Recommendations for the Muhlenberg College Men's Basketball Program

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Abstract

This paper utilizes a unique dataset from Division III basketball to investigate the statistical significance of different "hustle stats" and their impact on basketball outcomes before creating a strongly-correlated model proving the chosen metrics correspond with game outcomes, especially when controlling for home and significant games. We discuss existing literature connected to predicting NBA games, use similar methods to create prototypes of relevant models for the Division III level, and discuss the implications of our findings for the Muhlenberg College Men's Basketball Program. First, two regressions are run to determine significant offensive and defensive metrics and their impact on points scored and allowed respectively. Next, two more regressions are run, the first considering all six metrics in an attempt to verify correlation with net game outcome, and the second improving the model by introducing dummy variables. Of the created metrics, we found that offensive shot quality, as well as defensive rebounding effort and on-ball defense, had a statistically significant impact on points scored and points allowed respectively, while the combination of metrics chosen had a very strong correlation with game outcomes, especially when considering home/away and critical games. In the short term, the team should prioritize playstyles benefitting the three identified categories, whereas, in the long term, the team should invest the time to track these metrics for more games to expand the dataset, which can be used to confirm or adjust our findings and inform future strategic decisions that hopefully will lead to more successful outcomes.

Section I: Introduction

A strong 2022-23 campaign for the Muhlenberg College Men's Basketball team concluded with a crushing blowout defeat at the hands of Johns Hopkins University in the semifinals of the Centennial Conference Playoffs. Heading into the offseason, the team hired a full-time assistant who was tasked with finding ways to improve the program using analytics. In collaboration with head coach Kevin Hopkins, the assistant devised six unique metrics that both believed would strongly indicate how the team performed in a given game. The calculated metrics are as follows: Offensive shot quality, touch quality, and rebounding effort, as well as defensive ball-handler impact, shot defense, and rebounding effort. Each metric goes far beyond common box-score numbers such as free throws, shooting percentage, or turnovers, and each is related to effort instead of athletic performance. Especially at the Division III level, it is far easier to control areas of emphasis and individual effort than it is to control results like shooting percentage, and these areas most likely will still significantly impact game outcomes. However, collecting the data for these metrics is an incredibly time-consuming process, as it requires the assistant to re-watch game film to collect and grade each metric for each player on each possession. Therefore, the assistant started by collecting 10 games of data. This paper contains two separate analyses: The first investigates which metrics significantly impact points scored or points allowed, and in which direction, and the second investigates how strongly a model containing all six metrics can predict game outcomes. Overall, this paper provides recommendations for gameplay strategies as well as further analysis targets for the Muhlenberg College Men's Basketball team.

Section II: The significant metrics and their implications (Author: Charles Ohanian)

Using game statistics to predict the outcomes of basketball games has been an area of prevalent research on both the fan and team sides of the sport. While fans may be interested in generally predicting outcomes for sports betting purposes, teams are interested in identifying specific statistical metrics that are most impactful on score differential. Coaches can thus encourage their teams to focus on different areas of the game accordingly. There has been a great deal of research on what popular box score metrics, such as free throw percentage, field goal percentage, etc., influence outcomes, but there are many other areas of the game that much less research has been devoted to, such as the qualitative impact of additional effort. This paper will review some existing sports prediction modeling literature, discuss why popular box score metrics may become less effective at lower levels of the game, and create alternative models featuring non-box score, effort-based metrics. Games from the 2022-2023 Muhlenberg men's basketball season will serve as a case study for analysis. This paper uses regression analysis to determine if different effort-based metrics have a significant impact on points scored and points against. Finally, gameplay strategies are suggested based on the findings of the regressions.

Many researchers have investigated the impact of popular box score metrics on game outcomes. Thabtah et al. identify defensive rebounds as the most significant factor affecting NBA game results, along with other crucial factors like three-point percentage, free throws made, and total rebounds, which collectively improve prediction accuracy by 2–4% (Thabtah et al, 2019). The research of Cabarkapa et al. supports the idea that defensive rebounds are incredibly important. They also highlight field goal percentage and overall shooting efficiency as metrics that are important in NBA game outcome prediction models (Cabarkapa et al., 2022). Mikołajec et al. note some interesting results in their 2013 paper, namely that 3rd quarter points

per game have a significant positive impact on winning percentage in the NBA, indicating that an offensive push after halftime may catch the opponent off guard and help the team to open up a lead. They also mention the negative and positive impacts of fouls and steals respectively (Mikołajec et al., 2013).

The existing literature on this topic has only delved significantly into NBA and NCAA Division I game outcomes. However, at the Division III level, the game is very different, as there are fewer superstars and a lot more average players. This serves to increase the importance of hustle and working as a team, since a team of less skilled players that hustle for each other and play smart can beat a team with better players that don't put in the same level of effort. Hence, it serves as an interesting analysis to observe more effort-based team metrics, such as the ones this paper will discuss, in order to see what conclusions can be drawn about their impact on Division III game outcomes, such as those of the Muhlenberg men's basketball team.

The three offensive metrics that this paper will examine are positive touch quality percentage, easy shot quality percentage, and active offensive rebound percentage. Touches were judged as either positive, neutral, or negative. Positive refers to a quality touch such as finding an open man or executing a designed play, negative refers to a touch that lost possession of the ball or wasted time, and neutral refers to a touch that was somewhere in the middle, such as rotating the ball to the man next to you. A player's positive touch quality percentage, referred to as Pos. TQ% hereinafter, was calculated as the ratio of the players' number of positive touches to their total touches. Shots were judged based on their quality and make-ability: either easy or hard. An easy shot may refer to a layup or an uncontested jumper, while a hard shot may refer to a contested jumper. A player's easy shot quality percentage, referred to as Easy SQ% hereinafter, was calculated as the ratio of the player's number of easy shots to their total shots. Additionally,

players were judged based on how they responded to offensive rebound opportunities. They either attacked the basket for the rebound, hustled back to defend, or watched the play unfold. A player's active offensive rebound percentage, referred to as Active ORB% hereinafter, was calculated as the ratio of the number of times they attacked the basket or got back on defense, both seen as positive effort plays, to the total number of offensive rebound opportunities. Team totals for these three metrics were calculated for ten games during the Muhlenberg men's basketball 2022-2023 season. For all three metrics, the team's overall percentage was calculated the same as it was for a single player.

Table 1 shows the results when total points scored by the Mules in each game is regressed against the three aforementioned offensive statistics. As can be seen in Table 1, Pos. TQ% has a coefficient of 0.85, signifying that a one percent increase in the team's positive touch quality percentage is expected to increase the team's total points scored by 0.85. However, the p-value is quite high at 0.49, signifying that the range of possible values for the coefficient is large and the effect is not too different from zero. Furthermore, Easy SQ% has a coefficient of 1.26, signifying that a one percent increase in the team's easy shot quality percentage is expected to increase the team's total points scored by 1.26. Additionally, the p-value is 0.047, indicating that the variable is statistically significant at a 95% confidence level. The Mules put up around 75 shots per game during the 2022-2023 season. This means that each additional shot that is judged as easy as opposed to hard within this total is expected to increase the team's points scored by about 1.7, on average. In other words, holding the 75 shots per game constant, the marginal value of switching a shot from hard to easy was 1.7 points. Finally, Table 1 also shows that the coefficient for Active ORB% is -0.05, signifying that a one percent increase in the team's active offensive rebound percentage is expected to decrease the team's points scored by 0.05. Thus, this data

suggests that it would actually make sense to hustle slightly less for offensive rebounds. This could be because attacking the offensive glass is likely to tire players out and it is more efficient to get back and focus on getting the ball back that way. It is important to note, however, that the p-value for this coefficient is 0.88, signifying that the effect is not too different from zero.

The three defensive metrics that this paper will examine are impact percentage, contest percentage, and rebounding percentage. An impact represents any action to negatively influence the opposing team's ball handler, such as blocking his lane or attempting to steal the ball. A player's impact percentage was calculated as the ratio of the number of times they impacted the ball handler to the number of times they had the opportunity to. A player's contest percentage was calculated as the ratio of the number of times they contested an opposing player's shot to the number of times they had the opportunity to. Actions when rebounding were classified in three ways: either the player got the rebound, boxed out, or watched/ran ahead in transition. The team considered getting the rebound and boxing out as positive actions and watching or running ahead as negative actions, as they wanted to focus on securing the rebound. A player's rebounding percentage was calculated as the ratio of the number of times they got the rebound or boxed out to the total number of defensive rebounding opportunities. Team totals for these three metrics were calculated for ten games during the Muhlenberg men's basketball 2022-2023 season. For all three metrics, the team's overall percentage was calculated the same as it was for a single player.

Table 2 shows the results when total points allowed by the Mules in each game is regressed against the three aforementioned defensive statistics. The coefficient for contest percentage is 0.72, indicating that a one percent increase in the Mules' contest percentage increases the total points against by 0.72. This is interesting since contesting more shots would be expected to decrease points scored by the opposing team, however, the p-value is 0.15, so the

effect is not significant. This could be because, at the Division III level, players will still frequently miss open shots. As with offensive rebounding, it might be more productive to exert energy by pressuring the ball handler and securing rebounds, giving up the occasional open look. According to Table 2, the coefficients for impact percentage and rebounding percentage are -1.23 and -2.21 respectively. This shows that a one percent increase in impact is expected to decrease points against by 1.23, while a one percent increase in rebounding percentage will decrease points against by 2.21. Furthermore, both p-values are about 0.02, so these effects are statistically significant. Consequently, it seems that active defensive activities such as disrupting the ball handler or fighting for the rebound are very important in decreasing the opposing team's point total and thus giving the Mules the best possible chance for victory.

Valuable conclusions can be drawn when looking at the results of the two regressions in conjunction. Easy shot quality percentage on offense and impact percentage and rebounding percentage on defense were the three metrics found to have statistically significant desired effects. Thus these are the three areas that Coach Hopkins should encourage the team to prioritize in practices and games. Many players, especially at the Division III level may be tempted to put up a shot even when they just have a decent opportunity, but the numbers show that unselfish play and making the extra pass to an open man who has a better look is beneficial for overall offensive output. Great passing can also help to make players who may be naturally less athletic much more impactful in the game, which is very important in lower levels of basketball, including Division III (BasketballTrainer, 2014). This would suggest that a slow, five-out offense, with a focus on generating high-quality shots is ideal. This offense would create more easy shots at the expense of quality touches and rebounding, which were found to be insignificant. Additionally, when on defense, making sure that the ball handler never has an easy

time should be emphasized. Tight defense and thus higher impact percentage would likely cause the opposing team's easy shot quality percentage to decrease, forcing them to shoot more mid-range and long-range jumpers even if they are not contested, thus lowering the efficiency of their offense (Batra, 2021). Consequently, this would decrease the Mules' total points allowed. Crashing the boards on defense and limiting the other team's offensive rebounds is also an impactful area of the game according to this model. The numbers suggest that the impact of running down the court in transition is outweighed by the positive effect of going for the rebound or boxing out. Collectively attacking the boards is something that can definitely be worked on in practice and is expected to have a significant and positive effect on the Mules' point differential. This suggests that a high-pressure, chaotic defensive strategy might be best. Tactics such as double-teams, traps, and presses result in more on-ball impacts and quicker shots while creating more opportunities for players to easily box out their opponent. The tradeoff would be giving up more open shots, but that was found to be insignificant on opponent scoring at the Division III level. Although there are many common sense things that result in increased chances of winning, such as shooting percentage, they are hard to directly control. Our model finds easy shot quality percentage, impact percentage, and rebounding percentage to be three controllable, effort-based areas in which improvement will lead to better game outcomes for the Muhlenberg men's basketball team.

In conclusion, this paper delved into the realm of basketball game predictions by focusing on lesser-explored metrics, specifically those related to effort and team dynamics, at the NCAA Division III level. The analysis centered around the 2022-2023 Muhlenberg men's basketball season, utilizing regression models to examine the impact of various offensive and defensive metrics on points scored and points against. The findings shed light on the nuanced nature of

game dynamics at the Division III level, where teamwork and effort play pivotal roles in shaping outcomes. The results emphasized the importance of unselfish play and effective passing, suggesting that emphasizing these aspects in practice could significantly enhance offensive performance. The study also underscored the significance of active defensive strategies, such as disrupting the ball handler and securing rebounds, in diminishing the opposing team's scoring opportunities. Despite the useful conclusions drawn through this analysis, it is not without its limitations and possible extensions. Only 10 games worth of data were used due to the tedious nature of the collection process. More data would serve to enhance the strength of the conclusions and lead to further possible strategic development. An area of possible extension would be to take all six metrics for which there is data and determine if together they have a significant effect on net score (scored minus against) in games. This would illuminate if the model is truly correlated to a higher chance of winning. Ultimately, the synthesis of offensive and defensive insights provides valuable guidance for coaching strategies. These findings offer actionable recommendations for Coach Hopkins to enhance the team's overall performance and foster a competitive edge in Division III play.

Section III: Strength of the model in game outcome predictions (Author: Joshua Castro)

At the Division III level of the National Collegiate Athletic Association (NCAA), thousands of student-athletes dedicate years of their lives to playing the sport of basketball in games that are rarely televised and of little national significance compared to other divisions of the NCAA. However, the competitive drive of these athletes is arguably unmatched, as most play for passion, pride, and team success, rather than money, fame, or individual success. As it is at any level of basketball and with any team sport in general, winning is still paramount. Individual stardom is a big factor at the DI level, as the best collegiate players in the world vie to get drafted, and are capable of taking over games single-handedly through hot shooting, elite post scoring and rebounding, or flashy athletic plays. At the DIII level, much more importance lies in team play and effort, rather than individual talent. This paper looks at some NBA studies attempting to predict game outcomes in different methods and combines some of the methodologies to investigate if certain team hustle metrics correlate with overall game results using data from the Muhlenberg College Men's Basketball program during the 2022-23 season. Overall, it was found that an incredibly strong correlation can be made between the data and game outcome, though there is a major limitation stemming from a small sample size.

Many attempts have been made to determine game performance from box-score metrics, both predicting outcomes before the game from season averages and determining the significance of different metrics by looking at the actual statistics after games are played. Loeffelholz, Bernard; Bednar, Earl; and Bauer, Kenneth W. created a model that was able to predict the winner of an NBA game around 70-75 percent of the time only considering season-average shooting percentages (Loeffelholz, Bednar, and Bauer 2009). Huang M-L and Lin Y-J used regression to predict Golden State Warriors point totals given the box score of the

game and were accurate in 87.5% of tests (Huang, Lin 2020). Yang finds that a positive correlation exists between team PER (a sum of individual player efficiency) and win percentage (Yang 2015). It is clear that there is validity in using game statistics with methods like linear regression can show correlation and even predict game outcomes at a significant level. This justifies further examining additional metrics and how they might impact game outcomes.

Our dataset (provided by the Muhlenberg College Men's Basketball program) consists of ten games of observations of six different team effort percentages, three each on offense and defense. The first is positive touch quality percentage. Each time a player touched the ball on offense in each game, their contribution to the overall possession during that touch was judged as positive, neutral, or negative. A positive touch (beating a defender with a move, for example) benefited the possession, a neutral touch had no major impact, and a negative touch led to worse possession outcomes, such as a turnover or forced shot. Next was easy shot quality percentage, in which each shot was classified as easy or hard on a shot-by-shot and player-by-player basis (a center taking a deep three, no matter how open, would be a hard shot, while a strong shooter taking the same shot would have it recorded as an easy shot). The final offensive metric was active rebounding percentage: A player either crashing the offensive glass or running back to play transition defense was considered active, while a player watching the shot or casually backpedaling to the defensive end was not. Henceforth, these metrics will be referred to as TQ%, SQ%, and ORB%, respectively. On defense, the first metric was ball-handler impact percentage. For each offensive touch, the ball-handler was either impacted or not by his defender. Next is contest percentage, which is simply the percentage of total opponent shots that are contested (versus left open). The final percentage was defensive rebounding, in which, after each shot, every instance of a player boxing out or securing a rebound was a positive outcome, while a lack

of rebounding effort was negative. Henceforth, these metrics will be referred to as Influence%, Contest%, and DRB%, respectively. These six metrics were chosen for a specific reason, being that they broadly encompass most statistical elements of a game of basketball. On offense, TQ% directly relates to assists and turnovers, SQ% to shooting percentages and points, and the ORB% covers offensive rebounding as well as transition points allowed. On defense, Influence% relates to turnovers forced (steals, bad passes, shot clock violations, etc.), Contest% relates to blocks, opponent shooting percentage and scoring, and DRB% relates to rebounding. Overall, these six metrics cover scoring, passing, dribbling, rebounding, on-ball guarding, and shot contesting, which covers most stats in the game of basketball.

For each game, the total team percentages were calculated. In general, each metric took the form of the number of positive outcomes divided by total opportunities, resulting in a percentage roughly representing the percentage of effort in each major category. From this, a regression analysis was completed comparing the six metrics together with the net score of the game for all ten games. The primary goal is to determine if these six metrics correlate strongly with game results, which would justify further studies using larger datasets. The findings of this analysis are in Table 3 in Appendix 2. The results show that four of the six metrics had a positive impact on net score, while two (Active ORB% and Contest%) had a negative impact. Only one metric (Impact%) was significant at a 5% level, though four were significant at a 20% level and all were significant at a 50% level. More important than any individual coefficient or significance is the R-squared value of the entire model itself, which was a very strong 0.9, showing that the fit of the inputs to the game score was around 90.4%, a high level of correlation. The adjusted R-squared value (dependent on the number of predictors in the model) was lower, at only 0.712. The decrease stems from a combination of too many predictors and too

few occurrences in the data set. This drawback is also reflected in the F-statistic of 0.116, which is essentially a P-value for the entire model, showing that the model is significant at a 12% level. This combination of high correlation with (relatively) high F-statistic essentially suggests that the model fits the existing data well, but more data is needed to be statistically significant.

In an attempt to create a model with an even stronger correlation, other factors impacting the game outcome beyond the hustle metrics should also be considered. As it was determined that the six identified metrics broadly covered each on-court statistic, qualitative metrics beyond the basketball court should be considered. First, many studies exist showing the "home court advantage" in basketball settings. This advantage stems from teams playing in their home gym, in front of their own fans, and not having to travel. One writer compiled historical data of net performance of NBA teams at home and away, finding that teams ranged from 2.16 to 4.25 points better at home (Johnson 2021). Even if a team had identical hustle metrics, it is fair to expect that they would perform worse on the road than at home. Therefore, a dummy variable was added with a value of 1 for home games and 0 for road games, to the model. Next, another aspect that might impact team performance is the importance of the game. A playoff game or regular season game with significant playoff impact might lead the team to play with more focus and intensity or could cause jitters that result in worse team performance. As with before, even if a team has identical hustle metrics, the nerves or increased focus on a big game could harm or help the outcome. In general, it is expected that big games will result in lower total points, due in part to nervous shooters and more intense defense being played. A writer compiled data on game 6 and game 7 of NBA playoff series since 2005, finding that the overall point total was lower than the closing Las Vegas sports betting model prediction 58% of the time, a significant amount considering the Las Vegas attempts to predict a line for each game with a 50% probability of

each outcome occurring (Ewing 2021). Another dummy variable was added with a value of 1 for three “critical games” in the data set (two playoff games, and the final regular season game that had seeding implications depending on a win or a loss.) By incorporating these dummy variables, the new model now accounts for two important factors that impact a game but aren’t reflected in the hustle metrics.

With these two new dummy variables and the original six variables, another regression was completed. The results are in Table 4 in Appendix 2. Due to the limited number of occurrences used in this regression and the large number of input variables, the model does not allow for any relevant or significant conclusions about the impact of any one variable to be made. However, it can be seen that the coefficient of the “home game” dummy variable is positive, while the critical game coefficient is negative. This suggests that the team performs better at home, but worse in critical games when also accounting for the six hustle metrics. More important, again, however, is the R-squared value of the regression. The correlation coefficient is a massive 99%, meaning that the model creates a very close prediction for the final score of a game. The adjusted R-square is also quite high, at 92%. However, as before, and as expected, the F-statistic of the model (20%) shows that the model is far from significant or conclusive.

Overall, this study extends existing research predicting game outcomes from box-score averages and reveals a strong correlation between hustle statistics and game outcomes despite a limited data set. The chosen metrics span offensive and defensive facets of the game, resulting in a high R-squared value that signifies a strong fit of the data, highlighting the potential of these metrics to predict game results. In an effort to enhance the model, additional factors beyond hustle metrics were introduced, considering the impact of home-court advantage and the significance of critical games. The resulting model demonstrates an impressive correlation

coefficient of 99%, though there are limitations in drawing specific conclusions due to the limited occurrences and numerous input variables. The inherent nature of basketball suggests that expanding the dataset is likely to reinforce the correlation strength and could help determine the significance of individual metrics. As such, the process of collecting more data on hustle metrics at the Division III level is a worthwhile use of time for the new assistant working with the Muhlenberg Men's Basketball team.

Section IV: Joint Conclusion

In summary, this paper explores the predictive power of "hustle stats" in Division III basketball, revolving around a real-world connection to the 2022-23 Muhlenberg College Men's Basketball program. The introduction and evaluation of six key metrics showed that three have a statistically significant impact on game outcomes for the existing dataset: Shot quality, ball-handler impact, and defensive rebounding effort, at a 5%, 2.5%, and 2.5% level respectively. The overall impact of the six metrics on game outcomes exhibited a strong correlation with a 90.4% fit (R-squared value). When including additional factors, such as home-court advantage and critical game significance, the model was enhanced resulting in a notable 99% correlation. From the data provided, we recommend a slow-paced offense, spacing the floor and leaving the paint open for drives and cutters, which would help create easy shots. On defense, we recommend an up-tempo, high-pressure scheme that focuses on rebounding and swarming the ball, assuming the risk of letting up open shots. The primary limitation of the study is the small dataset, emphasizing the need for expanded data collection. Coach Hopkins and the Muhlenberg College Men's Basketball assistant should commit to continual tracking and analysis of these hustle metrics over a larger sample size which will provide a more comprehensive understanding of their impact and allow for more certainty in informing strategic choices. This research lays the groundwork for future studies, offers practical recommendations for enhancing team performance in Division III play, and justifies the time investment required to collect more data.

Appendix I (Charles):

Table 1: Offensive statistics regression output

	Coefficients	*Standard Error*	*P-value*
Intercept	-83.01322339	113.9318873	0.4936787
Pos. TQ%	0.846802168	1.50764205	0.59468106
Easy SQ%	1.263894315	0.507198681	0.04704033
Active ORB%	-0.054737569	0.35411021	0.88222284
R Squared = 0.565			

Table 2: Defensive statistics regression output

	Coefficients	*Standard Error*	*P-value*
Intercept	264.1081456	54.79663601	0.002940711
Impact %	-1.227431281	0.399181393	0.021805654
Contest %	0.723195694	0.43635089	0.148519876
Rebounding %	-2.206268331	0.732916199	0.023692573
R Squared = 0.712			

Appendix II (Joshua):

Table 3: Full model regression output

	Coefficients	*Standard Error*	*P-value*
Intercept	*-735.6319615*	*208.9992526*	*0.03892333*
TQ%	*4.555433642*	*2.318420267*	*0.1441634*
SQ%	*1.652179341*	*1.215997716*	*0.26737556*
ORB%	*-0.412266505*	*0.517072277*	*0.48354412*
Impact%	*2.525847594*	*0.656153827*	*0.03095122*
Contest%	*-1.18948534*	*0.689871657*	*0.18313715*
DRB%	*2.74375228*	*1.459983448*	*0.15680302*
	R Square	*0.904033485*	
	Adjusted R Square	*0.712100455*	
	Significance F	*0.115599354*	
	Observations	*10*	

Table 4: Full model regression output with home and critical game dummies

	Coefficients	*Standard Error*	*P-value*
Intercept	-1423.178963	243.3883353	0.10782989
TQ%	20.47664664	5.281646005	0.1607038
SQ%	7.989928436	2.344154399	0.18167878
ORB%	-5.927331591	1.841915058	0.19180671
Impact%	8.232195659	1.875150843	0.14257823
Contest%	-3.196581105	0.73006141	0.14294471
DRB%	-11.0834907	4.951980273	0.26749511
Home	84.74941617	29.97270767	0.21640875
Critical Game	-117.6418208	38.11835321	0.19948204
	R Square	0.991270726	
	Adjusted R Square	0.921436531	
	Significance F	0.202604647	
	Observations	10	

Raw Data

Team Total												
Game Number	Opponent	Pos. TQ%	Easy SQ %	Active ORB%	Impact %	Contest %	Rebounding %	Home	Critical Game	Points Scored	Points Allowed	Net Score
1	Hopkins	74	62	32	72	67	63	0	1	51	85	-34
2	Ursinus	73	67	36	84	69	73	1	1	74	53	21
3	Washington	77	79	42	77	83	76	1	1	86	60	26
4	F&M	75	81	41	70	75	75	0	0	81	60	21
5	Haverford	75	73	37	67	82	77	1	0	71	65	6
6	McDaniel	73	76	51	85	87	71	0	0	78	65	13
7	Dickinson	75	73	40	72	82	72	0	0	61	77	-16
8	Gettysburg	73	80	50	72	74	76	1	0	72	62	10
9	Swat	73	74	42	68	79	75	1	0	65	88	-23
10	F&M	80	73	68	62	65	71	1	0	73	77	-4

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