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Essays in Sports and Development Economics

Ivan Trestcov

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Dissertation Committee

Vasily Korovkin, Ph.D. (Pompeu Fabra University, Chair)

Sebastian Ottinger, Ph.D. (CERGE-EI, Local Chair)

Andreas Menzel, Ph.D. (University of Padua)

Referees

Luca Fumarco, Ph.D. (Masaryk University)

Rocco d'Este, Ph.D. (University of Sussex)

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Abstract

This dissertation is comprised of three applied studies investigating the effects of various environments, including surveillance, weather shocks, and work settings, on individual behaviour. The first study tests Becker's model of crime utilizing the introduction of the Video Assistant Referee to European football. The study disentangles the deterrence and monitoring effects, finds strong evidence for specific deterrence, and shows the spillover effect of deterrence outside of the surveillance environment. The second study explores the long-term effects of early-career environments using NBA data, and finds that early team success and experienced leadership positively influence the future individual performance of players. The third study investigates the relationship between climate shocks and gender discrimination in Kyrgyzstan, revealing that low rates of winter precipitation increases bride kidnapping and shifts societal attitudes, particularly among lower-income households.

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Introduction

This dissertation includes three applied studies that examine how different environments, including surveillance, climate shocks, and workplace environment, impact individual behavior.

The first chapter examines the impact of introducing the Video Assistant Referee (VAR) to European football. Firstly, the setting enables the decomposition of the deterrence and monitoring effects in Becker's (1968) model of crime. Secondly, I estimate the spillover of the deterrence effect beyond the surveillance environment. Thirdly, I uncover evidence of a relatively unexplored learning-by-punishment effect. Using a difference-in-difference strategy, this paper demonstrates that the implementation of VAR leads to a significant reduction in the number of fouls in two German football leagues. VAR has an immediate impact on severe fouls, while the effect on penalty fouls becomes evident after a 12-week adjustment period. Punishment enhances the deterrence effect, with punished players committing even fewer fouls than those who were not punished. The deterrence effect extends beyond the surveillance environment, manifesting as a spillover effect in international competitions. Specifically, players from countries with VAR commit fewer fouls in international competitions than do players from countries without VAR.

The second chapter investigates the long-term impacts of early-career environments on performance using data from the NBA Draft Lottery system. The analysis highlights the positive influence of early team success and experienced coaching on future player performance, while the presence of a star player during the debut season does not show a significant effect.

The third chapter explores the relationship between climate shocks and gender discrimination, focusing on the practice of bride kidnapping in Kyrgyzstan. Utilizing data from the Life in Kyrgyzstan Survey, the study finds that low rates of winter precipitation increases the likelihood of bride kidnapping and influences societal attitudes towards this practice. The effects are more pronounced among lower-income households, and households with daughters tend to have negative attitudes toward bride capture. The findings underscore the gendered consequences of climate change in developing countries and highlight the need for gender-sensitive adaptation strategies.

Chapter 1

Compliance Under Surveillance: Impact of the Video Assistant Referee in Football

1.1 Introduction

Governments and businesses spend billions on surveillance cameras to lower crime rates, and the number of surveillance cameras worldwide climbed above 1 billion in 2021[1]. The existing literature finds strong evidence of general deterrence caused by surveillance (Munyo & Rossi, 2019; Pricks, 2015). However, the evidence is scarce when it comes to understanding various dimensions of the link between surveillance and criminal behavior, including the mechanism of learning the increased probability of detection, rate of recidivism, and spillover effect to unmonitored areas.

Building on the economic model of crime proposed by Becker (1968), a substantial body of literature has examined the impact of enforcement and punishment on criminal behavior. While theoretical advancements have been significant (Stigler, 1970; Polinsky & Shavell, 1984; Kaplow & Shavell, 1999), empirical studies often face challenges in identifying causal effects due to issues such as endogeneity of enforcement intensity and confounding factors like incapacitation effects. Recent research has employed natural experiments and innovative data sources to address these challenges (Levitt, 1997; Di Tella & Schargrodsky, 2004; Draca et al., 2011). I contribute to this literature by leveraging a unique natural experiment in professional football to isolate the deterrent effect of in-

[1]See IHS Markit: Video surveillance: How technology and the cloud is disrupting the market

creased surveillance on misconduct and to explore previously unstudied spillover effects into unmonitored environments.

This paper addresses several under-studied aspects of the relationship between surveillance and crime using a novel setting of the introduction of a video assistant referee (VAR) to European football. The paper builds on McCormick & Tollison (1984), who propose testing the Becker (1968) model of crime using sports data. They treat referees as "police" and players as potential lawbreakers and find that the number of fouls in college basketball decreases by 30 percent after the number of referees changes from 2 to 3.

Several studies have applied this idea to different sports (Levitt, 2002; Heckelman & Yates, 2003; Kitchens, 2014; Jahnuba, 2018). In the setting of this paper, the source of the increased probability of detection arises not from the additional referee but the surveillance technology. VAR is a video footage technology in football that helps game officials to review decisions made by the head referee. Dozens of major football leagues have introduced it to increase the accuracy of officiating in matches.

First, I contribute to the literature by estimating the long-lasting change in criminal behavior outside the surveillance environment after being monitored. I use player-level data from two international competitions and apply the difference-in-difference estimation strategy to compare the changes in the number of fouls committed by players from leagues with and without VAR. Two international competitions - the Champions League and the Europa League - introduced VAR later than some domestic leagues. This timing opens a window for estimation of the spillover effect. I test the hypothesis that the general deterrence causing from use of VAR continues to affect players in games without the surveillance technology. I find that players from three domestic leagues start to commit 15-20 % fewer fouls immediately after the introduction of VAR. The effect strengthens with the number of games played under surveillance.

Second, this paper contributes to the literature on specific deterrence - the deterrence created by the experience of law enforcement[2]. It is an empirical challenge to isolate the learning-by-punishment channel. One reason is that the expectation of punishment often increases with prior convictions and implies a general deterrence effect. Moreover, punishment usually has a treatment effect that is simultaneous with incapacitation and aging (Ganong, 2012; Barbarino & Mastrobuoni, 2014), criminogenic peer effects (Bayer et al., 2009), diverging labor market consequences (Mueller-Smith, 2015; Bhuller et al.,

[2]The concept of specific deterrence proposes that punished criminals avoid future criminal activity. General deterrence suggests that punishment awareness prevents individuals from committing crimes.

2019), and non-trivial income effects (Kolm, 1973). For efficient isolation of the specific deterrence, punishment should be regular, constant, and non-severe. The focus on regular punishments ensures a sufficient number of observed punishment events, thereby enhancing the statistical power of the analysis. Consistent severity of punishments eliminates the confounding influence of punishment escalation commonly observed in recidivism, where repeated offenses are met with increasingly severe sanctions. By examining non-severe punishments, this study avoids the long-term consequences - such as diminished labor market prospects or income effects - that could obscure the specific deterrence mechanism. This paper mitigates these issues by focusing on punishments that are consistent, constant, and non-severe - penalties and red cards in football. I use the data on fouls detected by VAR to investigate whether players' experience with law enforcement may accelerate their learning about the increased probability of detection and intensify the general deterrence effect. I find that, after experiencing punishment, players commit significantly fewer penalty-kick and severe fouls, over and above the general deterrence effect. Moreover, I show weak evidence that players learn not only from their own mistakes but also when they witness VAR punishing other players.

Third, this paper contributes to the general deterrence literature by providing a clear link between monitoring and deterrence effects. The police literature offers estimates of the crime-police elasticity (Levitt, 1997; Draca et al., 2011). The surveillance cameras literature exploits the fact that police rarely use CCTV cameras for crime detection; hence only the deterrence effect is present (Armitage et al., 1999; Blixt, 2003; Brown, 1995; Caplan et al., 2011; Ditton & Short, 1999; Gill & Spriggs, 2005; Munyo & Rossi, 2019; Pricks, 2015). However, it is complicated to estimate the monitoring effect of additional police or cameras on the number of arrests due to the simultaneous nature of monitoring and deterrence, or the long time between a crime and its prosecution. This paper exploits the special timing of VAR decision-making to better distinguish between the monitoring and deterrence effects. The head referee always makes the initial decision regarding the game event, and only then may VAR interfere with the game and change the decision. Observing both initial and final decisions I estimate the effect of VAR on the number of fouls for two alternative datasets. A 37 percent increase in the number of fouls detected due to surveillance (the monitoring effect) leads to a 32 percent decrease in the number of fouls committed (the deterrence effect).

The rest of the paper has the following structure. Section 1.2 describes the introduction of the Video Assistant Referee to European football. Section 1.3 summarises the data and justifies the empirical strategy of the paper. Section 1.4 presents the results of the analysis. Section 1.5 concludes.

1.2 The Video Assistant Referee

VAR is a surveillance technology in football that helps head and assistant referees to officiate the game with greater accuracy. It is gradually spreading across all major football leagues in the world. In Europe, the German Bundesliga, Italian Serie-A, and Portuguese Primeira were the first three leagues to introduce the new technology, in all games for the 2017-2018 season. The International Federation of Association Football (FIFA) officially included VAR in the laws of the game in 2018. In the 2018-2019 season, four more European leagues incorporated the technology. Currently, approximately 40 countries use VAR in their top leagues.

The primary purpose of VAR is to increase the accuracy of referee decisions by correcting clear and obvious mistakes for possibly match-changing events, including goals, penalties, red cards, and mistaken identity. VAR can intervene when the head or assistant referee mistakenly calls, or overlooks one of these events.

KU Leuven's independent research (Spitz, 2020) on the data from the experimental phase of VAR introduction reports that 57 percent of checks were for penalty or goal incidents. VAR initiates approximately five inspections per match with a median check time of 20 seconds. On average, VAR detects one clear and obvious mistake every three games. The research estimates that the technology improved accuracy in decision-making from 93 to 98.9 percent.

According to the laws of the game, the VAR, supported by the VAR operator, reviews all video replays of game-changing events. If a review reveals that the head or assistant referee made an obvious mistake, the VAR suggests that the referee checks the preliminary decision. The head referee can overturn an initial decision based only on the information from the VAR. For subjective conclusions such as sending a player off, the head referee can review the footage on a monitor near the field before making a final decision. Another essential protocol rule is that the head referee must always make an initial decision as if there was no VAR, and he is not permitted to give 'no decision.'

1.3 Data and Empirical Strategy

I use player-level match statistics and VAR decision data from several publicly available sources, including fbref.com, whoscored.com, and goal.com. The dataset spans three years, starting from the 2015/2016 season. This study focuses on two major German leagues: the Bundesliga and 2. Bundesliga. Germany was among the first countries to officially implement VAR, and it offers high-quality data not only for its top-tier league but also for its second tier. The Bundesliga introduced VAR in the 2017/2018 season, while 2. Bundesliga adopted the technology in the 2019/2020 season, making it a suitable control group for this analysis.[3]

In addition, the sample includes data from two leading international competitions: the Champions League and the Europa League, neither of which incorporated VAR during the period under study. These European competitions provide an ideal setting to examine the spillover effects of VAR, because they feature players from both VAR and non-VAR domestic leagues competing against one another.

The sample is restricted to three years to maintain a clean identification strategy. Including later years would introduce potential confounding factors, as VAR was introduced at the 2018 FIFA World Cup - a globally significant event that likely exposed nearly all professional players to the technology, either through personal experience or by observing the tournament. Such exposure could diminish the ability to isolate the spillover and deterrence effects studied in this paper. By focusing on the period before VAR became a near-universal feature of football, this study ensures that the observed effects are attributable to the league-level implementation of the technology.

Table 1.1 presents summary statistics of the main variables of interest and outcome variables for two major German football leagues analyzed in this paper. The Bundesliga and 2. Bundesliga are the first and second tier leagues of the German football league system. I use several types of fouls as outcome variables. Penalty-kick fouls are committed close to the goal of an offender (inside the penalty area). A head referee shows the offender a yellow card if he commits a severe foul (e.g., persistent infringement of the Laws of the Game). If a player commits a second severe foul or an exceptionally severe foul (e.g., foul committed using excessive force), the head referee shows a red card to signify that

[3]The later introduction of VAR in the 2. Bundesliga resulted from delays in preparing the necessary infrastructure, including technology and facilities at second-tier stadiums. Top leagues usually adopt such technologies first due to their superior resources and infrastructure.

a player must be sent off. The number of games played with VAR by a player is the variable of interest.

Because player-level penalty data is the only unavailable statistic for 2. Bundesliga, I convert the team-level[4] penalty statistics into individual-level data by assigning a penalty kick foul to each player who participated in a game in which their team committed such a foul. This ensures consistency across the dataset and allows all analyses to be conducted at the individual level. A penalty kick occurs once in every two games on average. A yellow card is more frequent: every 7th player receives one in an average game. The rarest event is a red card, which occurs once in every five or six games. There are no players with VAR experience in 2. Bundesliga because the league did not implement VAR until 2019. In contrast, I observe players with experience of up to 34 games using VAR in the Bundesliga, because it introduced VAR in the last season analyzed.

Table 1.1: Summary Statistics, Germany 2015-2018 by Competition

	Mean	SD	Min	Max	N
Panel A: 2.Bundesliga					
Penalty Kick Fouls (Team)	0.24	0.49	0.00	3.00	24,525
Yellow Cards	0.16	0.37	0.00	2.00	24,525
Red Cards	0.01	0.08	0.00	1.00	24,525
Games with VAR before	0.00	0.00	0.00	0.00	24,525
Panel B: Bundesliga					
Penalty Kick Fouls (Team)	0.30	0.53	0.00	3.00	24,972
Yellow Cards	0.14	0.35	0.00	2.00	24,972
Red Cards	0.01	0.07	0.00	1.00	24,972
Games with VAR before	4.21	7.57	0.00	34.00	24,972
Punished by VAR before	0.01	0.11	0.00	1.00	24,972

Notes: All statistics were obtained from player-match level samples with 24 525 observations in 2. Bundesliga and 24 972 observations in the Bundesliga. Penalty Kick Fouls are assigned based on team-level statistics. "Games with VAR before" correspond to the number of games officiated with VAR which players had participated in before a current game. "Punished by VAR before" correspond to the number of times a player was caught and punished by VAR before a current game.

I estimate a difference-in-difference model of the following form:

$$Y_{imt} = \alpha_t + \lambda_c + \theta_i + \gamma_{mt} + \beta VAR_{ct} + \beta_e E_{imt} + \beta_x X_{mt} + \epsilon_{imt} \tag{1.1}$$

[4] By team-level data, I refer to team-match level statistics, such as the total number of penalty fouls committed by the entire team in a given game.

Y_{imt} is the number of fouls committed by player i, in matchup (pair of competing teams) m, competition c, and year t. I use three types of fouls committed: severe foul, penalty-kick foul, and common foul. The head referee shows a yellow or red card if a player commits a severe foul. A penalty kick foul is any foul committed inside the penalty area adjacent to the goal. I include fixed effects of the competition λ_c , game week α_t , player θ_i. γ_{mt} are the matchup level fixed effects: pair of teams and referee. I also include a variety of controls at the game level including shots, ball possession, and the difference in the final score etc. The treatment variable VAR_{ct} for the analysis of German leagues is a dummy which takes the value of one if it is a game officiated with VAR. For the analysis of the international competitions, VAR_{it} is a dummy which takes the value of one if player i participated in a match with VAR before time t.

The treatment timing is determined by the staggered introduction of VAR across leagues. The Bundesliga implemented VAR beginning in the 2017/2018 season, providing two years of pre-treatment data (2015/2016 and 2016/2017) and one year of treatment data in the sample. In contrast, the 2. Bundesliga, which introduced VAR only in the 2019/2020 season due to delays in preparing the necessary infrastructure at second-tier stadiums, remains entirely unexposed to VAR within the sample period, providing a robust control group. This staggered implementation allows for a clear identification of the treatment effect, leveraging the variation in VAR exposure both across leagues and over time to isolate the causal impact of the technology.

E_{imt} reflects the learning-by-punishment effect and equals one if, at time t, player i has been punished by VAR at least once. While E_{imt} may appear to be an outcome, it is effectively a subset of the main treatment variable of interest, VAR_{ct}, capturing only instances where a player has personally experienced punishment under VAR. This specification allows us to investigate whether the deterrence effect is magnified for players who are directly affected by VAR enforcement. Importantly, the timing of being caught by VAR is largely random, as it depends on specific in-game situations and the discretion of referees. This randomness enhances the robustness of the identification strategy, and ensures that the observed effects are not driven by systematic differences between punished and unpunished players.

To test the spillover hypothesis, I use international data. Mainly, I investigate players' compliance behavior in the Champions League and Europa League after being exposed to treatment. I compare the number of fouls committed by players from domestic championships with VAR versus players from championships without VAR. The evidence for the spillover effect would be a significant and negative β. One possible explanation of the spillover effect is a significant cost of switching over two regimes: “soft" (law-abiding) and “aggressive" (criminal). If a player anticipates treatment in future games, it might be optimal to stick to one “regime" to eliminate switching costs. Another explanation is a long adjustment period to a new environment; hence one game is merely insufficient time.

Another part of the analysis is an investigation of the link between monitoring and deterrence effects in the framework of Becker (1968). I use the German leagues' data and analyze two alternative datasets: initial and final head referee decisions. Assuming no changes in referees' behavior after the introduction of VAR, one can estimate the monitoring effect as a simple fraction of additional fouls caused by VAR to the number of fouls initially called by the head referee. I use DiD for the initial decisions dataset to estimate the deterrence effect. If VAR does not affect referees, then a possible drop in the number of fouls after the introduction of the surveillance can be explained by the deterrence of players.

The main concern for this analysis is the assumption of the unchanged referee behavior after the introduction of VAR. One argument supporting this assumption is the protocol rule which explicitly states that the referee must provide an initial decision as if there is no VAR. Moreover, he can not give a “no decision" call. To give a formal argument, I apply a similar specification as in Equation 1 to the data of Bundesliga 2 only. The league did not introduce VAR in 2017/2018; however, some referees officiating games in this season had already experienced VAR in the first Bundesliga. I change the variable of interest in Equation 1 to VAR_{rt} - a dummy that takes one if the referee r officiated at least one game with VAR before t. I find no significant changes in the number of fouls (severe and penalty kicks) called by referees with VAR experience (Table 1.2). I use the same fixed effects as in the main specification: time, players, and team pairs.

Parallel trends are the underlying assumption for using the difference-in-difference estimation procedure. To justify the parallel pre-trends, I provide event study graphs for the following specification:

$$Y_{igct} = \alpha_t + \theta_i + \sum \beta_t VAR_c + \epsilon_{igct} \tag{1.2}$$

Figure 1.1 shows β_t coefficients (average treatment effects of VAR on Severe Fouls) for the data aggregated to 7-week intervals. The choice of 7-week intervals strikes an optimal

Table 1.2: The effect of VAR on referees in Bundesliga 2

	(1) Penalty Kicks	(2) Severe Fouls
VAR	0.040	−0.016
	(0.177)	(0.021)
Observations	468	468
Time FE	Yes	Yes
Player FE	Yes	Yes
Teams FE	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: VAR indicates whether a referee officiated games with VAR in the past. Teams fixed effects control for a pair of two competing teams. I used data of all games in 2.Bundesliga for 2017-2018. Referee-clustered robust standard errors in parentheses.

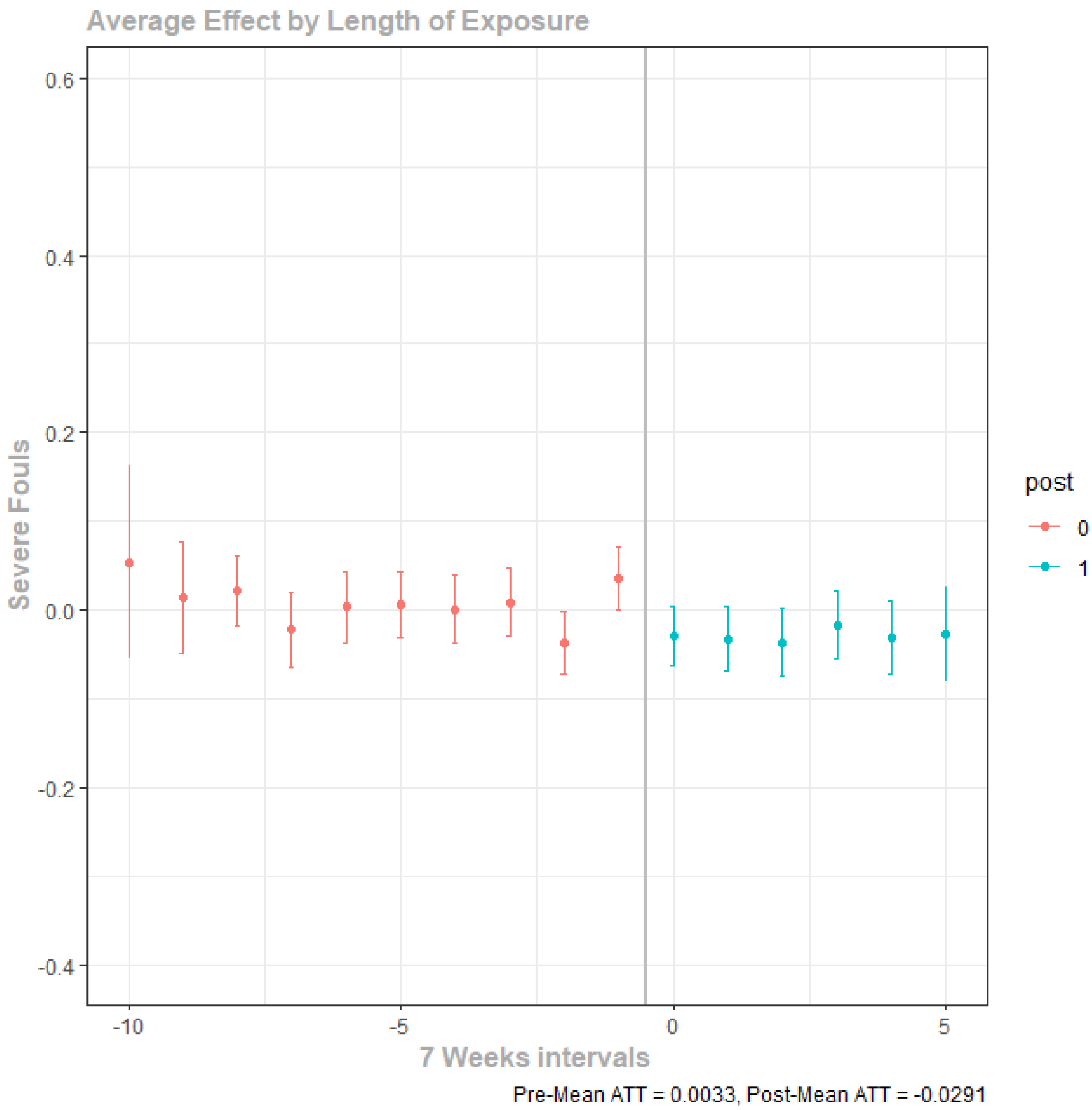
balance between reducing the noisiness inherent in game-level data and maintaining sufficient granularity to capture meaningful temporal dynamics. This approach effectively divides each season into five intervals, smoothing short-term fluctuations while preserving the structure needed for robust trend identification. While pre-treatment ATTs float around zero (parallel pre-trends) with $\sum_{t=-10}^{-1} \hat{\beta}_t$ = 0.0033, post-treatment coefficients are consistently below zero with $\sum_{t=0}^{5} \hat{\beta}_t$ = -0.0291. This pattern signifies the general deterrence effect kicking off immediately after introduction of VAR.

Figure 1.A1 (Appendix) plots the same ATTs but for penalty kick fouls as an outcome variable. The data for penalty-kicks is more volatile as it is a less frequent event. Nevertheless, the average pre-treatment effect is again close to zero (-0.0057), and the average post-treatment diverges significantly (-0.0701). Interestingly, the deterrence effect does not begin immediately as it does for severe fouls. It is close to zero for the first 12 weeks and only then drops below zero and consistently remains negative.

1.4 Results

First, I investigate the link between the monitoring and deterrence effects of introducing VAR into the German major football league. I use two alternative datasets: initial (before VAR intervention) and final (after VAR intervention) referee decisions. The num-

Figure 1.1: Parallel Pre-Trends: Severe Fouls



Notes: The vertical grey line corresponds to the introduction of VAR in the 2017-2018 Bundesliga season. Each point with confidence intervals refers to a 7-week period. A week here is a game-week as teams, mostly, play one game weekly. We use robust standard errors.

ber of fouls detected by referees and VAR can be compared to assess the monitoring effect. Table 1.3 shows the direct impact of VAR on the number of penalty and severe fouls in the Bundesliga's 2017/2018 season. VAR intervened in the game to overturn a penalty decision five times more than it did for a red card decision. Moreover, there is a substantial imbalance in the type of errors in penalty kick decisions that head referees make. A referee overlooks penalty fouls three times more often than he falsely calls for a penalty. The monitoring effect for penalty-kick fouls (37%) is three times stronger than for severe fouls (13%).

Table 1.3: VAR Overturns, Bundesliga 2017/2018

	Initial	Final	Overturns	Overturned to foul	Overturned to no foul	% Change in true fouls
Penalty Fouls	77	93	34	25	9	37 %
Severe Fouls	42	43	9	5	4	13 %

Notes: Severe fouls include yellow and red card fouls. The "Initial" column shows the decisions made by the head referee before VAR intervention. The "Final" column shows the decisions of the head referee after he consulted with the VAR assistant or reviewed the video replay himself. "Overturns" is the number of overturned decisions, which can be of two types: "Overturned to foul" and "Overturned to no foul." "% Change in true fouls" assumes a perfect accuracy of the decisions made with the help of VAR and calculates the percentage change as $\frac{OverturnedToFoul}{Initial-OverturnedToNoFoul}$.

Table 1.4 shows the results for the final decisions of the referees. The estimates reflect the overall VAR effect - monitoring and deterrence. The monitoring effect dominates the deterrence effect for penalty kick fouls due to a drastic increase in the number of penalties detected. The deterrence effect prevails for severe fouls. To support evidence from the event study for penalty kick fouls, I add a specification in which the treatment is a dummy that takes the value of one if a player participated in at least 12 games with VAR. This model confirms the findings for penalty kick fouls: following the adjustment period of 12 games, the deterrence effect rises and becomes dominant, supporting the idea of gradual learning as players update their beliefs game after game. However, for severe fouls, the deterrence impact is immediate, as is evident in the results. Therefore, I do not include the specification with 12 games for severe fouls, as additional investigation to determine when the effect begins is unnecessary. Implementation of VAR immediately began to lessen the number of severe fouls, signaling rapid behavioral adjustment by players.

There are several potential explanations for the difference in adjustment periods observed between severe fouls and penalty-kick fouls. First, players may find it more immediately apparent that VAR is highly effective at detecting severe fouls, such as violent conduct or handball offenses that deny a goal. These actions tend to be clear-cut, visually prominent, and more likely to attract the referee's attention during a video review. In contrast, penalty-kick fouls, particularly those involving minor infringements like soft holding or slight contact, are often more ambiguous and may not consistently lead to penalties even after a thorough video review. This uncertainty may delay players' behavioral adjustments as they learn the threshold for detection and punishment under VAR.

Second, the nature of compliance required to avoid different types of fouls. Avoiding severe fouls, which are typically deliberate and egregious, may involve straightforward behavioral restraint. In contrast, adhering to the rules in high-pressure situations close to the goal - where penalty fouls frequently occur - requires players to exercise greater control in fast-paced, highly competitive scenarios. The physical and psychological demands of intense goal-area contests likely make it more challenging for players to adjust their behavior immediately.

Table 1.4: Germany, Final Referee Decisions

	Penalty Kicks			Severe Fouls
	(1)	(2)	(3)	(4)
VAR	0.039^{***}		0.062^{***}	-0.026^{***}
	(0.013)		(0.014)	(0.010)
12 Games with VAR		-0.031^{***}	-0.051^{***}	
		(0.010)	(0.012)	
Observations	49379	49379	49379	49379
Time FE	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The player-level data covers all games in 2016-2018 for the Bundesliga and 2.Bundesliga. *VAR* indicates if the game is officiated with VAR. *12 Games with VAR* takes the value of 1 if player participated in at least 12 games with VAR before the current game. I include fixed effects of year, player, referee, opposing team, and position of the player. Player clustered standard errors in parentheses.

Table 1.5 shows results for the alternative dataset with the initial referee decisions. The introduction VAR induces significant general deterrence for severe fouls and penalty-kick fouls. The monitoring effect of the 37 % increase in the number of fouls detected leads to a deterrence effect of a 32 % decrease in the number of penalty-kick fouls. For severe fouls the 13 % monitoring effect leads to a 28 % deterrence effect. The effect is immediate for severe fouls and begins after a 12 game adjustment period for penalty-kick fouls. The results are supported by the event-study analysis.

Table 1.5: Germany, Initial Referee Decisions

	Penalty Kicks			Severe Fouls
	(1)	(2)	(3)	(4)
VAR	−0.004		0.011	−0.031***
	(0.013)		(0.014)	(0.010)
12 Games with VAR		−0.031***	−0.034***	
		(0.010)	(0.011)	
Observations	49224	49224	49224	49224
Time FE	*Yes*	*Yes*	*Yes*	*Yes*
Player FE	*Yes*	*Yes*	*Yes*	*Yes*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The player-level data covers all games in 2016-2018 for the Bundesliga and 2.Bundesliga. *VAR* indicates if the game is officiated with VAR. *12 Games with VAR* takes the value of 1 if a player participated in at least 12 games with VAR before the current game. I include fixed effects of year, player, referee, opposing team, and position of the player. Player clustered standard errors in parentheses.

Secondly, I test the 'learning-by-punishment' hypothesis by analyzing several variations of the variable E_{igct} from equation (1), which is a dummy that takes the value of one if the Player/Teammate/Opponent was punished at least once before time t. The second and fourth columns in Table 1.6 show the estimation results using only Bundesliga data, because player-level penalty kick data is not available for 2. Bundesliga. This lack of player-level data for 2. Bundesliga means that in Column 3, I rely on variables including whether the team was previously punished by VAR or whether VAR was used in a game where the player participated. In contrast, for severe fouls in Column 1, I can directly use the variable indicating whether a player was previously punished by VAR, as red card data is available for both leagues. Moreover, in Columns 1 and 3, I employ a Difference-in-Differences (DiD) strategy consistent with previous regressions, leveraging the 2. Bundesliga as a control group. However, in Columns 2 and 4, I restrict the analysis to Bundesliga data only, where player-level penalty kick data is available and allows me to directly test the variable indicating whether a player was previously caught by VAR and a penalty was called. Although the analysis in Columns 2 and 4 does not use the 2. Bundesliga as a control group, I rely on the fact that the timing of VAR punishments for individual players is random. This randomness ensures that the effects identified remain causal. The evidence of specific deterrence is robust and present in all specifications. After experiencing punishment, players commit fewer penalty kicks and severe fouls, over and above the general deterrence. Interestingly, there is weak evidence of players learning from the punishment of other players, as players commit fewer penalty fouls after witnessing VAR detection and punishment during a game (Column 3).

Lastly, I test whether deterred players remain compliant outside the surveillance environment. Table 1.7 shows the effects of VAR introduction on two international competitions: Champions League and Europa League. Three countries experienced VAR introduction in the 2017/2018 season: Germany, Italy, and Portugal. Players from these three domestic leagues begin to commit significantly fewer fouls immediately after the introduction of VAR. Moreover, there is evidence of a spillover effect for penalty-kick fouls for players who played more than 20 games with VAR. The results have a striking resemblance to those in Tables 4 and 5 and the event study analysis.

1.5 Conclusion

This paper argues that the analysis of the introduction of a video assistant referee to European football is a valuable setting for studying compliance behavior. It provides several unique features that can improve our understanding of behavior under surveillance. The setting allows me to observe the pure monitoring effect and consequently estimate the deterrence effect with higher precision. I can observe the behavior of treated players in unmonitored areas, which yields the estimates for the spillover effect. I can estimate the learning-by-punishment effect and its persistence. I use the difference-in-difference estimation procedure at the national and international levels to study the effects. The results show that the introduction of VAR at the national level leads to a significant decrease in severe fouls and penalty-kick fouls. The extraction of the pure monitoring effect using the data on initial referee decisions uncovers the deterrence effect for penalties. Moreover, the existence of the spillover effect is confirmed by analysis of international data. In particular, teams in games with VAR in domestic championships commit fewer fouls than teams in games without VAR. Law (of the game) enforcement plays a significant role in the process of behavioral adjustment after the introduction of surveillance. After experiencing punishment, players commit fewer penalty kicks and severe fouls, over and above the general deterrence. Moreover, players not only learn from their own mistakes

Table 1.6: Germany, Specific Deterrence Effect

	Severe Fouls		Penalty	
	(1)	(2)	(3)	(4)
VAR	-0.022^{**}		0.071^{***}	
	(0.010)		(0.016)	
Red Card	-0.112^{**}	-0.134^{**}		
	(0.056)	(0.056)		
Red Card (teammate)	-0.001	-0.001		
	(0.015)	(0.016)		
Red Card (witness)	-0.015	-0.016		
	(0.012)	(0.015)		
12 games w. VAR			-0.045^{***}	
			(0.013)	
Penalty (team)			0.008	
			(0.014)	
Penalty (witness)			-0.032^{**}	-0.004
			(0.014)	(0.003)
Penalty				-0.052^{***}
				(0.008)
Penalty (teammate)				-0.001
				(0.003)
Observations	49379	16754	49379	16754
Time FE	*Yes*		*Yes*	*Yes*
Player FE	*Yes*		*Yes*	*Yes*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: In columns (1) and (3) the player-level data covers all games in 2016-2018 for the Bundesliga and 2.Bundesliga. Columns (2) and (4) show results for the Bundesliga only. *VAR* indicates if the game is officiated with VAR. *Player Punished by Red Card/Penalty* takes the value of 1 if VAR overturned a no-call to a red card/penalty for the player at least once before the current game. *Teammates of Player Punished by Red Card/Penalty* takes the value of 1 if the player witnessed VAR overturning a no-call to a red card/penalty to his teammate at least once in a game in which he participated before the current game. *Witness to Red Card/Penalty Punishment* takes the value of 1 if the player witnessed VAR overturning a no-call to a red card/penalty at least once in a game in which he participated before the current game. *12 Games with VAR* takes the value of 1 if a player participated at least 12 games with VAR before the current game. *Team Punished by Penalty* takes the value of 1 if VAR overturned a no-call to a penalty for a team at least once before the current game. I include fixed effects of year, player, referee, opponent team, and position of the player. Player clustered standard errors in parentheses.

Table 1.7: International Competitions, 2015-2018

	Penalty Kicks		Fouls	
	(1)	(2)	(3)	(4)
VAR	0.002		-0.128^{**}	
	(0.007)		(0.065)	
VAR (20 games)		-0.010^{**}		-0.209^{**}
		(0.005)		(0.093)
Observations	6282	6288	6282	6282
Time FE	*Yes*	*Yes*	*Yes*	*Yes*
Player FE	*Yes*	*Yes*	*Yes*	*Yes*

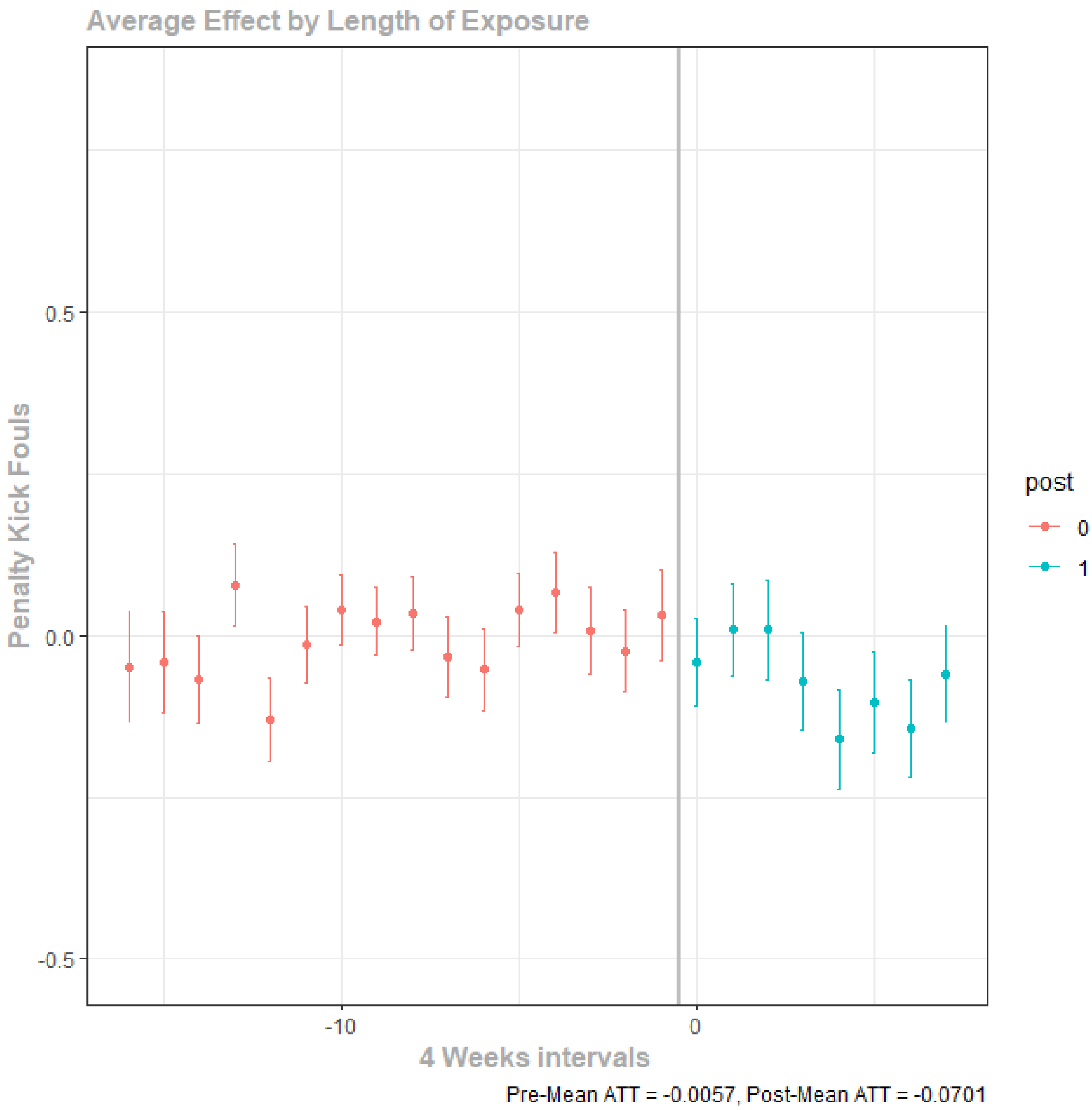
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The player-level data covers all games in 2015-2018 for the Champions League and the Europa League *VAR* indicates if the player participated in a game with VAR at least once before the current game. *20 Games with VAR* takes the value of 1 if a player participated in at least 20 games with VAR before the current game. I include fixed effects of year, player, competition, opposing team, position of the player, and stage of the tournament. Player clustered standard errors in parentheses.

but also the mistakes of other players.

1.A Appendix

Figure 1.A1: Parallel Pre-Trends: Penalties



Notes: The vertical grey line corresponds to the introduction of VAR in the 2017-2018 Bundesliga season. Each point with confidence intervals refers to a 4 game (weeks) period. I show four-week intervals as the deterrence pattern becomes noticeable after the 12th game in the season

Chapter 2

Winning Culture, Winning Future: Early Success and Long-Run Performance[1]

2.1 Introduction

The initial stages of a professional career are crucial in shaping long-term income, job satisfaction, and productivity. This formative period is influenced by a myriad of factors, including the work culture, the quality of mentorship and leadership, and the opportunities available for skill and personal development. In this complex landscape, individual performance is not merely a reflection of innate talent or skill but is also significantly shaped by these external factors. In particular, a more nurturing environment around an individual can boost professional growth (e.g., Kahn, 2010; Oreopoulos et al., 2012). Furthermore, the presence of a team leader can also profoundly influence an individual's development (e.g., Allen et al., 2004; Kram, 1985). A good mentor provides guidance and knowledge, sets a standard of excellence, and fosters an environment conducive to growth. Similarly, the characteristics of one's peers within a team or organization can have a significant impact (e.g., Sacerdote, 2001; Zimmerman, 2003). Working alongside skilled and motivated colleagues can inspire and challenge an individual, enhancing learning and performance. This study explores how these early-career environmental attributes, including team success, quality of leadership, and peer influence, shape an individual's long-term performance.

[1]**Co-authored with Aizhamal Rakhmetova (CERGE-EI)**

We investigate the influence of three key factors that National Basketball Association (NBA) players encounter in their first season and how these factors affect their long-term performance in the league. Our analysis is supported by a rich and detailed dataset, unique in its consistent and objective performance metrics measured across each player's entire career. This level of data detail is rarely achievable in related literature due to the lack of granularity and consistently-measured productivity metrics over the long term. Using data from the NBA, we examine the impact of the number of team wins in a player's first season, the career wins accumulated by their head coach before the player's first season, and the presence of a 'star' player on the team. Our study exploits a natural experiment provided by the NBA draft lottery system, allowing us to isolate the effects of this early experience on long-term player performance. This approach enables us to understand how the early-career professional environment shapes players' future trajectory and success in the NBA.

We apply an instrumental variable (IV) strategy to identify the effects of these three key variables distinctly. Our approach centers on exploiting the inherent randomness of the NBA draft lottery system, which impacts the allocation of new players to diverse initial environments. The expected draft order is usually determined by the reverse order of team standings from the previous season, meaning the team with the worst record is expected to pick first [2]. However, this order may vary due to the lottery and other factors like pick transfers. As a result, successful teams might occasionally secure top picks and choose the most promising players, while struggling teams might end up with lower picks. Our instrumental variable is the difference between a team's expected and actual draft order which is purely determined by the team's "luckiness" in the lottery. This method allows us to effectively isolate and examine the influence of each variable on a player's long-term performance in the league.

First, our research focuses on the influence of early-career team success on long-term individual performance. While existing studies primarily emphasize immediate outcomes, such as initial earnings or job placement rates (e.g., Audia et al., 2000; Bol et al., 2017), our approach extends to examining the impact on performance and career trajectory over a more extended period. Additionally, much of the current literature concentrates on how individual achievements affect future performance, often overlooking the role of a team's

[2] A "pick" is a team's right to select a player during the draft. Picks are numbered (e.g., first pick, second pick, third pick, etc.), and the team with the first pick has the right to choose any eligible player first, followed by the team with the second pick, and so on.

success and the overall organizational culture. Our findings indicate that the number of wins a player's team secures in his first season significantly enhances his performance five years later.

Second, our study explores the impact of coaching and mentorship on an individual's long-term performance. While numerous studies have delved into the influence of mentorship (e.g., Olivero et al., 1997; Serrat, 2017), they primarily focus on subjective outcomes such as job satisfaction or wages, often bypassing the direct impact on performance. This oversight partly stems from the challenges in consistently measuring performance over an extended period in real-world settings. Furthermore, existing research treats mentorship homogeneously, without distinguishing between varying mentor experience levels or success.

We exploit a precise, quantifiable measure of coach success, namely the number of NBA wins accumulated before the player's debut season. This approach allows us to differentiate between coaches based on their track records. Our findings indicate that having a coach with more accumulated wins early in player's career translates into significant and enduring improvements in a player's performance metrics. This highlights the critical role successful coaching plays in shaping long-term career trajectory.

Third, our study examines the impact of playing alongside a high-performing peer - specifically, whether a rookie's team included a player ranked in the top 15 in the previous season - on a rookie's long-term performance.[3] Contrary to the commonly observed positive effects of peer influence (e.g., Bandiera et al., 2010; Mas & Moretti, 2009), we find no significant difference in the long-term performance of players who played their first season with a 'star' player compared to those who did not. This could be attributed to factors such as the critical role of teamwork in basketball, competitive dynamics among players, or the limited influence of just one year of exposure to a top player. We explain this more thoroughly in the Results section.

2.2 Literature Review

A considerable body of the literature exists on the determinants of long-term career success, often focusing on factors including education, skills, and social networks.

[3]In this context, a "top-15 player" refers to a player who was included in the "All-NBA" first, second, or third team in the previous season. The "All-NBA Team" is an annual NBA honor awarded to the best players in the league following every NBA season. The voting is conducted by a panel of sportswriters and broadcasters throughout the United States and Canada.

However, the fewer studies have examined influence of the early-career environment on long-term professional outcomes. Research in labor economics studies how initial job placements, mentorship, and the quality of first jobs impact future earnings and job satisfaction (e.g., Oreopoulos et al., 2012; Kahn, 2010). Nevertheless, existing studies primarily concentrate on monetary outcomes, neglecting the long-term impact on performance.

Another strand of literature investigates the psychological and performance-related impacts of individual success or "winning" early in one's career, and the results are mixed. Some studies show that winning early increases motivation and promotes risk-taking, which may reinforce future success (e.g., Audia et al., 2000; Bandura, 1977; Bol et al., 2017). On the other hand, some research suggests that early success may also lead to complacency or overconfidence (Isidore & Christie, 2019; Kansal & Singh, 2018), which could have detrimental effects on future performance (e.g., Malmendier & Tate, 2005; Camerer & Lovallo, 1999). While these studies offer insights into the impact of individual successes, they often do not account for the surrounding team or organizational culture in which these wins occur.

Peer effects have been extensively studied across various domains, from education to workplace settings. For example, studies within academic environments have shown that high-achieving peers can elevate an individual's performance (e.g., Sacerdote, 2001; Zimmerman, 2003). In professional contexts, the presence of high-performing colleagues or mentors can lead to improved learning, motivation, and performance overall (e.g., Bandiera et al., 2010; Mas & Moretti, 2009).

The next area of interest in our study - mentorship - also receives plenty of attention in the literature, which shows various positive impacts. These range from improved job performance, career satisfaction, and commitment to the organization to enhanced professional identity and expanded networks (e.g., Allen et al., 2004; Kram, 1985; Olivero et al., 1997; Serrat, 2017; Shang et al., 2022). However, many of these studies rely on self-reported benefits, potentially introducing bias.

A handful of studies in sports economics have ventured into understanding career longevity and performance metrics (e.g., Berri & Krautmann, 2006; Leeds & von Allmen, 2014). These investigations often focus on factors including player skills, injuries, and contracts but tend to overlook the influence of team environment, particularly in the crucial early years of a player's career. However, the impact of early team success has received limited attention.

The remainder of this paper is organized as follows: In Section 3.2, we provide background information on the NBA and its draft lottery system, emphasizing its utility as a natural experiment for our study. Section 3.3 describes the dataset sourced from Basketball-Reference.com, elaborating on the variables and performance metrics under consideration. Our identification strategy, which hinges on the quasi-random variation introduced by the NBA Draft Lottery system, is articulated in Section 2.5. We present our core findings in Section 3.5, diving into the impact of early team wins, the significant role of coaches, and the nuanced influence of playing alongside a star player during the initial season. Lastly, Section 3.6 concludes the paper, synthesizing our findings and drawing broader implications for the sports industry and the general labor market.

2.3 Background

We exploit the setting of the National Basketball Association (NBA) to test our hypothesis. The NBA - the world's leading basketball league with a long history - consists of 30 teams from the USA and Canada. It employs a particularly interesting system of allocating new players accross teams, namely the draft lottery. The system includes randomness in the process, which is beneficial for identifying causal relationships.

The draft lottery mechanism involves a randomizer - a ping-pong ball machine. The balls are drawn to create a unique combination of numbers. Teams are assigned a set of these combinations based on their records from the previous season. The worse a team's record, the more combinations it can receive. For instance, the team with the worst position in the table might have a 14% chance of their combination being drawn first, while a better-performing team might have a 12.5% chance. This equalizes the teams to smooth out the previous season's results and effectively introduces progressive taxation.

Historically, this system has led to surprising outcomes. Interestingly, in the 2019 NBA Draft, the New Orleans Pelicans secured the top pick despite having only a 6% chance, eventually selecting Zion Williamson, one of the best prospects of the last decade. On the other hand, teams with the worst records have sometimes ended up with lower picks, adding a quasi-random element to allocating young talent across varying team environments.

The introduced randomness is crucial to our identification strategy. By serving as an exogenous source of variation in which players start their careers, this randomness allows us to isolate the impact of early-career environments on long-term performance.

In essence, the draft lottery system offers a natural experiment to study how varying levels of early-career success - often reflected in team wins during a player's first season - affect long-term career outcomes.

It is important to note that NBA teams generally possess an excellent ability to evaluate future talent, particularly for top draft picks (see Figure 2.1). For instance, there was a consensus in the 2019 NBA Draft that Zion Williamson would be the first player selected, regardless of which team secured the first pick. This suggests that a known or assumed ranking of new players within the NBA is often based on their projected future performance. This ability to effectively rank players, especially at the top of the draft, gives further credibility to our identification strategy. It allows us to control for individual talent levels while focusing on the quasi-randomness introduced by the draft lottery system.

2.4 Data

We utilize data from Basketball-Reference.com, which provides a comprehensive set of statistics spanning the early years of the NBA. For this study, we focus on data from 2000 to 2022 period, including draft information as well as player and team characteristics for each season. Our sample includes only players drafted in the first round, a total of 30 players per year. With approximately 30 players drafted annually over 20 years, this selection results in a sample size of around 600 observations.

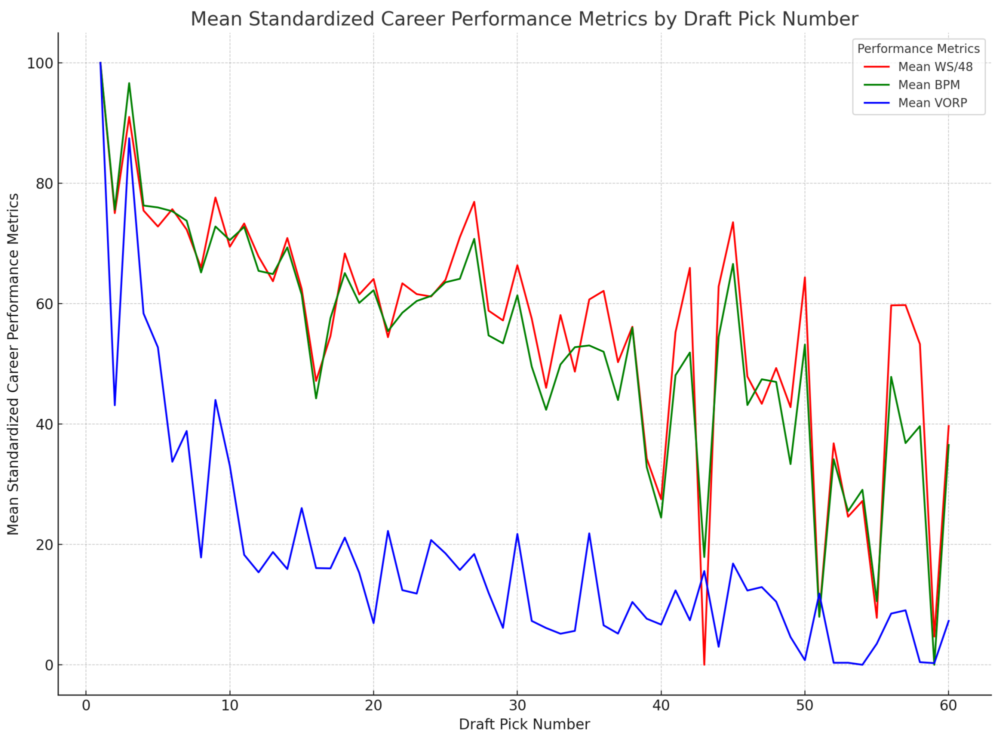
We collect individual statistics for the above mentioned period including the number of points, assists, rebounds, as well as advanced metrics including Box Plus/Minus (BPM), Win Shares per 48 minutes (WS/48), and Value Over Replacement Player (VORP). Considering multiple player performance metrics allows us to build a wider picture of the impact of early career success on individual performance.

The draft data includes information on the sequential order ("pick number") in which players were selected during the NBA Draft. This variable is central to our study as it indicates initial expectations surrounding a player's potential.

We also use team-level statistics to evaluate the team environment in which players start their careers. These statistics include season-by-season performance measures, including win-loss records, which help us to identify the 'winning culture' in which a player is initially embedded.

Our study focuses on four individual performance metrics, which we describe in de-

Figure 2.1: Players' Performance by Draft Pick



Notes: WS/48: Win Shares per 48 minutes is a performance measure that estimates the number of wins a player contributes per 48 minutes. Higher values signify greater contributions to team success. BPM: Box Plus/Minus is a box score-based metric that measures a player's contribution to a team when that player is on the court, compared to an average player. Positive values indicate above-average contributions, while negative values indicate below-average contributions. VORP: Value Over Replacement Player calculates the points a player contributes over a replacement-level player per 100 team possessions. It serves as an estimate of the player's overall contribution to team wins. All metrics are standardized to have a minimum value of 0 and a maximum value of 100 to facilitate easier comparison between different metrics. Draft Pick Number represents the sequential order in which players are drafted. Lower numbers indicate earlier draft picks, often signifying higher expectations for performance.
Source: Authors' calculation based on basketball-reference.com

Table 2.1: Summary Statistics

Variable	N	Mean	Std Dev	Min	25%	Median	75%	Max
Avg WS	590	0.00	0.06	-1.17	0.00	0.00	0.02	0.33
PER	599	13.18	4.52	-14.65	10.62	12.94	15.69	27.39
TS	599	0.52	0.06	0.00	0.49	0.53	0.55	0.72
VORP	590	0.14	0.34	-0.90	-0.01	0.06	0.20	3.30
N. of Seasons	599	6.16	2.66	1.00	4.00	6.00	9.00	9.00
Wins Before Draft	599	37.35	12.28	7.00	28.00	38.00	47.00	67.00
Draft Pick	599	14.93	8.32	1.00	8.00	15.00	22.00	29.00
First Season Wins	553	37.40	12.09	7.00	27.00	37.00	47.00	67.00
Draft Luck	599	-1.43	6.69	-27.00	-2.00	0.00	1.00	25.00

Notes: This table outlines summary statistics for key variables used in the regressions. "Average Win Shares" quantifies the player's contribution to team wins. "Player Efficiency Rating" is a measure of a player's per-minute productivity. "True Shooting Percentage" accounts for field goals, 3-point field goals, and free throws. "Value Over Replacement Player" measures the value a player adds over a replacement-level player. "Number of Seasons" indicates the player's career length. "Wins Before Draft" shows the drafting team's wins in the prior season. "Draft Pick Number" indicates the order in which the player was drafted. "First Season Wins" is the number of team wins in the player's first season. "Draft Luck" quantifies the deviation from the expected draft pick based on team performance.
Source: Authors' calculation based on basketball-reference.com

tail below and support with exact formulas in the Appendix. Win Shares is a player statistic that allocates team performance across individual players participating in the game (Oliver, 2004). It is calculated using player, team, and league-wide statistics (see Appendix 2.A.2 for calculations). The formula considers offensive win shares, defensive win shares, and marginal win shares. The metric is designed to isolate individual contributions and capture how many wins a player contributed to the collective success.

The Player Efficiency Rating is a per-minute metric that sums up various player's positive metrics, subtracts the negative ones, and returns a one number result (Hollinger, 2005). Since it is a normalized metric, it captures the efficiency of players even if they do not receive a high number of minutes on the court, which is relevant for new players (see Appendix 2.A.3 for calculations).

True Shooting Percentage is a purely individual metric that relies the least on other players' performance. It includes all kind of shots (3-point, 2-point, and free throws) making it a more complete and meaningful depiction of shooting efficiency than field goal percentage. The formula is $\text{TS\%} = \frac{\text{PTS}}{2(\text{FGA}+0.44\times\text{FTA})}$. Again, this metric reflects an individual's efficiency rather than the team's performance.

Value Over Replacement Player is a metric that estimates a player's contribution in comparisson to a "replacement-level" player, who is defined as a player on the minimum salary or not a regular starter. VORP is based on Box Plus/Minus (another advanced metric) and accounts for a player's minutes played (see Appendix 2.A.4 for calculations). The higher the VORP, the more a player contributes to team wins, above that which a replacement player would provide. The metric can effectively distinguish individual performance from team success.

2.5 Identification Strategy

Our identification strategy seeks to discern the causal impacts of multiple factors on a player's long-term performance development: early team success (measured by wins in the first season), the accumulated experience of a player's coach (quantified by their previous career wins), and the influence of sharing the court with a star player during a player's first season.

Our instrument capitalizes on the quasi-random variation introduced by the NBA Draft Lottery system. The instrument captures the difference between the expected draft order, based on team performance from the previous season, and the actual draft order post-lottery (see Table 2.2). Given the design of the draft lottery mechanism as a random process independent of player ability or future potential, this "luck" variable is exogenous. Moreover, it strongly correlates with first-season team wins, coach wins, and top player presence, making it a relevant instrument to isolate the causal effect of the early-career environment on future performance. Table 2.3 presents the first-stage results for all variables of interest. The instrument achieves a statistically significant level of 1% for each variable, indicating strong predictive power.

Table 2.2: Luck Variable Example

Team	Last Season Place	Exp. Draft Order	Actual Draft Order	Luck
Brooklyn Nets	30	1	3	-2
Orlando Magic	29	2	6	-4
Los Angeles Lakers	28	3	2	1
Boston Celtics	27	4	1	3

We define long-term performance as the average annual growth in key performance metrics (Win Shares, Player Efficiency Rating, True Shooting Percentage, and Value Over Replacement Player) over the first five years of an NBA player's career. These metrics are crucial as they reflect the evolution or decline of a player's skill set and overall impact in the league. This approach allows us to capture the enduring effects of his initial professional experience.

We acknowledge the potential 'reflection problem' in our analysis. This problem arises from the possibility that a new player's performance might influence the number of wins his team achieves in the first season, leading to a circular cause-and-effect relationship. It is important to note that rookies generally play a limited role in their teams, rendering their direct impact on team wins relatively minor. To further address this concern and avoid misinterpretation, our approach excludes the first season's performance from the dependent variables in models assessing the impact of first-season team wins. Focusing on the average growth in performance metrics from the second to the fifth seasons effectively circumvents the reflection problem and ensures a more accurate long-term performance analysis.

Another key concern in our identification strategy is that the probability of a team selecting a better player could be influenced by the team's performance in t-1 . Stronger teams may have a systematic advantage in scouting and evaluating players, which could introduce endogeneity into the instrument. To address this, we include team fixed effects and draft pick fixed effects in our models, which control for unobserved heterogeneity in team capabilities and the inherent advantages associated with specific draft positions. Moreover, we explicitly include team performance in t-1 as a control variable. This ensures that our instrument remains valid by isolating the random variation introduced by the draft lottery from any systematic differences tied to a team's prior performance.

A further concern stems from the fact that only the first 14 draft picks are determined by the lottery system, while subsequent picks are assigned in reverse order of team performance. This might suggest that the instrument's randomness is restricted to the top 14 picks. However, substantial random variation remains due to long-term draft pick trades. For instance, teams often trade players in exchange for draft picks that may only be exercised several years later, with no clear knowledge of the future draft class or their own team's future performance. This uncertainty introduces an additional layer of exogeneity to draft outcomes. By incorporating these trades into our analysis, we ensure that the "luck" variable captures meaningful random variation across the full spectrum of draft picks, bolstering the robustness of our identification strategy.

Another potential challenge arises from the endogenous selection of players into teams, which could bias the estimated effects of early-career environments on long-term performance. For example, certain teams may disproportionately select players based on specific attributes or perceived potential. The "luck" variable, constructed as the difference between the expected and actual draft order, mitigates this issue by exploiting the quasi-random variation introduced by the NBA draft lottery. This variable is independent of player characteristics and team preferences and only captures the randomness inherent in the lottery process.

To assess the relationship between these early-career factors and long-term performance, we employ a two-stage least squares (2SLS) regression model. In our models, the variable of interest, X, can represent early team wins, accumulated coach wins, or the presence of a star player in the debut season.

Stage 1:

$$X_i = \alpha + \gamma \cdot \text{luck}_i + \text{W}_i'\delta + \theta_{\text{team}} + \lambda_{\text{pick}} + \epsilon_i$$

Stage 2:

$$\text{Performance}_i = \beta \cdot \hat{X}_i + \text{Z}_i'\phi + \eta_{\text{team}} + \omega_{\text{pick}} + \mu_i$$

Here, the variable of interest, X, can represent the number of wins a player experienced with the team in his first season, the number of wins in the NBA a player's head coach accumulated before the player's first season, or a dummy variable identifying if the roster of the player's team in the first season included a top-15 player. Performance_i signifies the average annual growth of the four performance metrics described in the previous section over the first five seasons for player i. We exclude the first season if X is the number of team wins in the first season. W_i and Z_i are vectors of control variables, with θ_{team} and η_{team} as team fixed effects. λ_{pick} and ω_{pick} serve as a player's draft pick number fixed effects, which is a proxy for the rank of the player.

The "luck" variable serves as an instrumental variable for X, given its exogeneity and relevance. Using this instrumental variable approach, we aim to isolate the causal effect of early-career environments, represented by X, on the long-term performance progression of NBA players.

2.6 Results

In this section, we outline the main findings of our study. We start by examining the impact of early success, represented by the number of wins a player's team achieves in his first NBA season. Subsequently, we explore the influence of a coach's prior successes

Table 2.3: IV First Stage Regressions

	Team Wins	Coach Success	Top Peer
	(1)	(2)	(3)
Luck	0.381***	12.961***	0.011***
	(0.095)	(2.799)	(0.004)
Controls	Y	Y	Y
Team FE	Y	Y	Y
Draft Pick FE	Y	Y	Y
Observations	354	354	354
Note:		*p<0.1; **p<0.05; ***p<0.01	

Notes: Each column represents a different variable of interest of this study. Team Wins is the number of wins the player's team achieved in his first season. Coach Success is the number of player's coach NBA wins before player entered the league. Top Peer is a dummy variable that equals 1 if player's team included a top-15 NBA player (according to All-NBA vote in the previous season). All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses.

on player performance, quantified by coaches' career wins in the NBA. Finally, we assess the role of playing alongside a star player during the first season in the NBA. For each of these factors, we consider their effects on four key performance metrics: True Shooting Percentage (TS), Win Shares (WS), Player Efficiency Rating (PER), and Value Over Replacement Player (VORP).

2.6.1 Early Winning

Main Results

The results from Table 2.4 shed light on the significant impact of the early winning experience on the long-term performance of NBA players. This table presents four regressions, each representing a different performance metric (TS, WS, PER, VORP).

Our findings suggest that the number of wins a player's team achieves during his first season has a statistically significant positive effect on all four performance metrics (PER and VORP marginally significant). Specifically, for each additional win in the debut season, the annual growth in True Shooting Percentage increases by 0.003 ($p < 0.05$), in Win Shares rises by 0.003 ($p < 0.05$), in Player Efficiency Rating increases by 0.199 ($p < 0.1$), and in VORP increases by 0.015 ($p < 0.1$). All the effects are approximately 0.05 standard deviations, which is substantial since the number of wins in the first season varied in the sample from 7 to 72. We also analyze specifications with various sets of fixed effects as robustness check (see Appendix 2.A.5).

Several potential mechanisms might explain the result. First, psychological factors could be at play. Winning early in one's career can positively affect a player's mental state, enhance self-confidence and reduce performance anxiety. Second, elevated testosterone and dopamine levels triggered by positive experience of winning can also boost efficiency of training sessions, which is particularly beneficial for rookies still adapting to NBA rigors. Third, the experience of winning itself can be educational. It exposes players to correct strategies, teamwork, and plays that lead to success, effectively fast-tracking their learning curve. It is also worth mentioning that early wins are impactful for players and can signal teams and coaches to recognize potential talent and invest further in the development of players.

Table 2.4: The Impact of Early Winning on Long-Term Performance

	TS	WS	PER	VORP
	(1)	(2)	(3)	(4)
First Season Wins	0.003**	0.003**	0.199*	0.015*
	(0.001)	(0.002)	(0.105)	(0.008)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	553	547	553	547

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: Each column represents a different performance metric for NBA players. TS is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. First Season Wins is the number of wins the player's team secured during his first season in the NBA. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses.

Heterogeneity

This section describes the nuanced effects of early team success on long-term performance across different subsets of NBA players, specifically focusing on nationality and age at draft. Through a heterogeneity analysis, we aim to uncover whether positive impacts of early career wins vary among players, offering a richer understanding of how specific contexts influence professional development trajectories.

Table 2.5 investigates the interaction between a player's nationality (US-born or not) and the number of wins in his first NBA season. The findings indicate a significant interaction effect for True Shooting Percentage (TS%) and Player Efficiency Rating (PER), suggesting that non-US players benefit more from early team success compared to their US-born counterparts. Specifically, negative coefficients for the interaction terms in TS% and PER imply that the positive impact of first-season wins on these performance metrics is less pronounced for US-born players. This disparity could be attributed to several factors, including differences in prior exposure to competitive basketball, cultural adjustments, and variations in support systems available to players based on their nationality. Non-US players might experience a steeper learning curve upon entering the NBA, making the positive reinforcement from early career wins more impactful for their development.

Table 2.6 explores the interaction between players' age at the time of the draft (specifically distinguishing players older than 22[4]) and first-season team wins. The analysis reveals that the direct impact of first-season wins on Win Shares (WS) and Value Over Replacement Player (VORP) remains consistently positive. The presence of positive significant coefficients for the interaction term in WS and PER hints that older players might benefit more from early team successes compared to their younger peers. This difference could be due to older players being more experienced and thus more affected by the to influences of their initial NBA environment.

The heterogeneity analysis underscores the complex interplay between a player's background characteristics and his professional development within the NBA. The findings suggest that external factors such as nationality and age at entry can moderate the benefits derived from early career successes. For non-US players, early wins appear to be particularly beneficial, potentially due to their different paths to the NBA and the need to adjust to a new competitive and cultural environment. Similarly, there is an indication that older players may slightly benefit more from positive early-career experience.

[4]Median age in the sample.

Table 2.5: The Impact of First Season Wins Varies Based on Nationality

	TS %	WS	PER	VORP
	(1)	(2)	(3)	(4)
F. Season W	0.003**	0.003**	0.222**	0.010*
	(0.001)	(0.001)	(0.096)	(0.006)
F. Season W X US	−0.002*	−0.001	−0.131**	−0.002
	(0.001)	(0.001)	(0.065)	(0.004)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	553	547	553	547
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Each column represents a different performance metric for NBA players. TS % is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Coach Wins is the number of wins the coach of the player in the first season won in NBA prior to this season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses. Additionally, we include the interaction term of a US-born dummy with the number of first season wins.

Table 2.6: The Impact of Early Wins Varies Based on Age

	TS %	WS	PER	VORP
	(1)	(2)	(3)	(4)
F. Season W	0.002	0.002**	0.110	0.009*
	(0.001)	(0.001)	(0.085)	(0.005)
F. Season W X Age>22	0.001	0.003**	0.149*	−0.002
	(0.001)	(0.001)	(0.085)	(0.005)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	553	547	553	547
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Each column represents a different performance metric for NBA players. TS % is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Coach Wins is the number of wins the coach of the player in the first season won in NBA prior to this season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses. Additionally, we include the interaction term of a dummy that takes value 1 if player is older than 22 while being drafted with the number of first season wins.

2.6.2 Coach Experience

Main Results

The results depicted in Table 2.7 delve into the influence of coach success on the long-term performance metrics of NBA players. The table features four different models, each focusing on the same four performance indicators.

The number of wins achieved by a player's coach in past NBA seasons before the player's first season seems to significantly impact three out of four performance metrics. Specifically, for each extra win in the coach's career before the player's first season, the annual growth in True Shooting Percentage increases by 0.0001 ($p < 0.05$), in Win Shares rises by 0.0001 ($p < 0.05$), and in the Player Efficiency Rating improves by 0.008 ($p < 0.05$). While the per-win impact may seem small, it is crucial to remember that these coaches often have hundreds of career wins. When looking at a coach with 300 career wins, the incremental effects can translate into a notable advantage for a player: a 0.03 increase in True Shooting Percentage, a 0.03 increase in Win Shares, and a 2.4 increase in Player Efficiency Rating. These effects would be similar to ten additional wins in the first season according to the results from Table 2.4.

Several plausible mechanisms might explain this relationship. Firstly, a successful coach often has substantial experience and strategic insight, which can be invaluable for young players. Exposure to effective strategies, training regimes, and in-game decision-making can enhance a player's skills, offering a smoother transition into the league. Secondly, a winning coach can set a culture of excellence, instilling in young players attitudes, work ethics, and teamwork skills conducive to long-term success. Such a culture can have a 'ripple effect', benefiting not just individual players but the entire team. Last, it may be that successful coaches have more resources to invest in player development, amplifying the positive effects of their winning records.

Heterogeneity

Our analysis of heterogeneity in the impact of coach experience on player performance further elucidates how diverse player backgrounds modulate benefits derived from experienced coaching. By examining the interaction between coach wins and players' nationality (US-born versus non-US players) as well as their age at the draft, we uncover insights into the dynamics of professional development within the NBA. These findings complement our understanding of how early career environments, specifically the influence of a coach's

Table 2.7: The Impact of a Successful Coach on Long-Term Performance

	TS	WS	PER	VORP
	(1)	(2)	(3)	(4)
Coach Wins	0.0001**	0.0001**	0.008**	0.0004
	(0.0001)	(0.0001)	(0.004)	(0.0003)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	581	573	581	573
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Each column represents a different performance metric for NBA players. TS is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Coach Wins is the number of wins the coach of the player in the first season won in NBA prior to this season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses.

prior success, shape long-term player performance.

Table 2.8 examines how a coach's past successes impact players differently based on nationality. In contrast to heterogeneity results of early winning, there appears to be no significant differentiation in the effect of coach experience on player performance when comparing US-born players to their non-US counterparts. The interaction terms between coach wins and player nationality for all performance metrics are statistically insignificant. This outcome suggests that the beneficial influence of experienced coaching on player development offers a universal advantage to players regardless of their origin. It implies that the knowledge, strategy, and mentorship provided by a seasoned coach are equally valuable to all players, potentially leveling the playing field in terms of developmental opportunities afforded by coaching, irrespective of a player's nationality.

Table 2.9 examines the interaction between coach wins and the age of players at the time of drafting (specifically, those aged 22 or older). The interaction term for Player Efficiency Rating (PER) is both positive and statistically significant, hinting at a marginal propensity for older players to benefit more from experienced coaching in terms of efficiency on the court. This finding is consistent with previous results of early winning and suggests that older players may be in a better position to leverage the insights and guidance offered by seasoned coaches, potentially due to their greater maturity or prior experience that make them more receptive to high-level mentorship.

The findings from this heterogeneity analysis reveal that the benefits of experienced coaching in the NBA are broadly applicable across different player demographics, with limited evidence to suggest significant variations based on nationality or age. The lack of differentiation based on nationality reinforces the value of skilled coaching as a universal tool for player development, emphasizing the importance of investing in knowledgeable and experienced coaching staff to foster talent across the board.

The slight advantage observed for older players in terms of efficiency gains under experienced coaching could indicate the importance of targeting and tailoring coaching strategies to unique needs and receptiveness of players at different stages of their career. While the effects are not drastic, they underscore the potential for specific coaching approaches that consider the individual backgrounds and experience of players to maximize their development and performance outcomes.

Table 2.8: The Impact of Coaching X Nationality

	TS %	WS	PER	VORP
	(1)	(2)	(3)	(4)
Coach Wins	0.0001^{**}	0.0001	0.007^{*}	0.0003
	(0.0001)	(0.0001)	(0.004)	(0.0003)
Coach Wins X US	−0.00001	0.00004	−0.0004	0.0002
	(0.00003)	(0.00003)	(0.002)	(0.0002)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	581	573	581	573

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a different performance metric for NBA players. TS % is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Coach Wins is the number of wins the coach of the player in the first season won in NBA prior to this season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses. Additionally, we include the interaction term of the US-born dummy with the number of coach wins.

Table 2.9: The Impact of Coaching X Age

	TS %	WS	PER	VORP
	(1)	(2)	(3)	(4)
Coach Wins	0.0001	0.0001**	0.005	0.0004
	(0.00005)	(0.0001)	(0.004)	(0.0003)
Coach Wins X Age>21	0.00003	0.00000	0.004**	0.0001
	(0.00003)	(0.00003)	(0.002)	(0.0001)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	581	573	581	573

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a different performance metric for NBA players. TS % is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Coach Wins is the number of wins the coach of the player in the first season won in NBA prior to this season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses. Additionally, we include the interaction term of a dummy that takes value 1 if player is older than 21 while being drafted with the number of coach wins.

2.6.3 Presence of a 'Star'

Table 2.10 explores the potential impact of having a star player - defined as one of the top 15 players in the league - on a team during a player's first season. The variables examined are the same as in the previous tables: TS, WS, PER, VORP.

Contrary to the existing literature on peer effects, the presence of a star player in the debut season does not yield statistically significant results in affecting long-term performance metrics, except for marginal significance in Win Shares ($p < 0.1$). It is possible that the influence of a star player is not as straightforward as one might assume. For example, while a star player may offer a wealth of experience and skill, his dominating presence could overshadow the development of a new player or even contribute to a more rigid team dynamic that does not facilitate the growth of new talent.

This discrepancy in our findings compared to the existing literature may be attributed to the unique dynamics of basketball, which demands a high level of teamwork for success. Unlike many studies focusing on individual performance metrics - such as academic achievements that rely on personal abilities to excel in exams - basketball's success relies on effective team collaboration. The 'top player' in our study is identified based on individual performance metrics, which do not necessarily reflect their ability to collaborate or enhance team play. This distinction is crucial, as it suggests that mere the presence of a top individual performer in a team does not automatically translate into effective mentorship or positive peer effects for new players.

Another critical factor is the competitive nature of basketball, particularly regarding playing time. Rookies need more time on the court, which unavoidably create a competitive environment with established players, possibly limiting opportunities for mentorship and guidance. This competitive dynamic can impact the potential positive influence of top-performing players on rookies.

Moreover, our study differs from the literature in its temporal perspective. While most studies assess the immediate spillover effects of high-performing peers, our analysis examines the long-term impact. In our context, the 'treatment' - exposure to a star player - occurred in the past, and its effects are measured five years later. This raises the possibility that either continuous interaction with a top performer is essential or that a single year of exposure may not be sufficient to produce a lasting impact on a player's performance.

Table 2.10: The Impact of a Star Player on Long-Term Performance

	TS	WS	PER	VORP
	(1)	(2)	(3)	(4)
Star Presence	0.107	0.123*	8.031	0.511
	(0.069)	(0.071)	(5.329)	(0.341)
Controls	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Draft Pick FE	Y	Y	Y	Y
Observations	516	511	516	511
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Each column represents a different performance metric for NBA players. TS is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. WS represents Win Shares, an estimate of the number of wins contributed by a player. PER is the Player Efficiency Rating, a measure of a player's per-minute productivity. VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. Star presence is a dummy variable for playing with top-15 player in the league in the first season. All models include control variables such as player age, height, and college experience. Team Fixed Effects (FE) and Draft Pick Fixed Effects (FE) are included to account for team-level and pick-level heterogeneity. Standard errors are reported in parentheses.

2.7 Conclusion

This study explores the long-term impact of early-career environments on NBA players' performance metrics. We scrutinized three crucial factors: early team wins, coaching experience, and the presence of a star player during the first season. Our investigation reveals that early-career environments have a substantial influence on a player's long-term performance.

The number of wins in the first season positively affects all examined metrics. These findings echo broader labor market evidence that suggests the initial years of a professional career can set the stage for future success: choosing a successful team can boost worker's long-term performance.

Similarly, we find that the experience of a coach, measured by career wins, significantly affects player performance. This can be extended beyond the sports realm to emphasize the pivotal role experienced leadership can play in any profession.

Intriguingly, our results counter the established evidence of positive peer effects. Merely playing alongside a star player in a player's first year does not boost long-term performance metrics. This adds a layer of complexity to our understanding of professional development.

This research adds to the growing evidence that early-career environments have long-lasting impacts on performance metrics. It highlights the importance of a nurturing early-career environment and experienced mentorship.

2.A Appendix

2.A.1 Common NBA Abbreviations

In the National Basketball Association (NBA) context, several abbreviations are commonly used to denote various statistics and metrics. Below is a list of some of these critical abbreviations and their meanings:

PTS: Points Scored.

TRB: Total Rebounds, encompassing both offensive and defensive rebounds.

DRB: Defensive Rebounds.

ORB: Offensive Rebounds.

AST: Assists, indicating the number of times a player passes the ball leading directly to a score.

STL: Steals represent the number of times a player takes the ball from an opponent.

BLK: Blocks, denoting the number of times a player prevents an opponent's shot from scoring.

TOV: Turnovers refer to losing ball possession without a shot attempt.

PF: Personal Fouls, indicating a player's number of personal fouls.

3P: Three-Point Field Goals Made.

FG: Field Goals Made, including both two-point and three-point field goals.

FGA: Field Goal Attempts denote the total number of field goal shots attempted.

FTA: Free Throw Attempts, representing the number of free throws attempted.

FT: Free Throws Made.

FGM: Field Goal Made denotes the total number of field goal shots made.

PF: Personal Fouls denote the personal number of fouls committed.

MP: Minutes Played.

lg: League prefix.

TM: Team prefix.

DR: Defensive Rating.

OR: Offensive Rating.

POS: Possessions.

2.A.2 Win Shares Calculation

Win Shares is a calculation that distributes credit for team success to individual players. It is divided into Offensive Win Shares (OWS) and Defensive Win Shares (DWS):

$$WS = OWS + DWS$$

Offensive Win Shares (OWS)

Offensive Win Shares are derived from a player's offensive production in context with the team's overall efficiency.

$$OWS = \frac{PointsProduced}{PointsPerWin}$$

Where PointsProduced is calculated as:

$$PointsProduced = \text{PTS} + \text{FGM} \times (\text{tmAST} \times \frac{2}{3}) + \text{FTM} - \text{FGA} - \text{TOV}$$

PointsPerWin is based on the league's average efficiency:

$$PointsPerWin = \frac{lgPTS}{lgWins} \times \frac{1}{\text{tmPace}}$$

Defensive Win Shares (DWS)

Defensive Win Shares are based on the team's defensive efficiency and the player's role.

$$DWS = \frac{1}{2} \times \text{tmGames} \times \frac{\text{DR}}{\text{lgDR}} \times \frac{\text{POS}}{\text{tmPOS}}$$

Where Player Defensive Rating can be calculated as:

$$PlayerDefensiveRating = \text{Individual Defensive Stops} + \text{Defensive Stops Share}$$

Individual Defensive Stops (IDS) can be estimated by:

$$IDS = \text{STL} + \text{BLK} \times \text{BLK Factor} - \text{PF} \times \text{PF Factor} + \text{DRB} \times \text{DRB Factor}$$

Defensive Stops Share involves the percentage share of team defensive stops a player is estimated to have taken part in, based on minutes played and the defensive rating.

2.A.3 Player Efficiency Rating (PER) Calculation

PER is calculated as follows:

$$\text{PER} = \left(uPER \times \frac{\text{lgPace}}{\text{tmPace}} \right) \times \frac{15}{\text{lguPER}}$$

where $uPER$ is calculated as:

$$\begin{aligned}
uPER =& \frac{1}{\text{MP}} \times \Bigg(3P - \frac{\text{PF} \times \text{lgFT}}{\text{lgPF}} + \left[\frac{\text{FT}}{2} \times \left(2 - \frac{\text{tmAST}}{3 \times \text{tmFG}} \right) \right] \\
& + \left[\text{FG} \times \left(2 - \frac{\text{fA} \times \text{tmAST}}{\text{tmFG}} \right) \right] + \frac{2 \times \text{AST}}{3} \\
& + \text{VOP} \times \Bigg[\text{DRBP} \times \Big(2 \times \text{ORB} + \text{BLK} - 0.2464 \times [\text{FTA} - \text{FT}] \\
& - [\text{FGA} - \text{FG}] - \text{TRB} \Big) + \frac{0.44 \times \text{lgFTA} \times \text{PF}}{\text{lgPF}} \\
& - (\text{TOV} + \text{ORB}) + \text{STL} + \text{TRB} - 0.1936\,(\text{FTA} - \text{FT}) \Bigg] \Bigg)
\end{aligned}$$

where,
$\text{fA} = \frac{2}{3} - \left[\left(0.5 \times \frac{\text{lgAST}}{\text{lgFG}} \right) \div \left(2 \times \frac{\text{lgFG}}{\text{lgFT}} \right) \right]$,
$\text{VOP} = \frac{\text{lgPTS}}{\text{lgFGA} - \text{lgORB} + \text{lgTO} + 0.44 \times \text{lgFTA}}$,
$\text{DRBP} = \frac{\text{lgTRB} - \text{lgORB}}{\text{lgTRB}}$.

2.A.4 Value Over Replacement Player (VORP)

The Value Over Replacement Player (VORP) is based on Box Plus/Minus (BPM), which estimates a player's performance per 100 possessions above a league-average player's. The formula for VORP is:

$$\text{VORP} = (\text{BPM} - \text{Replacement Level}) \times \left(\frac{\text{MP}}{\text{tmMP}} \right) \times \left(\frac{\text{tmGames}}{82} \right)$$

where,

BPM is the Box Plus/Minus.
Replacement Level is typically set at -2.0 in the NBA.

Box Plus/Minus (BPM) is a basketball box score-based metric that estimates a player's contribution to the team per 100 possessions played compared to a league-average player, translated to an average team. The formula for BPM is derived from a regression analysis and is as follows:

$$\begin{aligned}\text{BPM} =&a_1 \cdot (\text{PTS}) + a_2 \cdot (\text{TRB}) + a_3 \cdot (\text{AST}) + a_4 \cdot (\text{STL}) + a_5 \cdot (\text{BLK}) - a_6 \cdot (\text{TOV}) \\ &- a_7 \cdot (\text{PF}) + a_8 \cdot (\text{3P}) + a_9 \cdot (\text{FG}) - a_{10} \cdot (\text{FGA}) - a_{11} \cdot (\text{FTA}) + a_{12} \cdot (\text{FT})\end{aligned}$$

where $a_1, a_2, \ldots, a_{12}$ are coefficients derived from the regression model. The actual coefficients are obtained through a linear regression model that predicts the player's impact on the team's performance. These coefficients are updated regularly based on evolving player data and may differ from the ones used in the original BPM calculation. This formula also adjusts for pace and team context.

2.A.5 Robustness Checks

Table 2.A1: The Impact of Early Winning on Long-Term Performance

	TS	TS	TS
	(1)	(2)	(3)
First Season Wins	0.015***	0.002**	0.010
	(0.001)	(0.001)	(0.007)
Controls	Y	Y	Y
Team FE	N	N	Y
Draft Pick FE	N	Y	N
Observations	553	553	553
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: TS is the True Shooting Percentage, calculated as the number of points divided by twice the sum of field goal attempts and (0.44) times free-throw attempts. First Season Wins is the number of wins the player's team achieved in his first season. Model (1) includes only controls, model (2) includes controls and draft pick fixed effects, model (3) includes controls and team fixed effects. All models include control variables such as player age, height, and college experience. Standard errors are reported in parentheses.

Table 2.A2: The Impact of Early Winning on Long-Term Performance

	VORP	VORP	VORP
	(1)	(2)	(3)
First Season Wins	-0.002	0.009^{*}	0.046
	(0.002)	(0.005)	(0.036)
Controls	Y	Y	Y
Team FE	N	N	Y
Draft Pick FE	N	Y	N
Observations	547	547	547
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: VORP stands for Value Over Replacement Player, which estimates the point difference between a player and a replacement-level player per 100 possessions. First Season Wins is the number of wins the player's team achieved in his first season. Model (1) includes only controls, model (2) includes controls and draft pick fixed effects, model (3) includes controls and team fixed effects. All models include control variables such as player age, height, and college experience. Standard errors are reported in parentheses.

Table 2.A3: The Impact of Early Winning on Long-Term Performance

	PER	PER	PER
	(1)	(2)	(3)
First Season Wins	0.293***	0.148**	1.090
	(0.042)	(0.071)	(0.746)
Controls	Y	Y	Y
Team FE	N	N	Y
Draft Pick FE	N	Y	N
Observations	553	553	553
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: PER is the Player Efficiency Rating, a measure of a player's per-minute productivity.Team Wins is the number of wins the player's team achieved in his first season. Model (1) includes only controls, model (2) includes controls and draft pick fixed effects, model (3) includes controls and team fixed effects. All models include control variables such as player age, height, and college experience. Standard errors are reported in parentheses.

Table 2.A4: The Impact of Early Winning on Long-Term Performance

	WS	WS	WS
	(1)	(2)	(3)
First Season Wins	-0.001^{**}	0.002^{**}	0.010
	(0.0005)	(0.001)	(0.007)
Controls	Y	Y	Y
Team FE	N	N	Y
Draft Pick FE	N	Y	N
Observations	547	547	547
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: WS represents Win Shares, an estimate of the number of wins contributed by a player. First Season Wins is the number of wins the player's team achieved in his first season. Model (1) includes only controls, model (2) includes controls and draft pick fixed effects, model (3) includes controls and team fixed effects. All models include control variables such as player age, height, and college experience. Standard errors are reported in parentheses.

Chapter 3

Weather Shocks and Bride Kidnapping in Kyrgyzstan[1]

3.1 Introduction

Climate change is one of the most pressing global challenges of our time, with significant implications for the environment, the economy, and human well-being (IPCC, 2022). Developing countries are particularly vulnerable to the impacts of climate change, given their limited resources, weak infrastructure, and high dependence on natural resources (Hsiang & Kopp, 2018; IPCC, 2022). Therefore, understanding the implications of climate change for developing countries is crucial for policymakers, scholars, and practitioners alike.

Despite nature's impartiality, the consequences of climate change are not gender-neutral either. This is primarily attributed to discriminatory social norms, pre-existing gender inequalities in society, and unequal power relations between women and men (Rao et al., 2023; Reggers, 2019; Terry, 2009). Such factors make women more susceptible to the consequences of climate change (Oswald Spring, 2019; Reggers, 2019).

One of the ways women can be adversely affected by climate change is through increased incidents of harmful marriage practices. Banerjee et al. (2013) argue that the degree to which a country's marriage institutions favor men, such as patrilocality and concern for girl's "purity," can help explain low female labor-force participation, reduced

[1]**Co-authored with Aizhamal Rakhmetova (CERGE-EI)**

investment in female human capital, and a higher tolerance for gender-based violence. The economic literature already contains a lot of research on the effects of various climate shocks on one particular practice - child marriage (Pope et al., 2022). This literature shows that the effect of shocks on child marriage varies significantly depending on cultural contexts and norms. In societies where a bride price is customary (e.g. Vietnam and countries in Sub-Saharan Africa), such shocks can raise the likelihood of child marriage as families may consider selling their daughters to offset economic losses. Conversely, in societies where dowry is the norm (e.g. India), shocks can decrease the probability of child marriage as the girls' families may not have the resources to meet the requirements for the dowry (Corno et al., 2020; Tsaneva, 2020; Trinh & Zhang, 2021).

This paper studies another harmful marriage practice - bride kidnapping or marriage by capture, in which a man abducts the woman he wishes to marry. According to a report by the United Nations, several countries, including Kyrgyzstan, Kazakhstan, Armenia, Ethiopia, Georgia, Moldova, and Uzbekistan, among others, have documented cases of bride kidnapping (UN Women, 2018). Bride kidnapping poses significant dangers to the victims, including severe physical, psychological, and social consequences. It can result in forced marriage, sexual and physical violence, unwanted pregnancies, social isolation, and mental health issues. The United Nations considers bride kidnapping a form of violence against women and girls that infringes upon their human rights and can negatively affect their physical and mental well-being (UN Women, 2018). Despite being detrimental, bride kidnapping receives little to no attention in the larger gender economics literature.

Despite sharing the unfortunate label of harmful marriage practices, bride kidnapping presents a fundamentally different dynamic than child marriage. While child marriage often involves economic transactions where parents receive payments or benefits from the other side, bride kidnapping eliminates any such transaction. In the case of bride kidnapping, the abductor, the prospective husband, forcibly takes the woman he intends to marry without offering any form of compensation to her family. This absence of a transactional element accentuates the coercive nature of bride kidnapping, making it not just a financial arrangement but a stark violation of a woman's autonomy and consent. This distinction is essential as it influences societal attitudes and impacts the victims differently. Understanding these unique features of bride kidnapping enriches the analysis of its correlation with climate shocks, thereby enhancing the depth of the discussion on gender-specific repercussions of climate change.

Our study aims to contribute to this gap by examining how climate shocks affect incidence and attitudes towards bride kidnapping in Kyrgyzstan - a landlocked country in Central Asia that is highly vulnerable to climate change and also has the highest rates of bride kidnapping in the world (United Nations Population Fund (UNFPA), 2018). By addressing the existing gap in the literature, our study aims to add to a fuller understanding of how climate shocks can disproportionately affect women, particularly by exacerbating harmful marriage practices. Our research not only examines the actual incidence of bride kidnapping but also explores societal attitudes toward this practice. This aspect of our study contributes to the literature, as previous studies did not study the question due to a lack of data.

Furthermore, our contribution extends beyond the realms of gender economics and environmental literature as it holds relevance for the general public and policymakers. The issue of bride kidnapping is particularly poignant in Kyrgyzstan, where it raises questions about whether it is a crime or a tradition to be respected. Recent incidents, such as the tragic murders of Burulai Turdaaly Kyzy in 2018[2] and Aizada Kanatbekova in 2021[3], who were both killed by their abductors due to neglect from police and government, have garnered significant attention from both national and international media and led to eruptions of protest in the largest cities of Kyrgyzstan. (see Figure 3.1). However, we must also consider the countless silent victims who suffer mentally and possibly physically due to the persistence of this harmful practice. By shedding light on these connections policymakers can incorporate this knowledge when formulating policies to mitigate the consequences of climate change and create a safer, more equitable environment for women.

We use monthly weather data on precipitation and a panel survey from Kyrgyzstan to answer our research question. The identification strategy employed in this study capitalizes on the exogenous and random variation in rainfall/snowfall patterns, specifically focusing on the occurrence of dry winters. In recent years, Kyrgyzstan's agriculture has been severely affected by climate shocks, particularly due to unprecedented droughts and a lack of irrigation water. One of the primary cause is insufficient snowfall during winter, which leads to reduced meltwater and impedes river flow in the spring-summer period, failing to fill regional reservoirs adequately (BIOM, 2021). Snowfall is crucial for replenishing groundwater, nourishing soil, and protecting winter crops from harsh conditions.

[2]retrieved from https://www.hrw.org/news/2018/05/31/young-womans-murder-kyrgyzstan-shows-cost-tradition

[3]retrieved from https://centralasiaprogram.org/bride-kidnapping-kyrgyzstan-reflection-conservative-values#_ftn1

The Ministry of Agriculture reports that inadequate snowfall has resulted in significant losses of 10% to 15% in winter crop yields. By leveraging the timing of the rainfall/snowfall shocks, the study aims to establish a causal relationship between the scarcity of precipitation and its impact on bride kidnapping occurrences and attitudes. The findings of this study provide evidence that climate shocks, particularly insufficient winter precipitation, have significant implications for bride kidnapping and the attitudes associated with the practice, with dry winters causing higher rates of bride-kidnapping marriages and shifting attitudes towards a more positive view on this tradition.

Our analysis reveals the intricate interplay between climate change and bride kidnapping in Kyrgyzstan, highlighting the nuanced nature of the consequences resulting from climate change. The relationship between dry winters, socio-economic factors, and attitudes towards bride kidnapping is complex and multi-faceted. One of the key findings is the crucial role of income as a determinant, as individuals from lower-income backgrounds display a higher susceptibility to attitude shifts. This suggests that economic vulnerability may exacerbate the impact of climate shocks on societal perceptions and behaviors.

Gender differences did not emerge as statistically significant; the study indicates a similar response to climate shocks among both males and females. We also did not find evidence that education level changes the effect of dry-winter shocks on attitudes. This implies that the influence of climate-related factors transcends gender and educational boundaries and affects the attitudes of individuals across the spectrum. Furthermore, the presence of daughters in households seems to play a role in shaping negative attitudes toward bride kidnapping, suggesting the potential influence of familial dynamics in perpetuating or challenging harmful practices.

The rest of the paper has the following structure. Section 3.2 describes the climate specifics of Kyrgyzstan and the bride kidnapping practice. Section 3.3 summarises the data. Section 3.4 justifies the empirical strategy of the paper. Section 3.5 presents the results of the analysis. Section 6 concludes.

3.2 Background

3.2.1 Climate in Kyrgyzstan

Kyrgyzstan, a mountainous country in Central Asia, faces various climate change challenges, including melting glaciers, changes in precipitation patterns, and increased frequency of extreme weather events such as floods and droughts. According to the National Communication of the Kyrgyz Republic to the UNFCCC (of Energy & of the Kyrgyz Republic, 2016), "climate change is expected to have significant impacts on key sectors in Kyrgyzstan, such as agriculture, water resources, health, energy, and infrastructure." Climate change can significantly impact the country's economy, which relies heavily on agriculture and livestock farming. Moreover, it can exacerbate existing social and economic challenges, including poverty, food insecurity, and gender inequality.

According to the World Bank (2021), Kyrgyzstan faces several challenges related to water resources, including water scarcity, inadequate infrastructure for irrigation, and water pollution. These issues have significant implications for agriculture, a critical sector of the Kyrgyz economy. Agriculture accounts for approximately one-third of Kyrgyzstan's GDP and employs more than half of the country's workforce (World Bank, 2021). The Climate Risk Index 2022 report by Germanwatch (2022) states that Kyrgyzstan is ranked among the countries most affected by extreme weather events from 2001 to 2020. One of the main factors contributing to this status is changes in precipitation patterns, particularly the increasing frequency and intensity of droughts and floods. We focus on precipitation shocks as the key variables of interest.

In recent years, agriculture in Kyrgyzstan has suffered a lot due to climate shocks. The country's agricultural lands faced an unprecedented drought and lack of irrigation water. Farmers attended numerous rallies and demanded that the authorities take action to preserve the crops.[4] The situation with insufficient water supply is majorly attributed to the lack of snow during the winter, according to BIOM (2021), a public non-profit voluntary organization unifying young specialists, scientists, and leaders who participate in addressing environmental problems of the Kyrgyz Republic and Central-Asian region. In Kyrgyzstan, water influx in river systems largely relies on seasonal snow accumulation. Recent observations reveal a trend of reduced snowfall during winter seasons. Conse-

[4]retrieved from https://economist.kg/novosti/2021/08/11/zasuha-i-potopy-chto-proishodit-s-klimatom-kyrgyzstana-i-pochemu-dalshe-budet-huzhe/?ysclid=ldcz4v41x93397284

quently, insufficient meltwater from seasonal snow cover has impeded river flow during the spring-summer period, leading to a shortage of water volume required to fill regional reservoirs to desired levels (BIOM, 2021). In addition, sufficient precipitation plays a pivotal role in the agricultural sector by serving as a vital water resource for crop cultivation. Snowfall plays a significant role in nourishing the soil, replenishing groundwater reserves, and fostering optimal plant growth. Another crucial aspect of winter snowfall in Kyrgyzstan is its protective capacity, shielding winter crops from harsh cold temperatures and gusty winds while facilitating adequate soil aeration owing to its loose composition. Data from the Ministry of Agriculture in Kyrgyzstan reveals that inadequate snowfall in some years resulted in notable losses ranging from approximately 10% to 15% in winter crop yield. [5] Based on the information above, we use the variable that indicates insufficient snowfall in winter compared to the historical mean (or dry winter) as our climate shock variable.

3.2.2 Bride Kidnapping in Kyrgyzstan

One particular issue of gender inequality in Kyrgyzstan is bride kidnapping, a form of forced marriage involving the abduction of young women by men who wish to marry them without their consent. Bride kidnapping is known as "ala kachuu," which translates as "to take and run away." Bride kidnapping is a widespread practice in Kyrgyzstan, and it has serious social, economic, and psychological consequences for women and their families (UN Women, 2018). According to CSCE (2017) data, an estimated 12000 young women are kidnapped and forced to marry their abductors yearly in Kyrgyzstan. As many as one out of five are raped in the process. The National Statistical Committee in 2017 estimated that up to 20% of marriages in Kyrgyzstan result from bride kidnapping[6], and United Nations Population Fund (UNFPA) (2018) estimates this number to be as high as 35%.

Bride kidnapping became illegal in 1994, but the practice continues today, especially in rural areas (CSCE, 2017). The laws forbidding bride kidnapping in Kyrgyzstan have been largely ineffective due to cultural acceptance of the practice - Kleinbach et al. (2005) reported that 38% of the population considers bride kidnapping a "good traditional way to

[5]retrieved from https://ru.sputnik.kg/20190219/kyrgyzstan-zima-posledstviya-ehnergetika-poliv-1043407465.html/

[6]retrieved from https://24.kg/obschestvo/45809_kraji_nevest_vkyirgyizstane_kakim_issledovaniyam_verit/

get a bride.". Despite the prevalence of this practice in Kyrgyzstan, only 79 incidents were officially reported to the Ministry of Internal Affairs between 2014 and 2016 (Bengard, 2017).

Traditionally, young women can reject marriage by abduction, but there are strong incentives against it. Becker et al. (2017) show that women who decline a proposal of kidnapping are less likely to find an appropriate partner with equal social and economic status afterward due to women's reputations being compromised by spending time at the abductor's house. It is also considered shameful for the woman's household if she refuses the proposal (Kleinbach et al., 2005; Naumova, 2016). The girl's family may pressure her to agree to the marriage and comply with social norms. While bride kidnapping occurs in various parts of the world, it has been reported to be more prevalent in Central Asia compared to other regions.

Although we do not know the exact reason why the practice is so persistent in this region, there are several factors that contribute to the higher occurrence of bride kidnapping. First, cultural and historical factors: bride kidnapping has deep cultural roots in Central Asia, particularly among certain ethnic groups. It has been practiced for centuries and is often associated with local traditions, customs, and notions of honor. Central Asia has a history of nomadic traditions, where male dominance and patriarchal norms were prevalent (Becker, 2019). These traditions often included bride kidnapping as a means for men to assert their power and control over women, perpetuating the practice over generations. The cultural acceptance and historical continuity contribute to its persistence in the region. Second, socioeconomic conditions, such as poverty and limited access to education and employment opportunities, can contribute to the prevalence of bride kidnapping. In some cases, men resort to kidnapping because they lack the financial means to afford a traditional marriage dowry or cannot meet the expectations set by the bride's family. Third, weak law enforcement and inadequate legal frameworks to address bride kidnapping contribute to its persistence. In some cases, local authorities and communities may turn a blind eye to the practice, viewing it as a part of tradition or considering it a private matter between families. Lastly, limited awareness about women's rights and gender equality can perpetuate the practice of bride kidnapping. Insufficient education and awareness campaigns addressing the negative consequences and human rights violations associated with this practice hinder progress in combating it effectively (UN Women, 2018).

3.3 Data

To answer the research question we use two data sources. The first is the Life in Kyrgyzstan Survey (LiK)[7], an ongoing longitudinal survey in Kyrgyzstan. The survey follows 3000 households and more than 8000 individuals across all seven regions (oblasts) of Kyrgyzstan, as well as the two administratively separate cities of Bishkek and Osh. This creates a nationally representative dataset encompassing both rural and urban areas and Northern and Southern regions. The sample was initially selected based on the 2009 national population census, and the survey was conducted six times: first in the autumn of 2010 and then repeated in 2011, 2012, 2013, 2016, and 2019. The LiK survey is suitable for our study since it contains information about how marriages happened (love marriage, arranged, kidnapping) and attitudes towards bride kidnapping. In addition to information about bride kidnapping, LiK also has data on the socio-economic and demographic characteristics of households and individuals in Kyrgyzstan, which allows us to investigate possible channels as well as other detrimental effects that climate shocks have on women.

Many datasets provide information about precipitation and temperature. Examples include the dataset produced by the Climatic Research Unit at the University of East Anglia, weather data obtained from the Center for Climatic Research at the University of Delaware, and NASA MERRA-2. These datasets provide information about precipitation and temperature on grids of 0.5 by 0.5 degrees, corresponding to about 50 by 50 kilometers. We use weather data obtained from the Climatic Research Unit at the University of East Anglia[8], particularly data about temperature and precipitation, which we use to investigate the effect of insufficient precipitation on marriage practices.

After combining the data about precipitation and temperature with different waves from LiK, we now have the individual-year panel dataset, which contains information about individuals in Kyrgyzstan with several socio-economic characteristics and the history of climate shocks experienced each year. Table 3.1 below shows the summary statistics of our panel dataset.

In our analysis, we extract precipitation data on a monthly scale to account for droughts during the survey period. We define our draught measure, dry winter, as a dummy variable, which equals one if the average deviation of winter precipitation from

[7]retrieved from https://datasets.iza.org/dataset/124/life-in-kyrgyzstan-study-2010-2019

[8]retrieved from https://www.uea.ac.uk/groups-and-centres/climatic-research-unit

Table 3.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
HH Members	42,789	6.28	2.60	1	20
Dry Winter	42,789	0.11	0.31	0	1
Age	42,789	37.35	16.87	15	105
Female	42,789	0.51	0.50	0	1
Rural	42,789	0.77	0.42	0	1
Married	42,789	0.61	0.49	0	1
Single	42,789	0.27	0.44	0	1
Year	42,789	2,013.53	3.08	2,010	2,019
Year Married	2,017	1,998.27	9.82	1,981	2,013
Age at Marriage	2,017	20.79	2.87	14	36
Husband Age at Marriage	2,017	24.36	4.14	16	99
Bride Kidnapped	2,017	0.14	0.35	0	1
Lost Love	11,622	−0.88	1.46	−3	3
Domestic Violence	11,622	−0.68	1.22	−3	3
Burdensome Demands	11,622	−0.63	1.17	−3	3
Cut From Friends	11,622	−0.50	1.17	−3	3

Notes: The table outlines summary statistics for all important variables used in the regressions. Dry winter is a dummy variable indicating that the amount of precipitation in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year Married, Age at Marriage, Husband's Age at Marriage, and Bride Kidnapped are cross-sectional and available only for 2010, 2011, 2012, and 2013. The last four variables are measures of attitude toward bride kidnapping evaluated as self-reported likelihoods of events (Lost Love, Domestic Violence, Burdensome Demands, and Being Cut Off from Friends) happening in marriage initiated with bride kidnapping. Likelihoods are measured from 1 very possible to 4 impossible and standardised by subtracting similar scores for love marriage.

the historical mean of winter precipitation in this district (calculated from 1980 to 2019) is more than 1.5 standard deviations in the left part of the distribution, zero otherwise. Put simply, our dry winter variable equals one for a given year in a given district if there was too little snow compared to what is the historically normal amount of snow in that district. Firstly, snowfall in a particular district by itself influences the amount of water in the ground in that district. Secondly, in Kyrgyzstan, the implementation of irrigation systems is primarily district-based rather than nationwide (World Bank, 2021). The country has a diverse landscape, with variations in water availability, climate, and agricultural practices across different regions. As a result, irrigation systems are developed and managed at the district level to cater to each area's specific needs and conditions. This characteristic of the irrigation system in Kyrgyzstan is one of the reasons it suffers from a lack of coordination in addressing challenges such as aging infrastructure and inadequate investments in irrigation infrastructure modernization. However, it allows us to build our identification by matching winter precipitation to districts and creating the Dry Winter variable for individuals living in these districts.

The LiK survey gives information about how marriages happen for respondents: was it a love marriage, arranged marriage, or did it happen through bride kidnapping? This question allows us to study how dry-winter shocks can affect the incidents of marriages through bride kidnapping. We define our measure of a bride kidnapping as one for a woman in a year when the marriage happened if it happened through bride kidnapping, and zero if the marriage for a woman occurred through love or was arranged. Our set includes women only to avoid the issue of double-counting.

In the last two waves of LiK there is also a section that asks about attitudes toward bride kidnapping. Respondents have to rank the following from 1 (very possible) to 4 (impossible) for bride kidnapping and love marriage: Separation from someone who one really loved/hoped to marry; Domestic violence and abuse by a husband toward wife; Burdensome demands on wife, e.g., work/serve husband's family; Be cut off from friends. To account for a general shift in attitudes toward marriage, we define our measure of the acceptability of bride kidnapping as the difference, or "gap," between the scores assigned to bride kidnapping and love marriage within each category. This gap can range from -3 to 3, with a larger gap indicating a greater acceptance of bride kidnapping relative to love marriage. For example, a gap of 3 for the outcome of domestic violence means that a respondent ranked the likelihood of domestic violence as "impossible" in the context of marriage by bride kidnapping but as "very possible" for love marriage. This suggests that the respondent considers bride kidnapping to be safer than love marriage in terms of how likely a woman will experience domestic violence. On the other hand, a gap of -3 means that a respondent ranked the likelihood of domestic violence as "very possible" in the case of a marriage by bride kidnapping but as "impossible" for love marriage. The final scores are normalized by zero mean and the standard deviation one. We link the residence of respondents who answer attitudes questions to the dry-winter shocks in the year the survey was conducted.

3.4 Identification Strategy

The amount of rainfall/snow in a particular location is exogenous and varies over time. Therefore, the identifying variation in our study arises from the random timing of the shocks of dry winters. We estimate two models. First, using a sample of women, we estimate the probability of the Marriage by bride kidnapping BK_{idt} of a woman i living in location d (a district in Kyrgyzstan) at a year when the marriage happened t as follows:

$$BK_{idt} = \alpha + \beta * DryWinter_{idt} + \gamma * X_{idt} + \mu_t + \mu_d + \epsilon_{idt}$$

where i indexes women, d indexes districts, and t indexes the year of marriage. X_{idt} is a vector of the control variables of the woman, μ_t and μ_d are time and district fixed effects. BK_{idt} is the bride kidnapping variable, which equals one if the marriage happened through kidnapping, and zero if it is a love/arranged marriage. For this model, we use a dataset of women that contains information on how the marriage happened. As marriages are one-time events, we use district fixed effects rather than individual ones in this analysis.

Our second model is the following:

$$ATT_{idt} = \alpha + \beta * DryWinter_{idt} + \gamma * X_{idt} + \mu_t + \mu_i + \epsilon_{idt}$$

where i indexes individuals, d indexes districts, and t indexes the year of the interview.

X_{idt} is a vector of the control variables of the individual, μ_t and μ_i are time and individual fixed effects. The outcome variable ATT_{idt} is a variable that captures attitudes of individual i towards bride capture - the larger the ATT_{idt}, the more accepting is individual i of the bride capture tradition. This regression analysis is done on the set of all individuals that responded to the bride kidnapping attitudes questions in the survey. The variable $DryWinter_{idt}$ is a dummy that equals one if district d was hit by climate shock, zero if not - this is our variable of interest in both models. We cluster standard errors on the district level to allow serial correlation across individuals in the same area. We observe 112 districts in our datasets.

3.5 Results

In this section, we present the main results of our study. We first examine the overall impact of climate shocks, specifically inadequate winter precipitation, on incidents of bride kidnapping and associated attitudes. Subsequently, we delve into a more nuanced analysis by considering different sub-samples and interaction terms including gender, compositions of children, education, and income levels.

3.5.1 Occurrences of Bride Kidnapping

Table 3.2 demonstrates the effect of dry winters on the occurrences of bride kidnapping in districts of Kyrgyzstan. Column 1 reports the estimated coefficient of the regression without control variables, and Column 2 does so with control variables. Since the data on the timing of marriage is recall data, we have limited information about the socioeconomic characteristics of the woman in the year when the marriage happened. The information we do have and include in the control variables is whether a woman was living in a rural or urban area, her age at marriage, and the age of her groom at marriage. We include district and time-fixed effects to control for unobserved heterogeneity across different time periods and districts. The standard errors are clustered at the district level.

Our findings suggest that insufficient snowfall during winter increases the incidents of bride kidnapping over the number of love/arranged marriages in Kyrgyzstan districts. If the district experiences the shock of dry winter, it is associated with a 10-11 percentage point increase in the probability of marriage through bride kidnapping for women. The average rate of bride kidnapping in the districts without dry winter in our data is 16.5 %. As discussed in the section with the overview of bride kidnapping in Kyrgyzstan, the rate of marriages through bride capture in the literature is up to 20-35%. The effect we find is substantial, but given the frequency of dry-winter shock (11%), the overall rate is within the limits of the rate given by literature sources. We also note that according to the World Bank, the percentage of the rural population in Kyrgyzstan is 63% [9], while in our sample, it is 77%. Since the rural population is oversampled and bride capture is more attributed to the rural areas, this might suggest a lower average rate of bride kidnapping and a smaller effect of dry winter for the overall population of Kyrgyzstan. Our positive effect of dry winter on the incidents of bride kidnapping is in line with findings of the previous literature that demonstrated a positive effect of climate shocks on the occurrences of child marriages in societies where bride price is customary.

[9] retrieved from https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?end=2021&locations=KG&start=2000

Table 3.2: The Impact of the Climate Shock on Bride-Kidnapping Rate

	Bride Capture	Bride Capture
	(1)	(2)
Dry Winter	0.104**	0.106**
	(0.051)	(0.051)
Controls	N	Y
Year FE	Y	Y
District FE	Y	Y
Observations	3,744	3,744
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: Bride Capture is a dummy variable that equals one if the marriage happened by bride kidnapping. The average rate of Bride Kidnapping for those unaffected by the shock regions is 16.5 %. Dry Winter is a dummy variable indicating that the amount of the precipitations in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and district fixed effects are included. Standard errors are clustered by the district. Controls include rural/urban residency, the bride's age at marriage, and the groom's age at marriage.

3.5.2 Attitudes toward Bride Kidnapping

We have identified evidence indicating that dry winters have a substantial impact on the actual occurrence of bride kidnapping incidents in Kyrgyzstan. As a next step, we aim to examine the dynamics of attitudes towards bride kidnapping, specifically focusing on how they evolve following dry winters.

Table 3.3 examines the impact of climate shocks on attitudes towards bride kidnapping. The table shows the effect of a dry winter on attitudes toward various events that might occur in a marriage that begins with a bride kidnapping. These events include "separation from someone who one really loved" (Lost Love), "domestic violence and abuse" (Domestic Violence), "burdensome demands on wife" (Burdensome Demands), and "being cut off from friends" (Cut From Friends). For those categories, a higher score indicates a stronger acceptance of bride kidnapping relative to love marriage. Consequently, a positive coefficient suggests that respondents perceive an adverse event (i.e., Domestic Violence) to be less likely in bride-capture marriages compared to love marriages following a dry-winter shock.

The results in Table 3.3 indicate that experiencing a dry winter is positively and significantly associated with an increase in the standardized scores for all four types of attitudes toward bride kidnapping. The effect of a dry winter ranges from 0.429 to 0.766 standard deviations, all significant at the 1% level, implying that experiencing a dry winter leads to an increase in the standardized scores for all measured attitudes. This suggests that dry winters not only increase the likelihood of bride capture but also change attitudes towards the potential negative outcomes of marriages that begin with bride kidnapping. Specifically, after experiencing a dry winter, respondents perceive these negative outcomes as more unlikely to occur in marriages from bride kidnapping relative to love marriages. Therefore, our findings suggest that dry-winter shocks affect both real incidents of bride kidnapping and attitudes towards this practice.

People in affected areas adjust their attitudes towards bride kidnapping in response to climate shocks, making them more accepting of this harmful practice. As previously mentioned, although the laws of Kyrgyzstan prohibit bride kidnapping, it continues to exist due to societal acceptance, resulting in a very low number of incidents officially reported to the Ministry of Internal Affairs. Since the persistence of this tradition is primarily attributed to the cultural acceptance of bride kidnapping, a positive shift in attitudes towards bride kidnapping after climate shock could be a mechanism for higher

Table 3.3: The Impact of the Climate Shock on Attitudes Toward Bride Kidnapping

	Lost Love	Domestic Violence	Burdensome Demands	Cut from Friends
	(1)	(2)	(3)	(4)
Dry Winter	1.108***	0.571***	0.498***	0.514***
	(0.184)	(0.161)	(0.152)	(0.149)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y
Observations	11,622	11,622	11,622	11,622
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a type of attitude toward bride kidnapping. Respondents answer how likely different events are to occur in a marriage that began with the bride being kidnapped. The events are 'separation from someone who one really loved', 'domestic violence and abuse', 'burdensome demands on wife', and 'being cut off from friends'. Respondents can range the answer from 1 to 4 where 1 is 'very possible' and 4 is 'impossible'. The scores are standardized by subtracting similar scores for love marriage. Dry Winter is a dummy variable indicating that the amount of the amount of precipitation in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and Region fixed effects are included. Standard errors are clustered by region. Controls include the age of the bride at marriage and the age of the groom at marriage.Average values for 'Lost Love', 'Domestic Violence', 'Burdensome Demands', and 'Cut from Friends', respectively, are -0.88, -0.68, -0.63, -0.5. Controls include: age, marriage status, gender, residence status.

incidents of marriages through bride kidnapping. We explore further nuances of this mechanism in the next section.

3.5.3 Heterogeneity Analysis

In this section, our aim is to investigate the potential variations in attitudes towards bride kidnapping across different sub-samples of our dataset in response to dry winters. Since we do not have much information about women in the years when marriage happens, we cannot perform a heterogeneity analysis on the actual incidents of bride kidnapping. However, the richness of the LiK survey allows us to do this analysis for the attitudes part of the results. We aim to explore the factors that contribute to either exacerbating or improving the issue of a positive shift in attitudes toward bride kidnapping amid climate shocks.

First, we explore the impact of climate shocks on attitudes toward bride kidnapping for the groups of respondents from high-, middle-, and low-income households by adding respective interaction terms. Table 3.4 presents an examination of the interaction between income levels and climate shocks on attitudes towards bride kidnapping. This analysis uncovers the differential impact of a dry winter on various income brackets. The results from Table 3.4 add another layer to the narrative by suggesting that income might serve as a significant mechanism in mediating the relationship between climate shocks and attitudes towards bride kidnapping. When climatic conditions like a dry winter occur, they can intensify economic stress, particularly among lower-income households. These households often rely heavily on weather-dependent sectors such as agriculture and livestock, making them more susceptible to the adverse effects of climate shocks.

The coefficients of the interaction terms Dry X Low and Dry X Mid indicate the differential effects of dry winters on attitudes towards bride kidnapping for different income groups. A dry winter, in combination with low income, has a more pronounced impact on attitudes towards bride kidnapping across all categories relative to the high-income group (our reference group). This effect is statistically significant at the 5% level for the likelihood of lost love, burdensome demands, and being cut off from friends and at the 1% level for the likelihood of domestic violence.

Furthermore, middle-income households also show some changes in their attitudes, albeit to a lesser extent. It seems that while the economic strains caused by climate shocks might affect them, the magnitude is comparatively lower, potentially due to their

Table 3.4: The Impact of the Climate Shock on Attitudes Toward Bride Kidnapping, Interaction Term Income

	Lost Love	Domestic Violence	Burdensome Demands	Cut from Friends
	(1)	(2)	(3)	(4)
Dry Winter	−0.002	−0.369**	−0.421**	−0.734***
	(0.212)	(0.185)	(0.175)	(0.176)
Low Inc.	−0.093	−0.023	0.016	−0.027
	(0.081)	(0.070)	(0.067)	(0.067)
Mid Inc.	0.093	0.069	0.066	0.056
	(0.059)	(0.051)	(0.049)	(0.049)
Dry X Low	0.677*	0.953***	0.800**	0.790**
	(0.398)	(0.348)	(0.329)	(0.331)
Dry X Mid	0.266	0.330	0.159	0.443**
	(0.267)	(0.233)	(0.221)	(0.221)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y
Observations	10,178	10,178	10,178	10,178

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a type of attitude toward bride kidnapping. Respondents answer how likely different events are to occur in marriage starting with the bride's kidnapping. The events are 'separation from someone who one really loved', 'domestic violence and abuse', 'burdensome demands on wife', and 'cut off from friends'. Respondents can range the answer from 1 to 4 where 1 is 'very possible' and 4 is 'impossible'. The scores are standardized by subtracting similar scores for love marriage. Dry Winter is a dummy variable indicating that the amount of precipitations in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and Region fixed effects are included. Standard errors are clustered by region. Controls include the age of the bride at marriage and the age of the groom at marriage. Average values for 'Lost Love', 'Domestic Violence', 'Burdensome Demands', and 'Cut from Friends', respectively, are -0.88, -0.68, -0.63, -0.5. Controls include age, marriage status, gender, and residence status. 'Low Inc.' is a dummy variable indicating the individual's income is below the 25th percentile; 'Mid. Inc.' is between the 25th and 75th percentiles.

more robust financial buffers. However, dry winter seems to have a statistically significant effect only on the likelihood of being cut off from friends, as indicated by the significant coefficient on Dry X Mid in column 4.

For the reference high-income group, dry-winter shock actually has a negative effect in all the categories of the dependent variable, meaning that for this group, attitudes shift from favoring bride kidnapping.

The disparity of these effects highlights that the implications of climate shocks like dry winters are not uniform across income groups, underscoring the importance of considering socio-economic stratifications in the evaluation of climate impacts on societal attitudes. Based on our findings, it can be inferred that the shift in attitudes towards bride kidnapping following dry-winter shocks is more pronounced among lower-income individuals.

The results support the idea that the mechanism behind shifting towards more positive attitudes to bride kidnapping after dry-winter shock might lie in men being too poor to attract a bride and facing tightening liquidity constraints. Bride kidnapping, in this case, allows them and their household to economize on paying the "kalym" but still get married. In times of economic duress, harmful practices such as bride kidnapping might appear as a potential avenue for households to ensure marital alliances without bearing the costs associated with traditional marriages. Consequently, climate shocks like dry winters could heighten acceptance or tolerance towards bride kidnapping among lower-income households, reflecting their struggle to cope with worsening economic conditions. This shift in attitudes might, in turn, lead to an increase in real incidents of bride kidnapping.

These findings suggest that income level potentially moderates the effect of dry winters on attitudes toward bride kidnapping, particularly influencing how individuals perceive the likelihood of adverse outcomes in marriages initiated by such practices. These observations deepen our understanding of how climate shocks intersect with economic conditions to shape societal attitudes towards harmful practices like bride kidnapping.

Table 3.5 explores gender differences in the impact of the dry winter on attitudes toward bride kidnapping. Specifically, we examine the interaction between gender (female) and the dry winter. The analysis explores whether there is a difference in the attitudinal response to climate shocks between male and female respondents. The coefficient for 'Female' is insignificant across all categories, suggesting that gender on its own does not contribute significantly to the variance in attitudes toward bride kidnapping. Furthermore, the interaction term 'Dry X Female' is not significant in any of the outcomes. This

Table 3.5: The Impact of the Climate Shock on Attitudes Toward Bride Kidnapping: Gender

	Lost Love	Domestic Violence	Burdensome Demands	Cut from Friends
	(1)	(2)	(3)	(4)
Dry Winter	1.153***	0.426*	0.525**	0.387*
	(0.255)	(0.223)	(0.210)	(0.206)
Female	0.020	−0.292	−0.279	−0.204
	(0.292)	(0.256)	(0.241)	(0.236)
Dry X Female	−0.093	0.297	−0.056	0.262
	(0.363)	(0.318)	(0.299)	(0.293)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y
Observations	11,622	11,622	11,622	11,622

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a type of attitude toward bride kidnapping. Respondents answer how likely different events are to occur in marriage starting with the bride's kidnapping. The events are 'separation from someone who one really loved', 'domestic violence and abuse', 'burdensome demands on wife', and 'cut off from friends'. Respondents can range the answer from 1 to 4 where 1 is 'very possible' and 4 is 'impossible'. The scores are standardized by subtracting similar scores for love marriage. Dry Winter is a dummy variable indicating that the amount of precipitations in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and Region fixed effects are included. Standard errors are clustered by region. Controls include age, marriage status, gender, and residence status.

suggests that the effect of a dry winter on attitudes toward bride kidnapping does not vary significantly between males and females.

To summarize, our analysis suggests that the effect of the dry winter on attitudes towards bride kidnapping is not significantly different between genders. Both males and females tend to undergo similar shifts in their attitudes after experiencing the shock. This implies that income, rather than gender, has a greater influence on shaping these attitudes.

Furthermore, our findings indicate that the change in attitudes is likely occurring at the household level rather than being driven solely by men. It is probable that the presence of young daughters in a household plays a role in influencing this change rather than gender itself. Next, we will delve deeper into this aspect.

Table 3.6 investigates the interaction between the dry winter and the daughters' share in shaping attitudes toward bride kidnapping across the following categories: lost love, domestic violence, burdensome demands, and being cut off from friends. This analysis enables us to understand whether the effect of dry winters on attitudes towards bride kidnapping varies depending on the presence of sons or daughters in the household. Our hypothesis is that it might not be the gender that is important for our effect but rather the presence of daughters in the households. Families with daughters might be more empathetic towards the abducted women and, consequently, exhibit a smaller shift in attitudes.

The interaction term 'Dry X Share' is negative and significant across all four categories, suggesting that households with a larger share of daughters might experience less of a shift in attitudes following a dry winter. In particular, a unit increase in the share of daughters in a household during a dry winter decreases the score change for 'lost love', 'domestic violence', 'burdensome demands', and 'being cut off from friends' by 0.814, 0.743, 0.328, and 0.683, respectively. This suggests that the presence of daughters in a household may indeed invoke more empathetic views toward abducted women, attenuating the impact of climate shocks on attitudinal shifts. These findings underscore the complex interplay of familial composition and climate shocks in shaping societal attitudes toward bride kidnapping, highlighting the potential role of familial empathy as a mitigating factor.

Lastly, Table 3.7 examines the interaction between the dry winter and low education in shaping attitudes toward bride kidnapping. The variable low education is a dummy variable indicating whether an individual has less than eight years of education (pri-

Table 3.6: The Impact of the Climate Shock on Attitudes Toward Bride Kidnapping, Interaction Term Daugters' Share

	Lost Love	Domestic Violence	Burdensome Demands	Cut from Friends
	(1)	(2)	(3)	(4)
Dry Winter	0.290*	0.188	−0.126	0.251*
	(0.171)	(0.151)	(0.142)	(0.143)
Daughters Share	0.118	0.014	−0.116	0.127
	(0.104)	(0.092)	(0.087)	(0.087)
Dry X Share	−0.814***	−0.743***	−0.328*	−0.683***
	(0.212)	(0.187)	(0.177)	(0.178)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y
Observations	8,727	8,727	8,727	8,727

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Each column represents a type of attitude toward bride kidnapping. Respondents answer how likely different events are to occur in marriage starting with the bride's kidnapping. The events are 'separation from someone who one really loved', 'domestic violence and abuse', 'burdensome demands on wife', and 'cut off from friends'. Respondents can range the answer from 1 to 4 where 1 is 'very possible' and 4 is 'impossible'. The scores are standardized by subtracting similar scores for love marriage. Daughters Share is a share of the number of females under 25 in the total number of HH members under 25. Dry Winter is a dummy variable indicating that the amount of the precipitations in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and Region fixed effects are included. Standard errors are clustered by region. Controls include age, marriage status, gender, and residence status. Average values for 'Lost Love', 'Domestic Violence', 'Burdensome Demands', and 'Cut from Friends', respectively, are -0.88, -0.68, -0.63, -0.5.

mary education). The analysis again focuses on the self-reported likelihood of different outcomes associated with bride kidnapping, including lost love, violence, burdensome demands, and being cut off from friends.

Table 3.7: The Impact of the Climate Shock on Attitudes Toward Bride Kidnapping: Education Interaction

	Lost Love	Violence	Demands	Cut Friends
	(1)	(2)	(3)	(4)
Dry Winter	1.360***	0.689***	0.857***	0.571***
	(0.233)	(0.207)	(0.195)	(0.191)
Low Educ.	0.265	0.272	0.221	0.001
	(0.338)	(0.299)	(0.281)	(0.276)
Wint. X Low Educ	−0.693	0.742	−0.975*	0.070
	(0.703)	(0.623)	(0.586)	(0.574)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Indiv FE	Y	Y	Y	Y
Observations	9,500	9,500	9,500	9,500

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: This table analyzes the interaction terms of low education. The dependent variable is the attitude toward bride kidnapping measured by the self-reported likelihood of lost love, domestic violence, burdensome demands, or being cut from friends in marriage initiated by bride kidnapping (standardized by self-reported likelihood of domestic violence in love marriage). Low Education is a dummy variable indicating that the individual has less than 8 years of education. Dry Winter is a dummy variable indicating that the amount of the precipitations in the winter of the year of marriage was lower than the historical mean by 1.5 standard deviations. Year and Individual fixed effects are included. Standard errors are clustered by region. Controls include age, marital status, residency status, and gender.

None of the coefficients for the interaction term reach statistical significance. Specifically, the coefficients for the interaction term (DW X Low Educ) in all four dimensions (lost love, violence, burdensome demands, and cut off from friends) are not statistically significant.

The lack of statistical significance and coefficients of different signs suggest that there is no discernible pattern in the relationship between the dry winter and attitudes toward bride kidnapping among individuals with low education. The coefficients for the interaction term do not provide evidence to support the notion that the dry winter has a differential impact on attitudes toward bride kidnapping based on education level. People with a lower educational level tend to give higher scores across all categories. This suggests that they often believe adverse events are less likely to occur in marriages resulting from kidnappings compared to love marriages. However, the coefficients are also statistically insignificant.

In summary, our investigation into the heterogeneity of attitudes toward bride kidnapping reveals several insights. Examining attitudes across income groups, we uncover pronounced disparities. Individuals from low-income households demonstrate a notably positive shift in perceiving bride-kidnapping marriages as less prone to domestic violence and lost love due to dry winters. This change in attitude somewhat reduces in intensity among middle-income households but is still discernible. High-income households, conversely, show a negative shift. Such patterns hint at an underlying mechanism where, in the face of economic challenges exacerbated by climatic adversities, traditional practices like bride kidnapping might be seen as economically viable methods to alleviate financial burdens, such as avoiding "kalym" payments.

Another mechanism relates to our results on gender differences. Climate shocks could potentially impinge on the perception of male masculinity. As communities transition into a "survival mode" due to the stresses of climate shocks, men might feel their traditional roles as providers and protectors are threatened, leading them to assert their masculinity in other domains, including upholding traditional practices like bride kidnapping. However, our findings indicate that both males and females demonstrate similar shifts in attitudes, suggesting that the potential threat to masculinity might not be the dominant factor influencing attitudes in the context of this study.

On scrutinizing the influence of daughters' share in households, our findings are not uniformly statistically significant, but a trend emerges. Households with a higher proportion of daughters lean towards a less favorable view of bride kidnapping, especially in the dimensions of domestic violence, post a dry-winter shock. This could be indicative of families being more empathetic or protective, possibly fearing the potential repercussions for their own daughters in a society where bride kidnapping has become more normalized.

Finally, we explore the interaction between the dry-winter shock and low education levels. One might hypothesize that in economically constrained settings exacerbated by climate shocks, families might prioritize immediate survival needs over long-term educational investments, thereby inadvertently fostering environments where traditional beliefs flourish over more contemporary or progressive ones. In such contexts, even individuals with prior education might find their attitudes aligning more with age-old customs as they seek solace or coherence in familiar societal structures amidst the chaos of environmental unpredictability. Our results do not support this channel since the coefficients for the interaction term are neither consistent in direction nor statistically significant. This suggests that education might not act as a robust buffer against traditional norms, at least in the context of this study. Even amidst broader education, deep-seated cultural norms and practices might persist, especially when communities face external pressures or challenges. Our analysis predominantly focuses on the immediate aftermath of short-term climatic shocks; hence we do not rule out the possibility that the education channel can have profound impacts on shaping attitudes over the long term.

3.6 Conclusion

Our study investigates the relationship between climate shocks, specifically insufficient precipitation in winter, and the incidence and attitudes towards bride kidnapping in Kyrgyzstan. This harmful marriage practice has significant negative consequences for the victims, including forced marriage, sexual and physical violence, unwanted pregnancies, social isolation, and mental health issues. Our findings demonstrate that climate shocks, such as insufficient precipitation in winter, increase the likelihood of bride kidnapping and positively shift attitudes towards this practice.

The paper's results highlight the complex interplay between climate change and bride kidnapping in Kyrgyzstan and emphasize that the consequences of climate change are not homogeneous. Our analysis underscores the complexity of the relationship between dry winters, socio-economic factors, and attitudes toward bride kidnapping. Income appears to be a crucial determinant, with lower-income individuals exhibiting a more susceptible attitude shift. Gender differences, while not significant, indicate a similar response to the shock among males and females. The presence of daughters in households suggests a potential influence in shaping negative attitudes.

Our results support the economic rationale behind more positive attitudes towards the bride-kidnapping practice in light of climate stress: lower-income households, perhaps driven by financial constraints, are more likely to reconcile with bride kidnapping as an acceptable norm, possibly viewing it as a strategy to navigate economic hardships.

On the other hand, our findings challenge the hypothesis that gender dynamics, particularly male dominance or attempts to assert masculinity, especially in the face of environmental stressors, play a primary role in perpetuating bride kidnapping. Both men and women seem to react similarly to climate shocks, suggesting that the practice is not merely an expression of male control or an outcome of heightened masculinity during tough times.

Our research has important implications for policymakers, as it suggests that climate change adaptation strategies need to consider not only the environmental and economic impacts of climate change but also its social and gender dimensions. This includes addressing harmful marriage practices like bride kidnapping, which can be exacerbated by climate shocks, and understanding the diverse ways in which climate change affects different groups within society.

Furthermore, our study contributes to a growing body of literature that seeks to understand the gendered dimensions of climate change impacts and highlights the need for more research on the links between climate change, gender inequality, and social norms in developing countries. By examining the implications of climate change for bride kidnapping in Kyrgyzstan, we have shed light on an under-researched aspect of the relationship between climate change and harmful marriage practices.

3.A Appendix

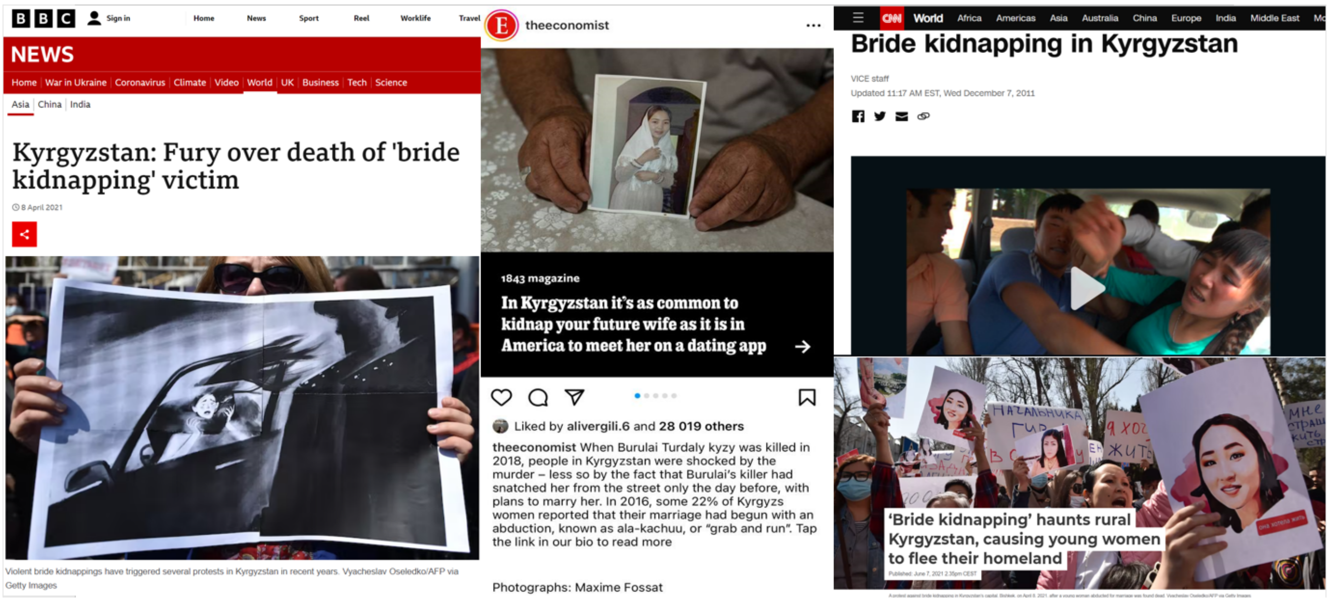


Figure 3.1: Media Coverage of the Protests against Bride Kidnapping in Kyrgyzstan

Table 3.A1: Summary Statistics by Marriage Practice

Variable	Levels	n	x̄	Min	Max
Age	arranged marriage	571	34.1	18	58
	bride capture	281	35.3	18	54
	love marriage	1165	33.5	18	59
	all	2017	33.9	18	59
Age When Married	arranged marriage	571	20.7	16	35
	bride capture	281	20.2	15	29
	love marriage	1165	21.0	14	36
	all	2017	20.8	14	36
Husband Age When Married	arranged marriage	571	24.5	18	51
	bride capture	281	24.6	17	60
	love marriage	1165	24.2	16	99
	all	2017	24.4	16	99

Table 3.A2: Summary Statistics by Gender

Variable	**Levels**	**n**	$\bar{x}$	**Min**	**Max**
Age	Female	5636	41.58	17	95.00
	Male	5173	40.80	17	92.00
	all	10809	41.21	17	95.00
Empl. Decions: Myself	Female	5636	0.16	0	1.00
	Male	5173	0.17	0	1.00
	all	10809	0.17	0	1.00
Rural Residence	Female	5636	0.72	0	1.00
	Male	5173	0.75	0	1.00
	all	10809	0.73	0	1.00
Married	Female	5636	0.69	0	1.00
	Male	5173	0.73	0	1.00
	all	10809	0.70	0	1.00
BK Attitudes	Female	5636	14.03	6	24.00
	Male	5173	14.02	6	24.00
	all	10809	14.03	6	24.00
HH Income	Female	5636	129.55	0	2698.41
	Male	5173	137.47	0	2698.41
	all	10809	133.34	0	2698.41
Have Permanent Job	Female	5636	0.08	0	1.00
	Male	5173	0.15	0	1.00
	all	10809	0.11	0	1.00

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