State of Play: How do College Football Programs Compete for Student Athletes?

Each year high school football players sign letters of intent with college football programs that spend resources to recruit the best talent to their teams. The NCAA governs this matching market with strict rules designed to protect amateurism. These restrictions create a puzzle: how do players and programs choose one another? J. Michael Dumond, Allen K. Lynch and Jennifer Platania develop a model of athlete choice. They find student athletes favor programs in BCS conferences and—other things the same—programs that are close to their home state. I consider the matching puzzle from the program's perspective: what factors increase the likelihood a school will recruit an athlete? Like Dumond, et al, I find the state of play matters. Athletes from Alabama, Florida and California are preferred, other things the same. However, my results suggest that football programs are willing to recruit outside their borders; schools in the Southeastern Conference (SEC) seem to have an advantage in this regard. In addition, the results align with prior findings about cheating in the NCAA. In contrast to Dumond, et al, programs with recruiting violations end up with a larger share of the top athletes. This extends the literature on college sport recruiting and may provide insight into other matching puzzles in academic, medical and business job markets.

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Introduction

Fans, schools and athletes anticipate National Signing Day each February. There is no shortage of analysis in its wake every year. The media covers questions like: where do the top-rated athletes choose to sign? Which schools walk away with the best matches? How do athletic programs compete with one another to sign the best quality recruits each year? Due to its popularity, college football receives the largest share of media coverage. Competitive balance is likely impacted by patterns in the college-athlete matching process. A strong recruiting class is often associated with increased probabilities of wins and championships. This study focuses on the football programs' choices. Using panel data, it introduces a negative binomial count model of the top 100 football players in Division I (DI) and the factors that may contribute to programs signing a larger (or smaller) share of these top-quality high school athletes.

The college football recruiting process is examined from the athlete's perspective by J. Michael Dumond, Allen K. Lynch and Jennifer Platania (2008). They review the broader literature surrounding college choices by non-athletes. However, there is a noticeable gap in the literature on the process from the college football program's perspective.[i] An interesting study on the market for football coaches by Todd Brown, Kathleen A. Farrell and Thomas Zorn (2007) reveals that good matches improve winning percentages. David J. Berri, Stacey Brook and Aju Fenn (2011) consider factors influencing the NBA amateur draft where teams select players. Similarly, Harris and Berri (2015) examine factors influencing the WNBA draft. While the NBA recruits players right out of high school, the WNBA rarely does so. Two-sided matching models of medical interns and hospitals and college students and schools have been considered extensively by Alvin E. Roth (1984, 1985) and Roth and Marilda Sotomayor (1992). Still, no paper that I have found investigates the college-athlete matching process from the college's perspective.

The theoretical framework is straight-forward. Football programs are firms that produce wins. Student-athlete labor is an input in the wins production technology. Because the number of scholarships is fixed by the NCAA and programs are not allowed to bid for athletes using wages, schools compete for the best quality athletes using non-price competition. The empirical approach is similar to DuMond, et al (2008) and Harris and Berri (2015). Findings from the count model align with some of the results from the DuMond, et al (2008) study but also contrast in intriguing ways. For example, DuMond, et al report that athletes are more likely to sign with Championship programs that consistently win their conference titles, have not been involved in NCAA enforcement actions and are located close to their home state. I find DI football programs successfully recruit a larger portion of the Rivals top 100 high school players when they have a higher number of conference championships, have earned a bowl championship and belong to the SEC. However, in stark contrast to DuMond, et al, I also find that NCAA infractions during the sample period are associated with a larger share of top quality recruits. This result makes economic sense in light of the extended literature on cheating in the NCAA. Before I summarize the data, empirical approach and the results, I present a brief review of the related literatures.

Literature Review

There are at least three strands of literature to consider for this puzzle: one describing the nature and behavior of the NCAA, one devoted to two-side matching models and the much smaller niche literature dealing with the college football market. This research is closest to the college football literature with a nod to the broad behavior of the NCAA. Key features of the most similar work are summarized here.

Amateur status is a key component of the NCAA's labor market power. Kahn (2007) explored this link and concludes college programs extract rents from revenue-producing student-athletes by limiting their pay and requiring amateur status. Monopsony rents earned by the cartel from this arrangement are sizeable. Estimates made by Brown (1993) and Brown and Jewell (2004 and 2006) range from $500,000 to $1,000,000. Due to the large number of transactions involved on the input side of the NCAA's business, the cartel tends to monitor outputs to decide whether an institution cheats on the agreement. On-field performance is the output measure of choice. Output monitoring behavior is predicted and documented by Stigler (1964), Fleisher, et al. (1988), Fleisher, Goff, and Tollison (1992) and Humphreys and Ruseski (2009). If cheating is discovered enforcement actions are taken. These actions affect the competitive balance of the organization. Depken and Wilson (2006) report the greater the level of enforcement in a conference the better the competitive balance. However, they also find that as punishments increase in severity competitive balance erodes. Using only observable variables available to all cartel members Humphreys and Ruseski (2009) predict instances of cheating detection and punishment with reasonable success. The results reinforce earlier findings about enforcement behavior and suggest the stability of the cartel is important to its members. These papers all support the notion that crime pays in the NCAA. Schools that break NCAA recruiting rules have much to gain by doing so. I incorporate a school's violation status to control for this effect and indirectly test whether NCAA crime pays by giving the cheating schools a larger share of the top 100 athletes each year.

It is not just athletic programs at large that benefit from on-field success. Coaches benefit, too. Brown, Farrell and Zorn (2007) test the value of good matches between football coaches and teams. They estimate team winning percentages over 35 years of coach-team matches using a generalized least squares approach. Their results suggest good matches are associated with approximately a five percent increase in winning percentages. I include controls for the number of conference championships a program has earned as well as national championships. If better coach-team matches increase win percentages then they probably increase championship ranks as well.

James Albrecht and Susan Vroman (2002) explore the variation in demand for high-skilled versus low-skilled labor. Their game theoretic model has two pure-strategy equilibria. Both predict a rise for high-skill workers and a decrease for the less-skilled. They also examine the impact of increasing the supply of low skill workers. My model includes controls for player positions, height, weight and the Rivals.com five star ranking. Depending on the maturity of its starting line-up, schools may have different preferences for player positions each recruiting year. Therefore, I expect the colleges to compete more fiercely for players in high-demand positions.

As a result, the share of high-demand players going to any single program in a recruiting year should be smaller than the share of low-demand players.

The football recruiting process is a vestige of the NCAA's market power. Dumond, et al, (2008) conclude students tend to sort themselves in accord with two-sided matching literature. Better students seek out better schools and vice versa. When it comes to athletes this means better quality athletes tend to seek higher quality schools. The strongest signals of quality from the school are past on-field performance and membership in the six largest conferences (these include ACC, Big 10 Big 12, Big East, Pac 10, and the SEC which constitute the Bowl Championship Series for the years 1998-2013). Not surprisingly (given the broader school choice research) athletes choose schools that are closer to their home state. In this study, athletes are about 10 percent less likely to choose a school that is on NCAA probation or rumored to be soon. These results are most closely related to my analysis.

The Model

Football programs are firms engaged in maximizing wins subject to physical, ethical and budget constraints. One of the key inputs for wins is student-athlete labor. Standard theory predicts wins will be maximized when each of the inputs, including athlete labor, is hired up to the point where the marginal revenue product is just equal to the price paid for the input. The market for athlete labor is unusual in that athletes are prohibited by NCAA rules from being paid wages (one of the ethical constraints). Athletes can only receive full or partial scholarships to attend the host program's school. Thus, these firms use non-price methods of "payment" for the labor inputs. Since the number of athletes recruited in the labor market each year is also limited by NCAA rules, the programs have an incentive to recruit the highest quality athlete labor they can, given their resources. Put differently, schools want to recruit athletes with the highest possible marginal products of labor. Of course, as discussed in Dumond, et al (2008), the athlete must agree to be "hired" by the school. This two-sided matching process is dynamic and can occur over a period of weeks or months; schools may extend an early recruiting offer or may wait until later on in the matching process. Athletes may sign early or wait until the last moment to commit to a program. The number of high-quality athletes the program acquires will be based, in part, on school specific effects, the relative demands for different types of players by position and other player characteristics. I specify a static model of the school's recruiting choice in the following way:

$$PICK_{jk1\sim n,t} = \Psi_{k1\sim n,t} + \Omega_{jt} + \Gamma_{jt} \qquad [1]$$

Equation one says that college (j) successfully recruits athletes ($k_{1 \text{ to } n}$) in year (t) dependent on $\Psi_{k1\sim n,t}$, a vector of athlete specific characteristics, Ω_{jt} a vector of college specific qualities and Γ_{jt}, a vector of controls for conference affiliation, championships, and other interacted college-athlete variables.

Data and Method

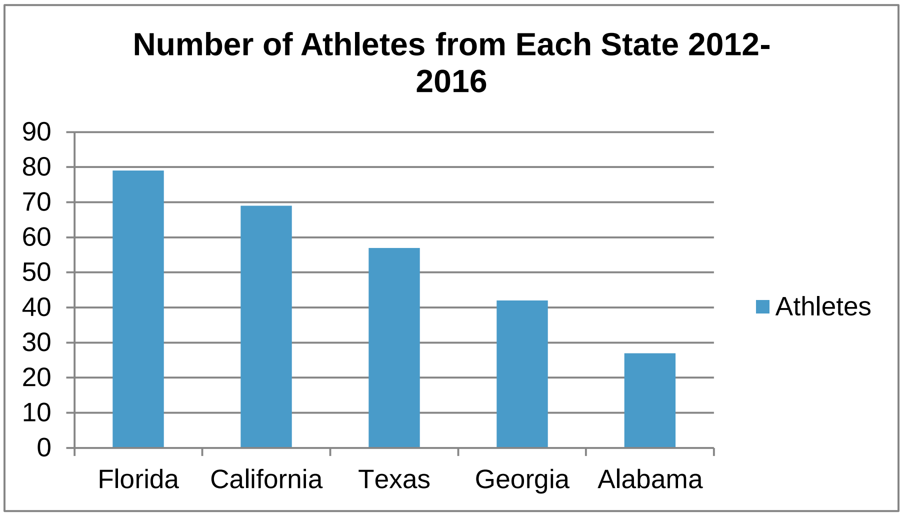
The data set includes the top ranked 100 athletes from www.rivals.com, colleges that signed them, and characteristics of both the players and colleges for the period 2012-2016.[ii] Descriptive statistics of key variables are highlighted in Table I.

Table 1 Descriptive Statistics of Key Variables n=500

Variable	Mean	S.D.	Min	Max
PICK	3.072	2.281	1	12
RANK	50.50	28.895	1	100
Ht	74.25	2.419	68	81
Wt	226.60	45.819	160.00	360.00
CHAMP	20.044	12.203	0	46
DSEC	0.33	0.471	0	1
DV	0.088	0.284	0	1
Dchamp	0.20	0.400	0	1
DSTATE	0.492	0.500	0	1

PICK is the number of athletes (out of the top 100 athletes in the recruiting class) a school signed in the given year. These college-athlete matches come from the rivals.com website. The data from rivals.com also included the athletes' ranking (RANK from 1 to100), height, weight, high school, hometown and state. CHAMP is the number of conference championships the football program has won. These counts were obtained from school websites and cross-referenced with sports-reference.com reports. DSEC is a dummy variable equal to one if the college belongs to the Southeastern conference and zero if otherwise. About one third of the programs in the dataset belong to the SEC. Conference affiliations were obtained from school websites and sports-reference.com. DV is a dummy variable equal to one if the college was on probation, experienced a violation or had come off a disciplinary action with the five year period and zero otherwise. Dchamp is a control for bowl championships; if the program was a bowl winner during the sample, the variable is equal to one and zero otherwise. DSTATE is a dummy variable equal to one if the college signed a recruit from within the home state. For example, if Florida State University signs a running back from Orlando, FL then DSTATE is equal to one. Figure 1 shows the five states with the largest number of recruited athletes during the sample period.

Figure 1. The total number of top 100 players from each state

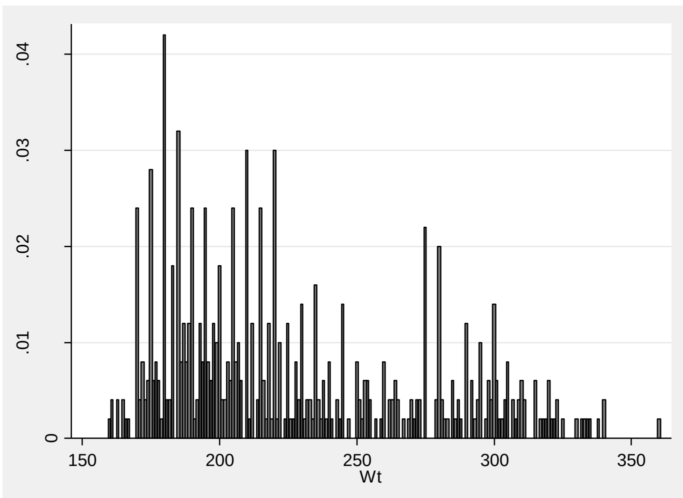


Almost half the college-athlete matches are between athletes and schools in the same state.

Controls are used for player position. The categories are: athlete, defensive back, defensive tackle, defensive end, linebacker, offensive lineman, quarterback, running back, tight end and wide receiver. Of the 500 athletes in the study, about 16% are defensive backs, a little over 14% are wide receivers, 14% are offensive linemen and 13% are defensive ends and 10% are running backs. Quarterbacks represent only 7.6% of the sample. The remaining positions range between 3-8% of the sample. Dumond, et al (2008) report similar distributions of positions in their study.

In general, recruited football players are tall: six foot or above. Weight varies more and is correlated with position played. Figure 2 shows a histogram of player weights with correlation coefficients for weight and player position.

Figure 2. Histogram of Player weights and correlation coefficients



	Weight
Dath	-0.1585
Ddb	-0.3751
Dde	0.1938
Ddt	0.4471
Dlb	-0.0289
Dol	0.5967
Dqb	-0.1828
Drb	-0.2003
Dte	0.0208
Dwr	-0.3417

Offensive linemen and defensive tackles tend to be the heaviest recruited players. Defensive backs and wide receivers are lighter as expected. The literature suggests physical attributes (like height for basketball players) are significant when decision makers build their rosters. I expect, other things the same, that college programs might prefer "big" players over smaller players.

Empirical Strategy and Results

I use a maximum likelihood estimator to regress college program fixed effects, athlete characteristics and interacted college-athlete effects on the number of high-quality athletes each college recruits in a given year. Because the observations on PICK are counts of the number of top 100 athletes the school signs each year, a negative binomial distribution is used to model the data with over-dispersion. The main specification is

$$PICK_{jk1\text{-}n,\ t} = \beta1 + \beta2(RANK)_{k1\text{-}n,\ t} + \beta3\ (Dposition)_{k1\text{-}n,\ t} + \beta4(Ht)_{k1\text{-}n,t} + \beta5(Wt)_{k1\text{-}n,\ t} + \mu Z_{,jt} + \eta\theta_{jk1\text{-},t} + e_{jk1\text{-}n,\ t}\ . \qquad [2]$$

Equation [2] tests whether the athlete-specific characteristics (the variables with the beta coefficients), the college-specific characteristics (the vector Z_{jt}) and some combination of interacted effects (the vector $\theta_{jk1\text{-}n,t}$) have any influence on the number of high-quality athletes a college program signs in a year. The main specification is estimated using both the negative binomial, poisson distribution and OLS as a robustness check. A reduced form specification is presented for comparison. Finally, the economic significance of key marginal effects is examined.

Table 2 Estimation Results Main Model Dep. variable = PICK n=500

Variable	**NegBi**	**Z**	**Poisson**	**Z**	**OLS**
RANK	0.0103***	10.32	0.0103***	10.32	0.0302***
HT	0.0086	0.45	0.0089	0.45	0.0313
WT	-0.0017	-0.88	-0.0017	-0.88	-0.0044
CHAMP	0.0207***	8.07	0.0207***	8.07	0.0597***
Dchamp	0.1937**	2.66	0.1937**	2.66	0.6697**
DSEC	0.5265***	8.23	0.5265***	8.23	1.555***
DSTATE	-0.0074	-0.12	-0.0074	-0.12	-0.0343
DV	0.3880***	3.78	0.3880***	3.78	1.1880***
DALdb	-9.456**	-2.28	-9.456**	-2.28	-24.522**
DALrb	-46.907**	-2.15	-46.907**	-2.15	-177.735**

DCAlb	6.845*	3.948	6.845*	3.947	35.557**
DFLol	-5.340**	-1.97	-5.340**	-1.97	-16.268*
Player&college FE	YES		YES		YES

*** = significant at the 1% level **= 5% *=10% Wald Chi2 for both Negative Binomial and Poisson 335.63 with Prob > Chi2 = 0.000 Rsquare for OLS = 0.43

The estimated marginal effects from the main specification are stable across the three models. No signs switch and most are significant at the 5% level or above. To clarify, a positive sign on a coefficient means a positive change in the regressor results in *a larger number* of the top 100 athletes being recruited by the school and a negative sign means *a smaller share* of the top 100 athletes would be recruited by the program. By this reasoning, a negative sign on a coefficient could indicate stronger competition between the schools for athletes with that attribute. One surprising feature of the results is that neither height nor weight seems to impact the colleges' recruiting decisions. This might be true for several reasons. First, there is not a great deal of dispersion about the mean height for players in the sample. Second, teenage males graduating from high school may not have reached their maximum physical development and college conditioning coaches are good at bulking up players once they arrive. Finally, the signal from the RANK variable is quite strong. College programs may learn all they need to know about the athlete's physical ability from that ranking alone.

Another striking result is that college programs do not appear to strongly prefer athletes from within their state. Even though almost half the recruits in the sample end up playing for programs in their home state, this attribute alone does not seem to influence the number of top athletes signed by the schools. The sign on RANK makes intuitive sense; as the rank number increases (say from 25th in the class to 50th in the class), it is more likely that colleges can sign multiple athletes out of the pool. Conversely, if you sign the number one athlete it is likely you may expend more resources to do so and, therefore, will have a smaller overall share of the total top 100 class. As Dumond, et al (2008) suggest, a reputation as a Bowl champion and the overall number of conference championships won by the program both increase the share of athletes recruited out of the top 100. If a school does any of the above and belongs in the SEC, the likelihood they will have more top 100 recruits more than doubles. The sign and relative magnitude of the marginal effect from cheating (DV) is notable. In fact, as Table 4 shows, this variable has the largest "economic" impact when I factor in standard errors. As the literature reveals, breaking NCAA rules to attract better quality players is a rational economic strategy for DI football programs—especially those in BCS eligible conferences. This result supports the idea that crime pays in the NCAA. It also stands in contrast to the results Dumond, et al (2008) report. High school athletes may be less likely to choose a school on probation or rumored to be soon, but the data here suggest those schools have an advantage in recruiting them. My current approach does not offer any insight into the precise mechanism or timing of the violation behavior and its influence on successful recruiting. But, it does indicate the relationship exists.[iii]

Of all the positions, competition for running backs from Alabama is most fierce. This is followed by the demand for defensive backs from Alabama, and offensive linemen from Florida. During the period 2012-2016, college programs signing players in these positions from these states are less likely to have a high number of the top 100. However, linebackers from California may have been a relative bargain during the same time. Possible explanations for these particularly strong position and state-of-origin effects involve unique college-athlete matches. For example, USC is located in southern California which is the second highest producer of top

100 athletes in the sample. USC also has a strong tradition of recruiting from feeder high school programs that emphasize family and alumni relationships. This type of strong peer effect could have the unintended consequence of making California linebackers more of a bargain than they otherwise would be. In similar fashion, Florida State might be expected to have some type of advantage in recruiting offensive linemen and other positions since they are the number one producer of top 100 athletes in the sample. However, the data does not support this. In spite of these anecdotally strong peer effect cases, the results do not suggest any one single program (i.e., Alabama, Ohio State, Florida State or USC) has a location or positional advantage when it comes to a larger share of the top 100.

Table 3 shows results for a reduced form model including only the significant regressors from the main specification. Estimated effects are stable in this reduced form without a substantial impact on goodness-of-fit. A variety of additional specifications including interactive effects between player position and state of origin, player position and weight, conference affiliation and player positions are not reported here but available upon request.

Table 3 Estimation Results reduced form model Dep. Variable = PICK n=500

Variable	**NegBi**	**Z**	**Poisson**	**Z**	**OLS**
RANK	0.0106***	11.33	0.0106***	11.22	0.0314***
CHAMP	0.0206***	8.81	0.0206***	8.81	0.0604***
Dchamp	0.1995**	3.02	0.1995**	3.02	0.6976**
DSEC	0.4964***	8.23	0.4964***	8.23	1.4610***
DV	0.4088***	4.26	0.4088***	4.26	1.1912***
Player & College FE	YES				
Pos. Dummies	NO				

***=significant at 1% level **=5% *=10% Wald chi2=287.16 prob>chi2=0.00 R squared for OLS = 0.36

Lastly, I include Table 4 to give some context for the relative magnitude of the marginal effects. Although being a member of the SEC had the largest estimated marginal effect from Table 2, its impact is dwarfed by the program's violation status. Essentially, the data suggests that cheating potentially increases your share of the top 100 athletes by 45 per cent. Winning a bowl game increases the recruiting share by 7 per cent. This table may shed some light on past, present and future NCAA infractions. There is only one Nick Saban; if a college is looking to increase the number of high quality players it recruits out of the top 100, it may rationally decide to bend the recruiting rules to do so[iv].

Table 4 Economic Impact of Key Variables on PICK

Variable	Std. Error	% change PICK
DV	0.10269	45.27
DSEC	0.06397	10.21
Dchamp	0.07273	7.04

Percentage change reported is estimated by multiplying the estimated marginal effect by a one standard deviation increase in the variable, adding that to the mean then dividing by the mean. For dummy variables, the change is computed when the value goes from 0 to 1.

Discussion and Conclusion

Division I football programs successfully recruit a larger portion of the Rivals top 100 high school players when they have a higher number of conference championships, have earned a bowl championship, belong to the SEC or have committed NCAA infractions during the sample period. Generally, programs appear to prefer athletes from Florida, California and Alabama. Competition is particularly fierce for defensive and running backs from Alabama, line backers from California and offensive linemen from Florida. In contrast to other research on athlete choice, football programs do not strictly prefer athletes from their home state over athletes outside their state. Taken together, these results reveal something about what constitutes a “best” match between student athletes and football programs. Dumond et al (2008) find the best players seek out the best schools. My results suggest the best players—at least those in highest demand—may come from Florida and California. These players gravitated to Alabama, USC and Florida State.

One limitation of my approach is the restricted sample of just the top100 athlete-school matches. A clear next step for this research is to expand the number of observations to include the top 250 college-athlete matches (and beyond). Theory suggests the competition between football programs for the top 100 best high school athletes might differ significantly from the competition for the lower-end of the top talent distribution. I could test for the importance of weight, position and ranking (and other athlete specific characteristics) in the larger sample for comparison. As I complete this article, National Signing Day has just passed. One additional extension of this research is to attempt some out-of-sample predictions. If the model predicts or explains a reasonable likelihood of matches from the 2017 recruit class (or past classes), it may shed light on a number of ongoing issues in NCAA research. For example, competitive balance could be negatively impacted if SEC schools consistently recruit the largest percentage of the top 100 athletes in the nation. This point is made in DuMond, et al (2008). Both athletes and programs benefit from improved information about the matching market. For example, a linebacker might avoid holding out for his top school (and missing his second-best option) if he knows running backs are the high demand position that year. If these results lead to improved information and better decision-making about recruiting resources, the matching market could see efficiency gains. Lastly, this model indicates that breaking NCAA recruiting rules increases the likelihood of recruiting a higher number of the top quality athletes. The notion that “crime” pays in the NCAA is not new;[v] when programs are prohibited from using price competition for athletes, they resort to other means.

Even though the NCAA labor market is atypical, these results can potentially provide insight into other employer-employee matching puzzles with uncertain information. Academic job markets routinely try to match the top PhD candidates with the top employers; medical residents scramble for their top choices to complete their educations and, to some extent, all businesses face uncertainty about the quality of their job applicants. When price competition is fierce (or when it is prohibited), studying the behavior of the NCAA helps us understand how other two-sided matching markets operate.

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Appendix Variable Names and Descriptions

PICK	Number from 1-12 representing the number of athletes recruited from the top 100 in a given year
RANK	Number from 1-100 assigned by Rivals.com indicating player ability
HT	Reported height of the athlete from Rivals.com in inches
WT	Reported weight of the athlete from Rivals.com in pounds
CHAMP	A number from 0 to 46 representing the number of conference championships the college has won
Dchamp	A dummy variable equal to 0 if the college program has not been a national champion in the sample period and 1 if they have been a national Champion
DSEC	A dummy variable equal to 0 if the college is not in the Southeastern conference and 1 if they are a member of the conference
DSTATE	A dummy variable equal to 0 if the college-athlete match is not within the same state and 1 if the match is within the same state
DV	A dummy variable equal to 0 if the college is not under probation or rumored to be during the sample period and 1 if they are under probation, sanctions or rumored to be
DALdb	An interacted dummy term equal to 1 if the player is from Alabama and is a defensive back
DALrb	An interacted dummy term equal to 1 if the player is from Alabama and is a running back
DAClb	An interacted dummy term equal to 1 if the player is from California and is a linebacker
DFLol	An interacted dummy term equal to 1 if the player is from Florida and is an offensive lineman

[i] A larger literature exists around the professional football draft. See Berri D.J. and Simmons R. (2011), Hendricks, deBrock, and Koenker (2003) and Grier and Tollison (1994) and for examples.

[ii] Initially, I chose the top 100 because of my interest in the Dumond, et al study. For comparison purposes, it seemed prudent to examine the same cross-section of athletes they did.

[iii] In this study, the significance of the NCAA violation effect is largely driven by USC's program.

[iv] Under Saban's leadership, Alabama was the BCS Champion in 2009, 2011 and 2012.

[v] See Harris (2016) and Fleischer, Goff, Tollison (1988) for more detailed reviews of the NCAA crime literature.