



Queen City Sabermetrics

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Ideal Traits

Our approach to the problem was to isolate pitching data of pitchers who pitched as both a reliever and a starter in the same year and build multiple linear regression models that predicted the greatest improvement in stats across pitching roles.

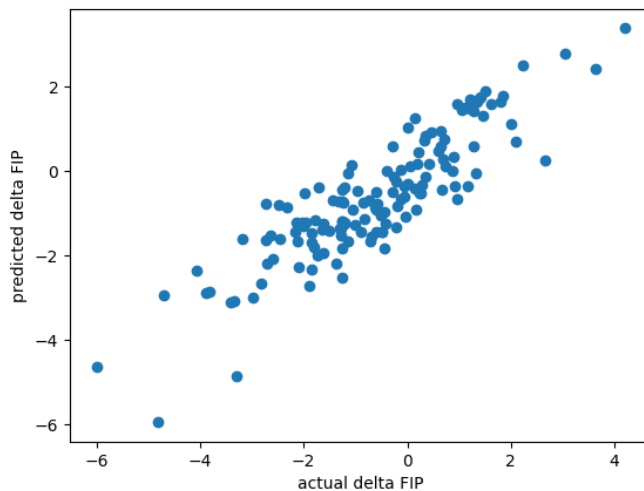
The first step in this process was to determine our ideal traits; the metrics we use for measuring change across pitching role that best encapsulated performance. We decided on using ERA, WHIP, FIP, and SIERA as our “ideal traits”. The tried-and-true stat of ERA measures the average amount of runs earned on a pitcher per nine innings. Because ERA is measured in the same metric as the scoring unit of baseball, it is a straightforward representation of value. WHIP, walks plus hits per inning pitched, is a brass-tacks stat measuring how many baserunners a pitcher is giving up each inning. Each baserunner given up has the potential to score a run, so pitchers that minimize baserunners typically are more successful and thus valuable. FIP, fielding independent pitching, focuses solely on the outcomes that the pitcher directly controls and omits events of balls hit into play. FIP isolates the direct impact the pitcher has on the game and removes factors caused by good or poor defensive play which makes it a good measure of value. Lastly, skill interactive earned run average (SIERA) bridges the gap between ERA and FIP. While FIP ignores balls hit into play, SIERA takes them into account, but assigns different values to the different ball in play outcomes. Using these four statistics alongside each other gives us an overall understanding of a pitcher’s quantitative value.

After choosing our ideal traits, we had to narrow down our leading indicators to use as features for our model. Our goal was to pick statistics that fully encompassed a pitching style while also considering specific stats associated with different roles all while keeping in mind the one in ten rule. Looking first at the role-specific stats, we chose age, pitching plus, stuff plus and location plus. Age is typically associated with smaller workloads making older pitchers potentially more suitable as relievers. The pitching plus, stuff plus and location plus stats quantify the pitchers command as well as his pure pitching ability. Relievers may specialize in certain matchups, whereas starters generally must be more balanced as they are expected to face entire lineups. Our other chosen indicators for our model mainly focus on outcomes per nine innings as to paint a picture of what is happening when a specific pitcher is on the mound. Our per nine stats included: runs scored, strikeouts, bases on balls, hits, and home runs. The remaining indicators were average against (AVG), batting average on balls in play (BABIP), left on base percentage (LOB_pct), groundball percentage (GB_pct), line drive percentage (LD_pct), flyball percentage (FB_pct), groundball to flyball percentage (GB_to_FB), and infield hit percentage (IFH_pct). Along with the per nine stats these indicators further illustrate the style and effectiveness of the pitcher in different categories.

Training Model

With ideal traits in mind, we began to preprocess the data for analysis. The idea was to train multiple linear regression models to predict ERA, FIP, WHIP, and SIERA statistics for each player. First, we decided to compare our statistics from the Relief Pitcher's perspective (RP – SP). This would mean that the more positive the resulting delta values, the better it was for this player to switch roles.

We began by separating all RP data and SP data. From there, we created tuple values of each unique MLBAMID and Season pairs in both SP and RP sets. Next, we intersected the two sets to find common pairs in both RP and SP data. This gave us all players who had played RP and SP within the same season. Given each of these unique MLBAMID and Season tuples, we created datasets for each ideal trait (ERA, FIP, WHIP, SIERA) to predict delta values and compare them with actual delta values. For ERA, the training model resulted with a r^2 value of 0.43. For FIP, the training model resulted with a r^2 value of 0.77. For WHIP, the training model resulted with a r^2 value of 0.89. For SIERA, the training model resulted with a r^2 value of 0.62.



These “predicted delta” for each statistic value allows us to predict whether each player's performance is better or worse if they switched from RP to SP.

Final Model

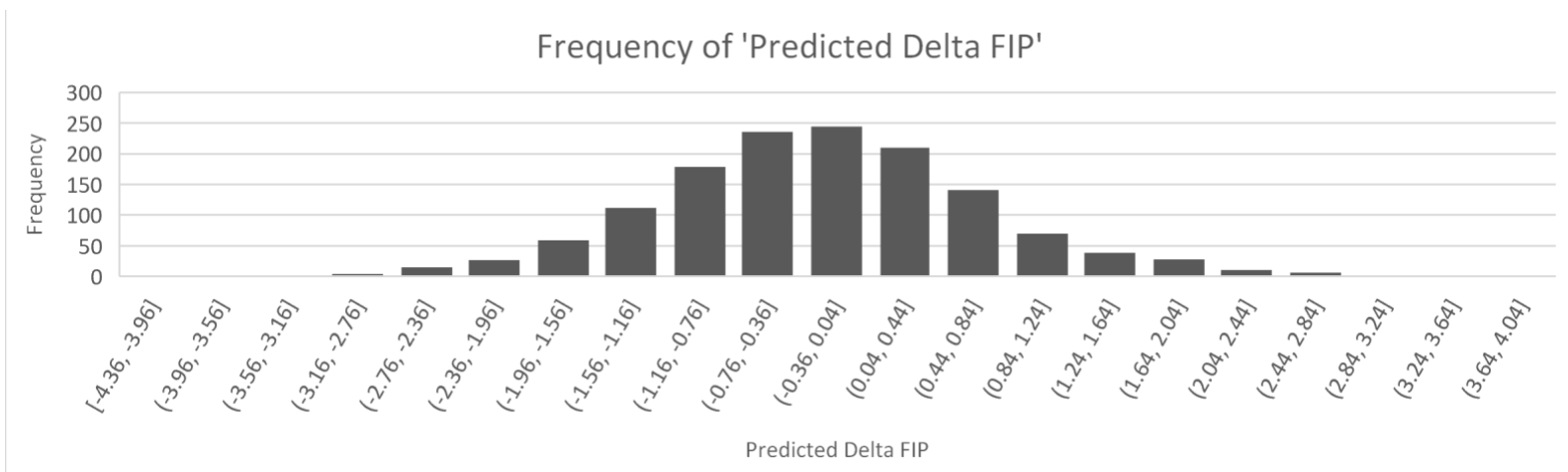
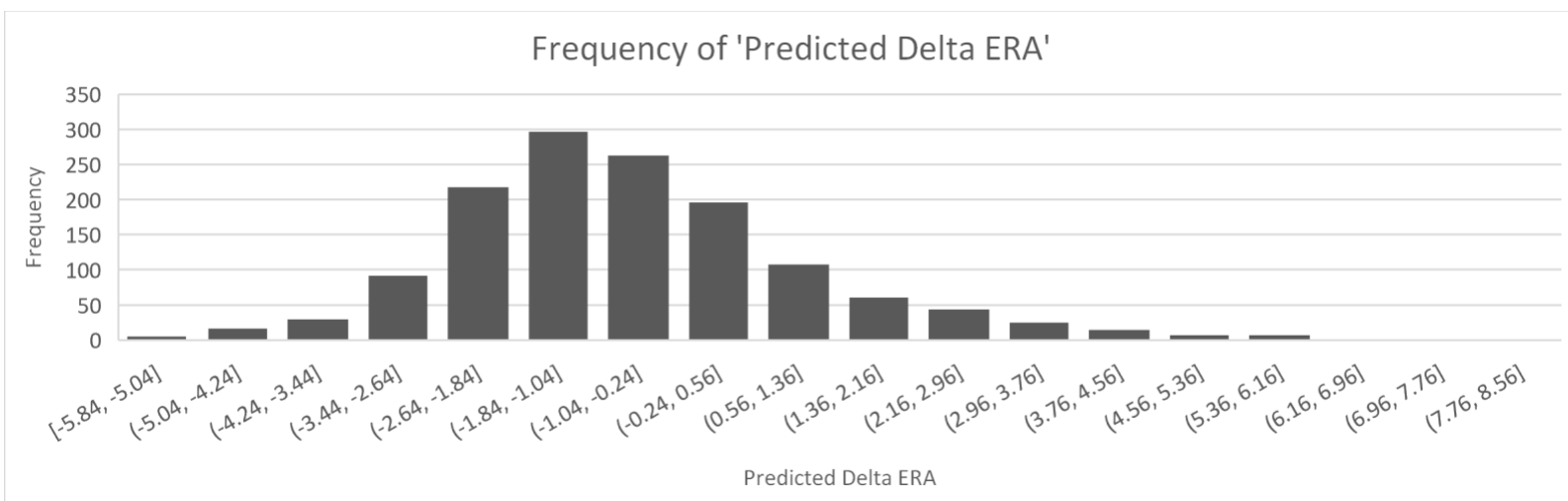
For the final model, we began with placing initial constraints for data cleaning. From all the players from the fangraphs_season_level file, we isolated all relieving pitchers who had played at least 9 innings (to ensure that these players had played at least one full game's worth of baseball). Given these players' MLBAMIDs, we prepared a new dataset with all ideal traits of all relief pitchers who had played at least nine innings. Furthermore, we then removed all NaN values to create our dataset for the final model. We then generated predicted delta values for each ideal trait for each relieving pitcher (and appended each corresponding "predicted delta" value to each respective MLBAMID for analysis)

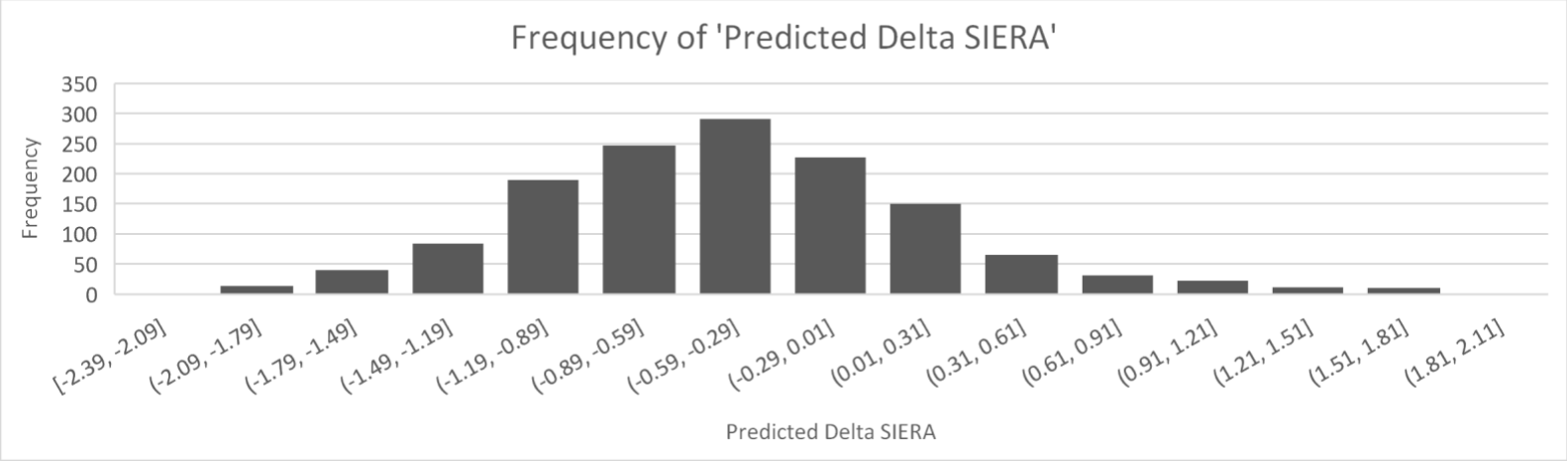
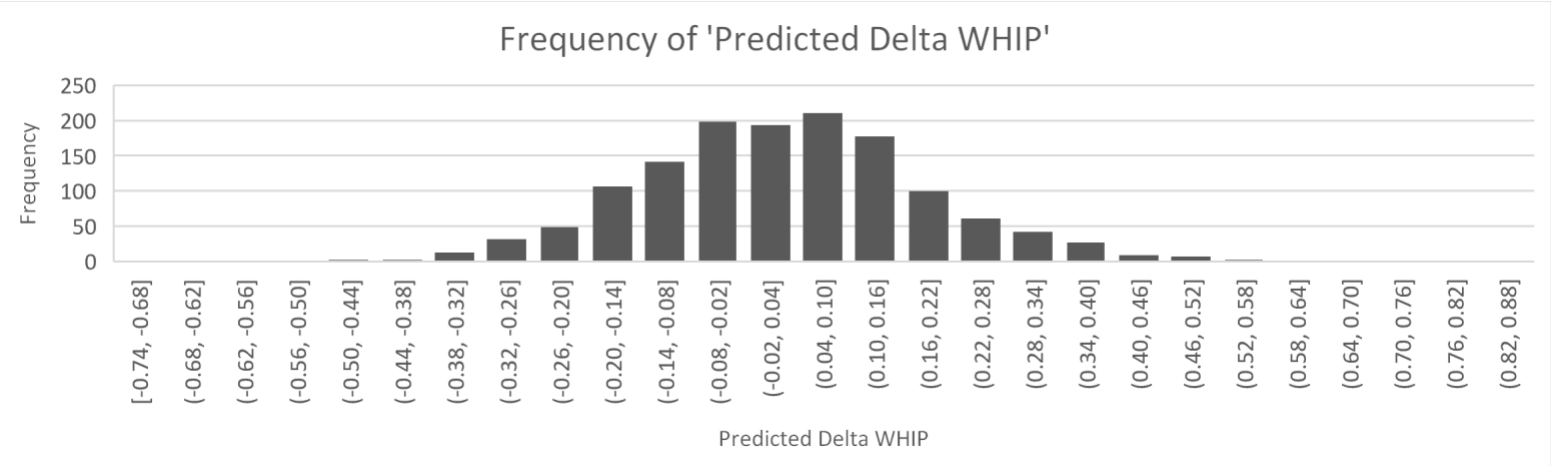
MLBAMID	Predicted Delta ERA	Predicted Delta FIP	Predicted Delta WHIP	Predicted Delta SIERA	Delta Average	Predict ERA Z score	Predict FIP Z score	Predict WHIP Z score	Predict SIERA Z score	Average of Predicted Z scores
669093	2.317243913	3.848692728	0.783569273	1.582710864	2.133054195	1.668764566	4.243854633	4.46504324	3.192473169	3.392533902
663399	1.80260084	2.147013344	0.753032995	1.410371535	1.528254678	1.384315922	2.4788703	4.283681445	2.921074695	2.76685959
621593	2.524846154	3.414316237	0.512344932	0.450273507	1.725557657	1.78350851	3.793318705	2.854181126	1.40982903	2.460209343
664776	-0.943597981	1.883435432	0.668685314	1.722412582	0.832733837	-0.133537078	2.205486906	3.782721676	3.412474216	2.31678643
676979	-0.7682161	1.201137001	0.723795033	1.619473598	0.694047383	-0.036601666	1.49780598	4.11003064	3.250368802	2.205400439
665896	0.121322401	0.953774486	0.596278979	1.560216086	0.807897988	0.455055629	1.24124122	3.352684232	3.157048589	2.051507417
677053	7.880255937	0.624170415	0.481020565	-0.592369493	2.098269356	4.743499878	0.899375398	2.668138692	-0.232824421	2.019547387
657228	5.39207004	2.789639508	0.294157291	-0.459545003	2.004080459	3.368253338	3.145403093	1.558315852	-0.023653572	2.012079678
664161	-1.219182696	1.027632629	0.836000243	0.969928743	0.40359473	-0.285855651	1.317846994	4.776442513	2.227469226	2.00897577
664076	0.332340107	2.329203671	0.626888057	0.233856759	0.880572148	0.571687336	2.667838372	3.534478401	1.06830948	1.960578397
676265	1.97232185	2.957756694	0.24468479	0.67514156	1.462476224	1.478122511	3.319774483	1.264487588	1.763240939	1.95640638
544727	-0.550395275	1.640258051	0.396141025	1.488946708	0.743737627	0.083790197	1.953262973	2.16402009	3.044814193	1.811471863
658551	-2.337663233	2.673588989	0.512876281	0.921451376	0.442563353	-0.904051619	3.025035325	2.857336928	2.15112749	1.782362031
657585	0.919663144	0.670818543	0.553968205	0.939134467	0.77089609	0.896306962	0.947758904	3.10139107	2.178974669	1.781107901
640444	2.083538978	0.533184251	0.420481796	1.066552977	1.025939501	1.539593388	0.805004416	2.308585385	2.379632227	1.758203854
641420	1.527790808	2.019441402	0.402308825	0.274393085	1.05598353	1.232425524	2.346552495	2.200652038	1.132145734	1.77943948
668984	0.421252751	1.889994677	0.474487747	0.463492258	0.812306861	0.62083029	2.212290164	2.629338825	1.429937478	1.723099189
676092	-0.208304074	1.539167808	0.415220952	1.002479632	0.68714108	0.272867606	1.948412026	2.277340053	2.278730082	1.669337442
592135	-0.107462086	2.354760854	0.375559036	0.48147629	0.776803523	0.328604034	2.694346319	2.04177905	1.45825856	1.630746991
665620	-2.25647093	2.021073831	0.30882396	1.695790471	0.442304333	-0.859175778	2.348245654	1.645424485	3.370549948	1.626261077
676206	-2.276272451	2.45643248	0.346585257	1.237603938	0.441087306	-0.870120288	2.799800278	1.869697285	2.64900179	1.612094766
592390	1.180812292	1.772480002	0.263349696	0.755158678	0.992950167	1.040646485	2.090403772	1.375342643	1.889251199	1.598911115
670329	5.396118339	1.787465375	0.175232156	-0.430854588	1.731990321	3.370490875	2.105946623	0.851992838	0.021527844	1.587489545
571946	0.297936419	1.567321075	0.258718485	1.117747275	0.810429676	0.552672055	1.877612635	1.347836844	2.460245396	1.559591733
681402	0.994174067	0.416985046	0.528797335	0.607718722	0.636918792	0.937489933	0.684482432	2.95189563	1.657064041	1.557733009
686294	1.460787533	1.998135004	0.289789383	0.295289589	1.011000377	1.195392109	2.324453469	1.532373866	1.165053366	1.554318202
665048	-1.64069014	1.019358233	0.372393049	1.617590421	0.342162891	-0.518827253	1.309264777	2.022975543	3.247401191	1.515203565
664157	-2.985668358	1.565773217	0.304640732	1.953944735	0.209672582	-1.262210874	1.876007194	1.620579359	3.777089034	1.502866178
667376	-2.156777611	2.728929922	0.271063149	0.952369813	0.448896318	-0.804074231	3.082435021	1.421154569	2.199817575	1.474833234
642770	-1.190863269	0.895796174	0.346219143	1.514734216	0.391471566	-0.270203206	1.18110603	1.867522854	3.085424136	1.465962454
666168	0.752226502	0.827930853	0.568628589	0.037102561	0.546472126	0.803762967	1.11071602	3.188462375	0.758462685	1.465351012
518858	0.409823688	2.786494778	0.076222523	0.630567069	0.975777015	0.614513327	3.142141374	0.263952451	1.693045419	1.428413143
607237	-1.250988988	1.457627013	0.499628549	0.413040338	0.279826728	-0.303435324	1.763837794	2.778655682	1.350486219	1.397386093
605276	3.035191547	1.653663594	0.257421101	-0.308441623	1.159458655	2.065581782	1.967167221	1.340131389	0.214302714	1.396795777
605463	2.383647326	0.734248411	0.349750356	0.148623848	0.904067485	1.705466432	1.013548455	1.888495519	0.934085435	1.385398986

Analysis

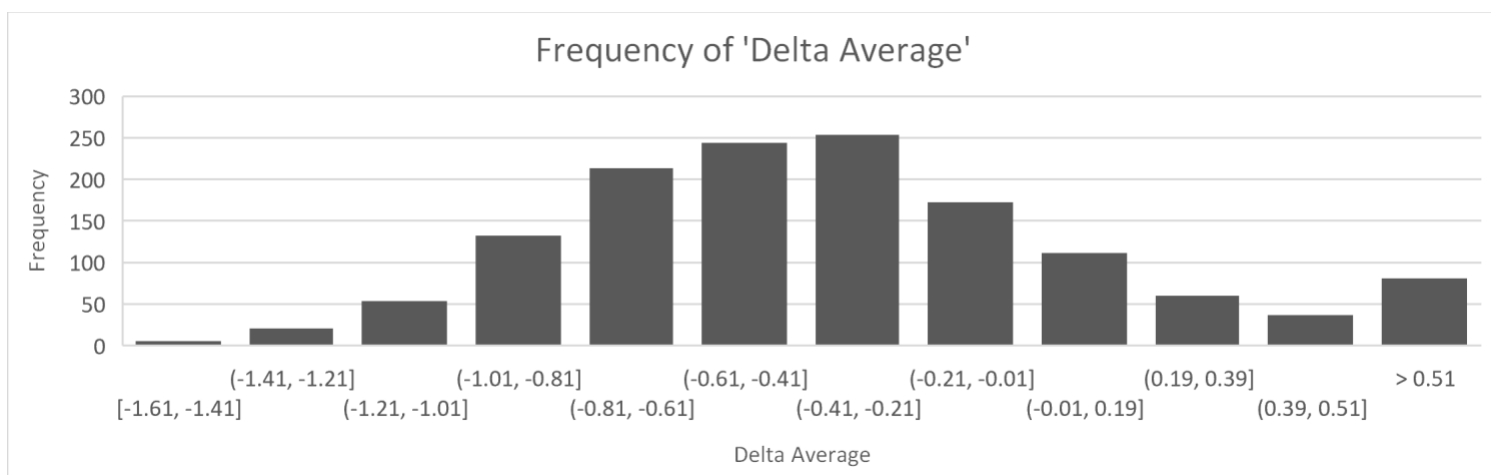
With each of these “predicted delta” statistics, we are presented with all the players and their prediction of improving or deteriorating from switching from RP to SP. The more positive these predicted deltas are, the better that player is predicted to perform as a SP.

There are several methods of deriving support for role switching decisions. With each ideal trait’s predicted delta values, we found that these delta values were fairly normal in series.

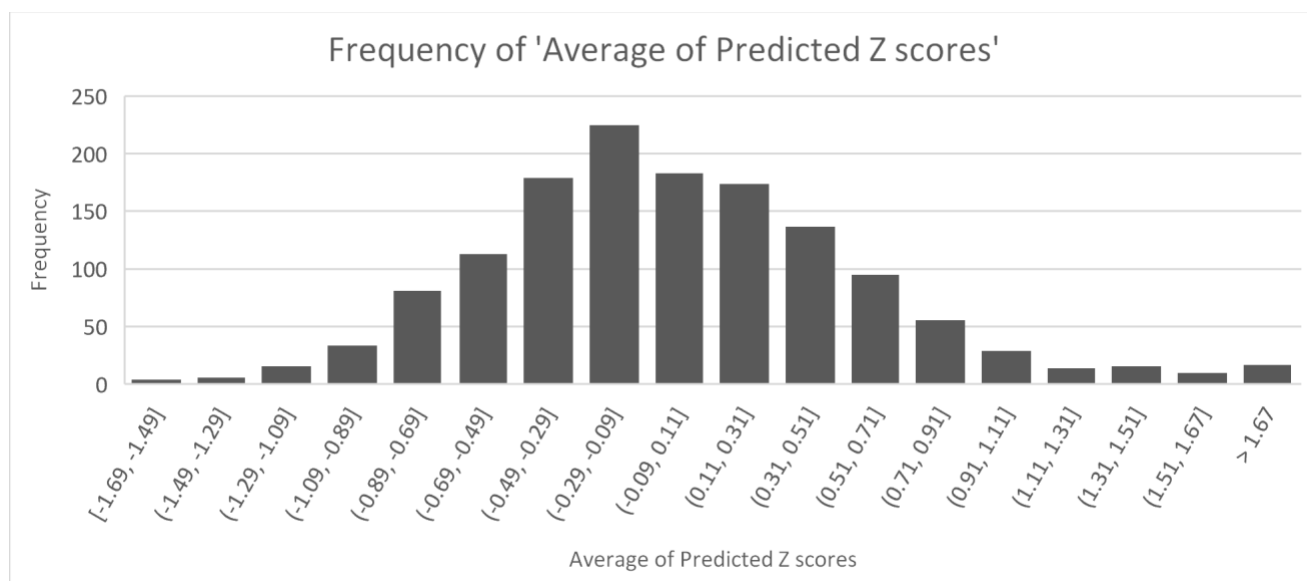




From these figures, we can see the players that are in the upper percentiles of each ideal trait given their “predicted delta” values. You can use this data to find the corresponding MLBAMID values to find exact players. This is applicable to all Predicted ERA, FIP, WHIP, and SIERA values. Additionally, you may consider taking a well-rounded approach to see which players had highest average predicted delta values across their Predicted ERA, FIP, WHIP, and SIERA values.



This could potentially be prone to biases and an increase in outliers, so we wanted to further analyze the data to be as holistic as possible. We decided to take each entity's predicted delta values for each ideal trait, and calculate the z-score of each player's predicted ideal traits across, and take the average of all the z-scores across ideal traits to see which players had the most positive change in overall z-score.



With further time and research, we would like to create a more streamlined and effective method of retrieving the MLBAMID of each player to more easily analyze players against their predicted statistics. Additionally, we would like to further improve our model with more inclusive constraints and perhaps further data cleaning/refinement.