more ambiguous, but since *Rostered* suffers little from this issue, we can rely more on this outcome. Additional analysis on left censoring will be presented in the results section. Another data limitation is that we do not have data on undrafted players, making us unable to capture the variation in whether being drafted.

The DDD estimator needs the parallel trend assumption to hold to deliver causal estimates. Formally, the parallel trends assumption requires

$$\begin{aligned}(\mathbb{E}[Y_0|NA, Q4, 2nd] - \mathbb{E}[Y_0|NA, Q4, 1st]) - (\mathbb{E}[Y_0|NA, Q1, 2nd] - \mathbb{E}[Y_0|NA, Q1, 1st]) = \\ (\mathbb{E}[Y_0|NNA, Q4, 2nd] - \mathbb{E}[Y_0|NNA, Q4, 1st]) - (\mathbb{E}[Y_0|NNA, Q1, 2nd] - \mathbb{E}[Y_0|NNA, Q1, 1st])\end{aligned} \tag{9}$$

where Y_0 is the potential outcome in the absence of the NHL upper age limit (Olden and Møen, 2022). This assumption states that across players selected in the their first and second eligible drafts, the relative outcomes for Q4 and Q1 North-American players trend in the same way as the

relative outcomes for Q4 and Q1 non-North-American players, in the absence of upper age limit on the annual NHL draft.

5.2 Summary Statistics of Q1 and Q4 Players

Figure 5 shows a histogram of the distribution of players' quarter of birth for North American (NA) and non-North American (NNA) players for the first and second drafts they were eligible for. In the full sample of 4,751 players, more than 3,000 were born in Q1, suggesting the presence of statistical discrimination against Q4 players, since roughly the same number of people should be born in each quarter. The ratio of Q1 players to Q4 players indicates the magnitude of statistical discrimination. This discrimination appears less pronounced for North-American players, because the Q1/Q4 ratio is lower compared to non-North-American players (2.13 versus 2.28).

In addition, among North-American players, statistical discrimination appears less pronounced for players selected in their second eligible draft compared to those drafted in their first attempt, as indicated by a lower ratio as well (2.10 versus 2.24). These observations are consistent with theories, as players from North America and selected in the second eligible draft should reveal their productivity better and be able to provide more information for NHL teams, which reduces statistical discrimination against them. Another explanation for reduced discrimination against Q4 North-American players selected in the second eligible draft is that this is their last chance and thus teams are more likely to select them.

Table 5 presents summary statistics for the eight groups of players in the DDD model specifications, based on quarter of birth, place of birth, and draft. Among players drafted in their first eligible draft, whether from North America elsewhere, Q4 players were drafted earlier and have better post-draft outcomes than Q1 players. This also holds for non-North-American players selected in the second eligible draft, lending credibility to the parallel trends assumption. However, the difference in draft position turns out to be the opposite for Q1 and Q4 North-Americans selected in their second eligible draft, providing preliminary evidence for the causal effect of the NHL upper age limit on player performance.

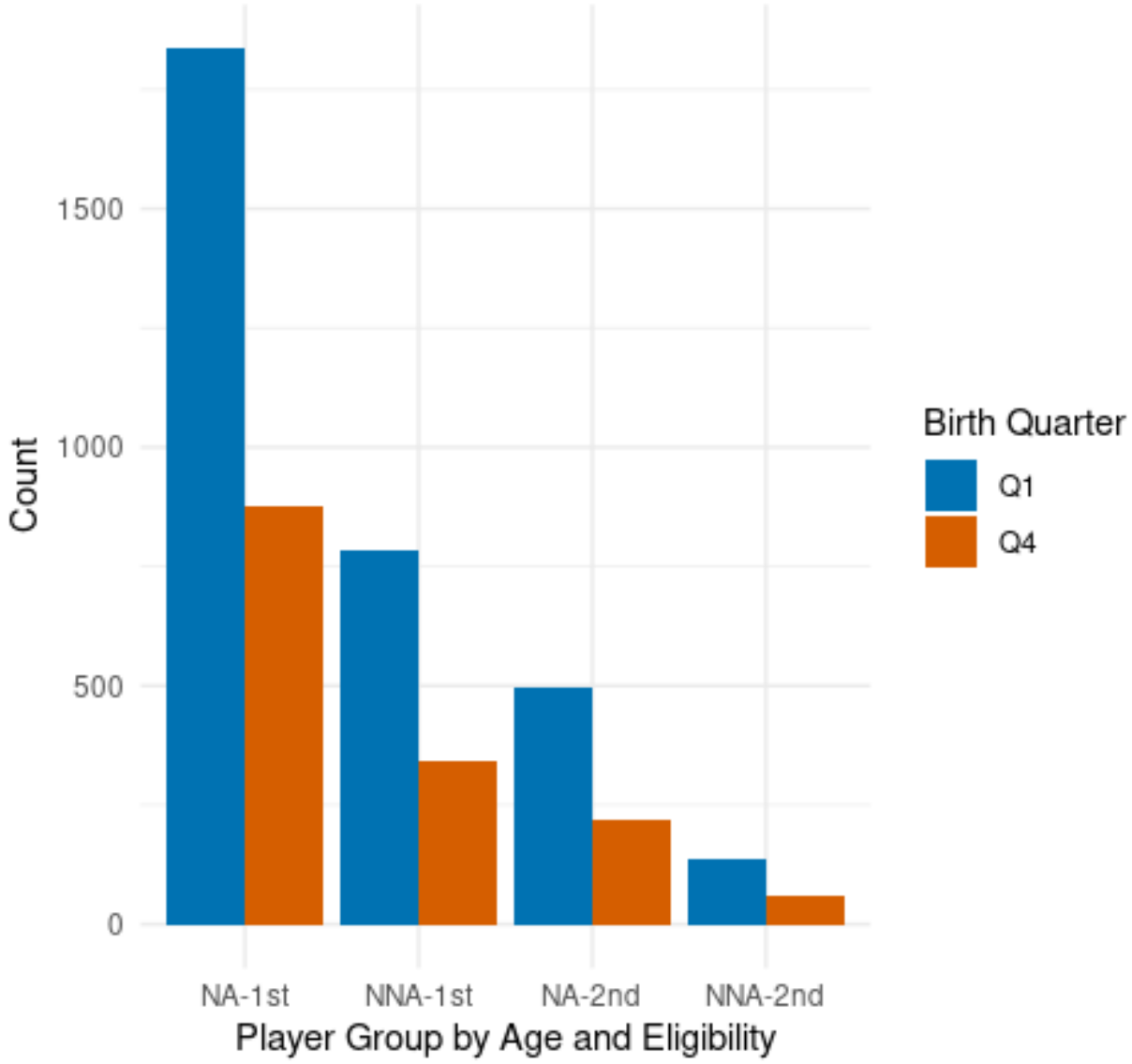


Figure 5: Histogram of different player groups

Notes: This histogram compares the numbers of players drafted at different ages from different continents.

Table 5: Summary statistics by player group

Player group	Draft position	Made roster	Career length	Games played	All-star	Obs
NA-Q4-2nd	158.43	0.43	4.42	82.24	0.00	221
NA-Q1-2nd	147.56	0.34	3.21	45.43	0.03	494
NA-Q4-1st	98.85	0.45	4.56	88.62	0.15	875
NA-Q1-1st	105.84	0.39	3.83	65.78	0.08	1836
NNA-Q4-2nd	137.45	0.44	4.00	75.15	0.06	62
NNA-Q1-2nd	155.95	0.30	2.88	50.08	0.12	139
NNA-Q4-1st	98.85	0.46	3.99	85.35	0.11	342
NNA-Q1-1st	109.21	0.32	2.91	50.82	0.06	782

Notes: This table presents summary statistics of eight player groups.

5.3 Evidence of Inaccurate Statistical Discrimination against Q4 Players

DDD results presented in Table 6 show better post-draft outcomes for Q4 players even conditioning on draft position, which indicates that, these players are selected later than they should be due to inaccurate statistical discrimination. In this sense, there is market inefficiency in drafting these players, and teams are relying on inaccurate beliefs of group differences in productivity when making hiring decisions. Since player salary in an entry-level contract is positively associated with draft position, such inaccurate statistical discrimination, together with the NHL's monopsony power, leads to distortion of labor supply and welfare loss of Q4 players. On the other hand, these results suggest that teams are able to learn about the quality of workers through their career, similar to previous studies (Bordón and Braga, 2020).

In the previous analysis, for players never made the team roster, we assign a zero value to outcomes including career length, games played, and All-star appearances. While this approach increases sample size and improves statistical power, it causes the left censoring problem. As an alternative, these variables are assigned with missing values if a player never made the team roster, which is equivalent to constructing a sample containing only players who made the roster. Then, we estimate equation 8 again using this sample and present the results in Table 7. Null results indicate that results in column 3-5 of Table 6 are driven by players who were drafted but did not make the team. In this sense, although there is inefficiency in the drafting process, the probationary process in NHL is effective enough to reveal true player productivity, evidenced by insignificant differences in subsequent performance among players who made the team.

Results in column 2 in Table 6 are immune to the left censoring problem, and show that Q4

players are 10.6 p.p. more likely to make a team roster conditioning on draft position. Even if there is relative-age-based discrimination, as long as such discrimination is accurate, the drafting market should be efficient and there should be no difference in the probability of a Q1 and Q4 player making an NHL team roster in equilibrium. In another word, in a well-functioning, efficient player draft market, the equilibrium draft position and number of drafted Q1 and Q4 players should make two groups equally likely to make a team roster.

The observed higher probability of Q4 players making an NHL roster conditional on draft position, is thus caused by excess discrimination against them. A Q4 player are assigned a later draft position by NHL teams than they would have been if his productivity is correctly perceived. If his productivity would have deserved a position at the end of the draft, he is likely to be undrafted because of such discrimination.

Therefore, an immediate implication is that, NHL teams should adjust their valuation of Q4 players, and draft Q4 players more and earlier, until the probability of Q4 players making the roster conditioning on draft position is the same as that of Q1 players. In this case, statistical discrimination against Q4 players is accurate and the drafting market is efficient. This drafting strategy should be able to lead to Pareto improvements for NHL teams.

Lastly, as shown in Table 6, North-American players eligible for the NHL draft for the last time, are selected about 27 positions later. Combining these results with figure 5, we can conclude that the NHL upper age limit causes more of these players being drafted, leading to a later draft position on average though. These players demonstrate better post-draft outcomes conditional on draft position as well, specifically longer careers and more games played. Overall, our results indicate that the NHL upper age limit reduces inaccurate statistical discrimination against Q4 players.

In Appendix B.3, we undertake robustness checks by adopting alternative specifications and samples. First, we separate players into different age subsamples and run DiD regressions. Second, we run DDD regressions with a subsample consisting of players born in December or January, which is expected to be a sharper comparison. All of these results are consistent in terms of direction and magnitude, showing the robustness of our results.

Table 6: DDD Results of Statistical Discrimination and the NHL Upper Age Limit

	Draft position	Rostered	Career length	Games played	All-star
	(1)	(2)	(3)	(4)	(5)
Last	27.261**	0.128	1.692*	51.604**	0.039
	(12.570)	(0.083)	(0.953)	(25.163)	(0.085)
NA-Q4	−0.825	−0.054*	−0.202	−9.810	0.009
	(5.281)	(0.031)	(0.360)	(10.377)	(0.045)
Q4-2nd	−9.121	−0.057	−0.811	−26.294	−0.110
	(11.008)	(0.073)	(0.824)	(21.807)	(0.078)
NA-2nd	−10.314	−0.051	−0.828	−26.681**	−0.118*
	(7.037)	(0.045)	(0.511)	(11.521)	(0.064)
Q4	−6.403	0.106***	0.815***	28.162***	0.046
	(4.441)	(0.026)	(0.294)	(8.685)	(0.033)
2nd	49.514***	0.125***	1.346***	32.575***	0.114*
	(6.136)	(0.039)	(0.451)	(10.272)	(0.062)
Obs	4,751	4,751	4,751	4,751	4,751

Notes: This table presents DDD results by estimating equation 7 and 8. All regressions control for draft year, position, and nationality fixed effects. Column 2-5 control for draft position. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

Table 7: DDD results with the sample actually played NHL

	Career length	Games played	All-star
	(1)	(2)	(3)
Last	1.158	73.055	0.134
	(1.461)	(54.164)	(0.211)
NA-Q4	0.408	−7.142	−0.002
	(0.513)	(20.922)	(0.102)
Q4-2nd	−0.279	−18.960	−0.184
	(1.320)	(47.961)	(0.203)
NA-2nd	−0.452	−43.353	−0.290*
	(0.908)	(28.804)	(0.176)
Q4	−0.197	28.548	0.055
	(0.434)	(17.846)	(0.081)
2nd	−0.039	27.063	0.224
	(0.831)	(26.379)	(0.176)
Obs	1849	1849	1849

Notes: This table presents results by estimating equation 8 with the sample of players who made the roster. All regressions control for draft position, draft year, position, and nationality fixed effects. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

5.4 Is Discrimination against Q4 Players based on Experience?

Lepage (2024) develops a theoretical framework to explain how employer statistical discrimination against minority groups, whether accurate or not, is built through hiring experiences. A key assumption in their model is that signals of productivity are private and only available through an employer's own hiring–an employer does not learn about the minority group unless they hire workers from the group. Although this assumption are very likely to be violated in the context of professional sports, as long as teams put some weight on their own hiring experiences, model predictions are still likely to hold. In a follow-up empirical paper, Lepage and his coauthor examine how negative and positive experiences of individual managers influence the race of their future hires (Benson and Lepage, 2024).

In this section, we follow their practice to investigate the effects of experience. In our setting, experience with a group is measured by the probability of a drafted player from that group making the team roster. Two types of experiences are of interest, specifically latest experience and cumulative experience. Latest experience refers to the experience of a team in the most-recent previous draft, while cumulative experience refers to the cumulative experience of a team up to the most-recent previous draft. As an example, the specification for latest experience is:

$$Q4\%_{jt} = \beta_1 Q4roster\%_{j,t-1} + \beta_2 Q1roster\%_{j,t-1} + \theta_t + \lambda_j + \epsilon_{jt}, \tag{10}$$

where $Q4\%_{jt}$ is the ratio of Q4 players to the sum of Q1 and Q4 players drafted by team j in year t. $Q4roster\%_{j,t-1}$ is the probability of players making the team roster drafted by team j in year $t-1$. $Q1roster\%_{j,t-1}$ is calculated in the same way for Q1 players. Team and year fixed effects are included. A higher $Q4roster\%_{j,t-1}$ represents positive latest experience of drafting Q4 players, and a lower $Q1roster\%_{j,t-1}$ represents negative latest experience of drafting Q1 players. Thus, we expect β_1 to be positive and β_2 to be negative. Notably, as a result of the deviation from the private information assumption, there might be downward biases in the magnitude of two estimates.

The phenomenon of RAE reversal documented by Deaner et al. (2013) and Fumarco et al. (2017) are consistent with the results of the "Overcomer" analysis in Benson and Lepage (2024). In the context of NHL, negative experiences of a team with Q4 players may not only lead to fewer subsequent Q4 draft picks, but also yield positive selection in future Q4 draft picks if they have to

overcome a greater bar to get drafted. In that case, negative hiring experiences in the past should positively correlate with positive experiences in the future.

Table 8 and 9 report results of the above analyses, and show how future hires and experiences are associated with past experiences. In table 8, future Q4 hires appear to be unaffected by past experiences with Q4 players, but positive cumulative experiences with Q1 players are associated with fewer Q4 hires. Moreover, in column 2 of table 9, we find positive selection in Q4 players, evidenced by the negative correlation between the cumulative probability of making the team roster among Q4 players in drafts up to $t-1$ and the probability of making the team roster among Q4 players in draft t. In another word, negative cumulative experiences with Q4 players are positively correlated with positive experiences in the future, which is consistent with Benson and Lepage (2024). Overall, our results suggest that discrimination against Q4 players is partly driven by team's own draft experience.

One may notice that in both table 8 and 9, there are fewer observations in column 1 than column 2. This is because if a team didn't draft any Q4 (Q1) player in the previous draft, the denominator in "Q4 (Q1) roster%, latest draft" is 0, making them coded as NA and dropped from the regression. There are 306 team-season observations that did not draft Q4 players and 63 observations that did not draft Q1 players, which means sample attrition is nonrandom and primarily come from Q4 players. Such a sample restriction may introduce selection bias to our results, because teams that avoid drafting Q4 players likely have worse perceptions of them, meaning that there could be upward bias in "Q4 roster%, latest draft".

6 Risk Preferences, Statistical Discrimination, and Team Performance

Firms may have different risk preferences, and it's of interest to investigate the relationship between risk preferences and firm performance (Brenner, 2015; Brown et al., 2023). In addition, inaccurate statistical discrimination should have negative impacts on firm performance theoretically (Huber et al., 2021). In our setting, although profit data of NHL franchises is not available, we can test whether team performance is associated with risk preferences and relative-age-based discrimination. An implicit assumption we make here is that a team's risk preferences and relative-age-based

Table 8: Experience Results

	Q4%	
	(1)	(2)
Q4 roster%, latest draft	−0.005	
	(0.025)	
Q1 roster%, latest draft	−0.008	
	(0.032)	
Q4 roster%, cumulative		−0.053
		(0.068)
Q1 roster%, cumulative		−0.216*
		(0.122)
Obs	786	1117
Year FE	X	X
Team FE	X	X

Notes: This table presents experience results. Both columns control for team and year fixed effects. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

Table 9: "Overcomer" Results

	Q4 roster%	
	(1)	(2)
Q4 roster%, latest draft	−0.030	
	(0.043)	
Q4 roster%, cumulative		−0.428***
		(0.126)
Obs	639	835
Year FE	X	X
Team FE	X	X

Notes: This table presents "Overcomer" results. Both columns control for team and year fixed effects. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

discrimination behavior are stable over time.

There are many approaches to measuring team performance based on different assumptions of team utility functions. Our measures include the variance of season winning percentage, average winning percentage, relative frequency of making the playoffs, relative frequency of making the finals, and relative frequency of winning the championship. Risky% is calculated by the ratio of 18+ to the sum of 18+ and 19-. Q4%, Q4 roster%, and Q1 roster% are calculated in the same way as in the previous section. $Roster\%, Q4 - Q1$, is calculated by Q4 roster% subtracted by Q1 roster%. Results are presented in Table 10.

Consistent with our intuition, both Risky% and Q4% are positively associated with Variance(win%), indicating that teams with more variance in performance are more likely to be risk-seeking, who select more risky players and Q4 players. However, unlike firm performance such as yearly profits, the instability of season winning percentage is not necessarily a negative indicator, especially when a team's goal is to maximize championships instead of wins. Such teams might strategically lose games in some seasons to get a better chance of winning earlier draft picks, and achieve great success in the following seasons.

Q4% is negatively associated with other team success measures, which seems to suggest that teams with larger relative-age-based discrimination are more successful. However, there is significantly positive association between team success and Q4 roster%. Combining these results, our interpretation is that less successful teams are less risk averse and tend to select more Q4 players, while more successful teams are better capable of predicting player productivity and thus more likely to draft a Q4 player competent enough to make the team.

Most importantly, Dif in roster% is negatively related to winning percentage and the relative frequency of making the playoffs. According to our previous analysis, this variable measures the magnitude of inaccuracy of relative-age-based statistical discrimination, which is 0 if it is accurate and positive if it is excess. 27 out of 32 NHL teams have positive Dif in roster%, indicating excess statistical discrimination at Q4 players for most NHL teams. Therefore, our interpretation of the negative association is that, as Dif in roster% approaches 0 from the right, teams exhibit more accurate statistical discrimination, and generate greater success.

Table 10: Team risk preferences, discrimination behavior, and performance

	Variance(win%) (1)	Win% (2)	Playoff% (3)	Final% (4)	Champion% (5)
Risky%	0.011*	0.002	−0.098	−0.079	−0.044
	(0.006)	(0.033)	(0.139)	(0.068)	(0.042)
Q4%	0.038**	−0.283**	−1.550***	−0.649***	−0.380***
	(0.019)	(0.127)	(0.451)	(0.222)	(0.122)
Roster%, Q4	−0.014	0.190**	1.025**	0.400**	0.262**
	(0.015)	(0.087)	(0.382)	(0.163)	(0.105)
Roster%, Q4 - Q1	0.009	−0.122**	−0.990***	−0.085	−0.029
	(0.010)	(0.052)	(0.280)	(0.135)	(0.085)
Obs	32	32	32	32	32

Notes: This table presents the association between team performance and risk preferences as well as relative-age-based discrimination. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

7 Conclusion

Firms often make hiring decisions under the condition that there is varying uncertainty about productivity across job applicants. Usually, it is difficult to establish clean identification of which group is more risky. Utilizing the exogenous cutoff date in NHL draft age requirements, we are the first to provide causal estimates of firm risk preferences. RDD results show that teams are generally risk averse in NHL drafts. Moreover, teams are less risk averse when they select goaltenders or in later rounds, consistent with previous studies. Lastly, teams are less risk averse over time.

Another consequence of uncertainty about productivity is that firms tend to classify job applicants into different groups based on some signal, and make hiring decisions based on their beliefs of group differences in productivity distribution. If these beliefs are accurate, the labor market is still efficient. However, we find excess relative-age-based statistical discrimination against Q4 players and thus inefficiency in NHL drafts. An immediate implication is that teams can benefit from drafting more of these players or drafting them earlier, which improves market efficiency as well. In addition, we find negative-experience-associated positive selection in Q4 players, which suggests that discrimination against Q4 players is partly driven by team own draft experience.

We also relate risk preferences and discrimination behavior to team performance. We find that less risk aversion and larger statistical discrimination against Q4 players are associated with larger variance in team performance, consistent with economic intuition. In addition, we find that less

successful teams are less risk averse, while more successful teams are better capable of predicting player productivity. Lastly, teams with more accurate statistical discrimination are more successful.

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Appendix

A Dynamic Effects

A.1 Dynamics of Team Risk Preferences

Our baseline sample consists of 44 NHL entry drafts from 1980 to 2023. Given that teams can learn about the productivity distribution of different player groups, team risk preferences might change over time. In addition, the number of draft rounds has been changing as well, which might have impact on group differences in draft positions. Therefore, to explore the dynamics of team risk preferences, we divide the baseline sample into 2 subsamples based on the number of draft rounds, and estimate equation 5 with each subsample respectively. Results presented in Panel A of Table A.1 show that teams are more risk averse in 1980-1994 when there were 10-12 rounds in each draft, and less risk averse in 1995-2023 when there were 7 or 9 rounds each.

Table A.1: Dynamics of team risk preferences

	Panel A		Panel B	
	1980-1994	1995-2023	1980-2001	2002-2023
	(1)	(2)	(3)	(4)
Risky	61.76***	40.23***	46.59**	42.51**
	(23.38)	(15.05)	(19.18)	(16.50)
Obs	79+92	183+188	120+145	142+135

Notes: This table presents RDD results using different subsamples. Divided by the number of draft rounds, column 1 and 2 are results of the 1980-1994 and 1995-2023 subsample. Divided equally, column 3 and 4 are results of the 1980-2001 and 2002-2023 subsample. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. All regressions control for draft year, position, and nationality fixed effects. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

A.2 Dynamics of Statitical Discrimination

Similar to risk preferences, team discrimination behavior might change over time as well. Especially, the existence of NHL Supplemental Drafts in 1986-1994 might have impact on team discrimination behavior. Therefore, we divide our baseline sample into 3 subsamples, including the 1980-1985 subsample, the 1986-1994 subsample, and 1995-present subsample.

Table A.2 presents DDD results of different subsamples. In Panel B, coefficients of $Q4$ are insignificant, indicating that with the cushion of NHL Supplemental Drafts, teams did not exhibit inaccurate statistical discrimination based on relative age. However, in both Panel A and C, when NHL Supplemental Drafts were not in place and labor market conditions were more risky, teams tend to have excess statistical discrimination at Q4 players. Moreover, the magnitude of inaccurate statistical discrimination decreases in 1995-present compared to 1980-1985, suggesting teams are learning through their hiring experiences.

As for *Last*, coefficients in Panel A show that, treated players are selected later on average (marginally insignificant though), which is again interpreted as a larger number of Q4 North-Americans being selected. In addition, treated players demonstrate much better post-draft outcomes than control players conditional on draft position, according to column 2-4. These results suggest that teams benefited a lot from drafting treated players before NHL Supplemental Drafts were implemented. However, after NHL Supplemental Drafts were implemented, or even when it was removed later on, teams have been able to draft treated players efficiently, according to results

in Panel B and C.

Table A.2: Dynamics of statistical discrimination

	Draft position (1)	Rostered (2)	Career length (3)	Games played (4)	All-star (5)
Panel A: 1980-1985, pre Supplemental Drafts					
Last	72.115	0.778***	8.877***	188.850**	−0.055
	(45.686)	(0.278)	(3.288)	(75.582)	(0.158)
Q4	−18.243	0.520***	4.737**	76.236	0.010
	(23.003)	(0.111)	(1.854)	(48.104)	(0.065)
Obs	660	660	660	660	660
Panel B: 1986-1994, with Supplemental Drafts					
Last	27.155	−0.127	0.232	80.579	0.267
	(28.513)	(0.182)	(2.595)	(68.808)	(0.287)
Q4	−23.754	−0.110	−0.353	52.324	0.055
	(17.304)	(0.106)	(1.579)	(44.102)	(0.196)
Obs	953	953	953	953	953
Panel C: 1995-present, post Supplemental Drafts					
Last	11.186	0.162	2.003*	44.622	−0.011
	(15.105)	(0.106)	(1.119)	(31.064)	(0.092)
Q4	−5.120	0.114***	0.887***	27.107***	0.050
	(4.678)	(0.027)	(0.286)	(8.738)	(0.032)
Obs	3138	3138	3138	3138	3138

Notes: This table presents results by estimating equation 7 and 8 with different subsamples. All regressions control for draft year, position, and nationality fixed effects. Column 2-5 control for draft position. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

B Robustness Checks

B.1 Continuity of Covariates at the Cutoff

We check the continuity of covariates around the cutoff date of September 15, and present results in Table B.1. No significant differences in nationality, position, and draft year are found between 19- and 18+, which lends credibility to the validity of our RDD approach.

Table B.1: Balance Table of 19- vs. 18+

Variable	19-	18+	Difference
Forward	0.56	0.59	-0.03
			(0.04)
Defender	0.32	0.32	0.01
			(0.04)
Goaltender	0.12	0.09	0.03
			(0.03)
US	0.26	0.24	0.01
			(0.04)
Canada	0.52	0.48	0.04
			(0.04)
Euro/Asia	0.23	0.28	-0.05
			(0.04)
Draft Year	2002.5	2001.1	1.4
			(1.08)
Obs	262	280	

Notes: This is a balance table of 19- versus 18+ using the September sample. Standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

B.2 Placebo Tests with Other Cutoff Dates

As a robustness check, we perform placebo tests using August 15 and October 15 as placebo cutoff dates. We still use 15 days as the bandwidth, which is roughly equivalent to using the August sample and October sample respectively. Results presented in Table B.2 show null effects, which means whether players born before or after (August or October) 15th does not matter for team drafting decisions. These null results imply that the jump we observe at the cutoff date of September 15 is caused by the minimum age requirement of NHL drafts rather than other unobservables, lending credibility to our identification.

B.3 Alternative Specifications and Samples

By separating players into different age subsamples, we present DiD results in Table B.3, which represents a robustness check for DDD results. Results show that statistical discrimination results are mainly driven by players drafted in their first attempt (Panel B), which is consistent with economic intuition. There is less information about these players and thus more uncertainty about their productivity, leading to a higher risk discount on draft position or even fewer Q4 players being

Table B.2: Results with Placebo Cutoff Dates – August 15 and October 15

	August 15			October 15		
	All rounds	First 3 rounds	Last 3 rounds	All rounds	First 3 rounds	Last 3 rounds
	(1)	(2)	(3)	(4)	(5)	(6)
Risky	−13.63	2.52	−4.88	−18.65	−5.96	6.05
	(11.81)	(7.99)	(11.41)	(14.28)	(8.45)	(15.19)
Obs	306+307	75+95	102+84	254+295	101+118	49+59

Notes: This table presents RDD results using August 15 and October 15 as placebo cutoff dates respectively. The dependent variable is draft position. All regressions control for draft year, position, and nationality fixed effects. In the row of observations, the number of 19- players is on the left and the number of 18+ players is on the right. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

drafted. In addition, both Table 6 and Panel B in Table B.3 show a lower probability of making a team roster for Q4 North American players (significant at 10% level), indicating more accurate statistical discrimination against them. It is consistent with economic intuition as well, because for NHL teams, there should be less uncertainty about North Americans compared to players from other continents.

We further estimate Equation (8) using a subsample consisting of players born in December or January, who should be affected by the calendar year cutoff and the NHL upper age limit most. In this subsample, there are 1,186 players born in January, and 443 players born in December. Therefore, the ratio is 2.68, higher than all the previous comparisons, indicating a stronger discrimination against players born in December. Table B.4 presents DDD results with this subsample. The causal effect of the NHL upper age limit is much bigger than that in table 6, indicating a larger reduction in discrimination against players born in December. In addition, players born in December again have better post-draft outcomes conditional on draft position, indicating excess statistical discrimination at December players.

Table B.3: DiD Results of Statistical Discrimination and the NHL Upper Age Limit

	Draft position (1)	Rostered (2)	Career length (3)	Games played (4)	All-star (5)
Panel A: Full sample					
$Q4 \times NorthAmerican$	3.90	−0.03	0.09	−0.72	0.01
	(4.77)	(0.03)	(0.33)	(9.45)	(0.04)
Q4	−18.72***	0.08***	0.51*	20.56***	0.03
	(4.10)	(0.02)	(0.28)	(8.09)	(0.03)
Obs	4,751	4,751	4,751	4,751	4,751
Panel B: Just below and just above 19					
$Q4 \times NorthAmerican$	−1.00	−0.06*	−0.22	−9.96	0.01
	(5.27)	(0.03)	(0.36)	(10.36)	(0.04)
Q4	−6.30	0.11***	0.81***	27.74***	0.05
	(4.44)	(0.03)	(0.29)	(8.65)	(0.03)
Obs	3,835	3,835	3,835	3,835	3,835
Panel C: Just below and just above 20					
$Q4 \times NorthAmerican$	25.92*	0.05	1.27	32.01	0.01
	(11.64)	(0.08)	(0.91)	(23.96)	(0.07)
Q4	−16.45	0.06	0.09	9.00	−0.03
	(10.32)	(0.07)	(0.80)	(20.70)	(0.07)
Obs	916	916	916	916	916

Notes: This table presents results of different subsamples. All regressions control for draft year, position, and nationality fixed effects. Column 2-5 control for draft position, and Panel A control for player age. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.

Table B.4: DDD results with the December and January subsample

	Draft Position	Rostered	Career Length	Games Played	All-Star
Last	44.469**	0.242*	1.164	12.685	0.064
	(22.605)	(0.144)	(1.899)	(49.931)	(0.170)
NA-Q4	−9.729	−0.024	0.107	−7.543	−0.071
	(9.574)	(0.056)	(0.658)	(21.108)	(0.075)
Q4-2nd	−23.688	−0.075	0.367	1.499	−0.072
	(19.371)	(0.122)	(1.639)	(44.291)	(0.158)
NA-2nd	−13.154	−0.044	−0.852	−34.361*	−0.110
	(12.635)	(0.078)	(0.922)	(20.328)	(0.104)
Q4	−1.599	0.128***	1.219**	39.559**	0.065
	(7.889)	(0.047)	(0.535)	(18.082)	(0.062)
2nd	51.759***	0.109	1.717**	49.318***	0.140
	(11.050)	(0.068)	(0.801)	(18.396)	(0.093)
Obs	1629	1629	1629	1629	1629

Notes: This table presents robustness check results by estimating equation 7 and 8. All regressions control for draft year, position, and nationality fixed effects. Column 2-5 control for draft position. Robust standard errors are in parentheses. * indicates 10% significance level, ** indicates 5% significance level, *** indicates 1% significance level.