Quantifying framing run value in the 2024 MLB season

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Any casual fan of baseball could tell you that catchers are generally among their teams' most underappreciated players. The best backstops aren't able to deliver the flash of a slick infielder or rob home runs in the outfield. They're relegated to a far less dynamic role. To the uninitiated, this can easily be conflated with a lack of importance to a team's defense. It is easy for the impact of catchers to get lost among more traditional fielding statistics, which don't capture catcher-specific fielding events well. I will focus on the most consistent way that a catcher, and perhaps any position player, can make an impact defensively: receiving pitches.

I offer an updated descriptive statistic to determine runs saved through receiving pitches as well as an overview of framing for the 2024 MLB season. The goal is to supplement statistics like Defensive Runs Saved (DRS) to better measure catchers' influence on a pitch-by-pitch basis. Using pitch tracking data from Statcast, I assign an expected runs saved value to each ball (strike) a catcher frames (misses) via receiving to arrive at the total runs saved for each catcher over the season.

2 Framing

Catchers are responsible for receiving every pitch thrown during a game with the exception of balls in play, foul balls, and wild pitches. Their ability to "frame", i.e. present a pitch as a strike, can influence umpires' decision-making. If a catcher is successful at this, he will generate more called strikes from pitches that are either true balls or close to the edges of the strike zone (dubbed the "Shadow Zone" by Statcast).

Pitches that are clearly a strike or ball generally aren't considered frame-able, but catchers can "miss" strikes. When a pitch thrown in the zone is called a ball, that catcher should be charged with the penalty for increasing the count in the hitter's favor. Obviously, there is umpire error, but I am operating under the assumption that this impacts all catcher's equally due to umpires rotating frequently.

3 Data

To gather pitch-level data for the framing analysis, I pulled called strikes and balls from Statcast independently for each game by catcher, filtering by Statcast's zone areas to separate the "out of zone" pitches (balls) and "in zone" pitches (strikes), relying on Statcast's assessment to account for batter height differences. To classify pitches as frames, I filtered for all called strikes that were either deemed "out of the zone" or within 2 inches of the edge of the plate. Misses were called balls within the strike zone. Table 1 ranks catchers by total frames. Frame and miss rates are calculated by taking the total number of frames (misses) divided by the number of frame (miss) opportunities. The frames per miss ratio (number of framed pitches per missed strike) is also shown.

Table 1: Top 20 Catchers by Total Frames

Catcher	Total Frames	Frame %	Miss %	Frames per Miss
Bailey, Patrick	1001	17.38	8.73	4.47
Raleigh, Cal	990	15.82	9.70	3.82
Contreras, William	967	15.43	10.63	3.62
O'Hoppe, Logan	921	13.64	10.47	3.27
Langeliers, Shea	872	13.04	12.25	2.44
Heim, Jonah	849	14.07	10.78	3.10
Naylor, Bo	827	15.45	9.96	3.61
Stephenson, Tyler	813	13.64	11.00	2.80
Wells, Austin	805	14.54	9.08	4.03
Kirk, Alejandro	773	16.45	8.81	4.44
Fortes, Nick	773	14.15	11.18	2.97
Ruiz, Keibert	770	13.42	11.58	2.71
Diaz, Yainer	742	13.17	12.54	2.47
Smith, Will	734	12.13	11.19	2.38
Amaya, Miguel	730	13.87	10.63	2.82
Rutschman, Adley	729	13.56	10.60	2.95
Rogers, Jake	703	16.52	7.60	4.82
Lee, Korey	682	12.06	12.42	2.42
Realmuto, J.T.	681	13.61	10.68	2.78
Perez, Salvador	677	14.39	10.46	3.12

On average, catchers framed 14.1% of their opportunities and missed 10.9% of possible strikes.

4 Results

Figure 1 visualizes the relative ability of each catcher to generate frames and avoid misses, showing the frame percentage vs the miss percentage for catchers in 2024. The graph utilizes a z-score to better gauge the relative quality of each player at receiving, with positive scores representing an above-average percentage. As such, better receivers are those towards the bottom right corner of the graph:

Figure 1: Frame Percentage vs Miss Percentage for Catchers in 2024

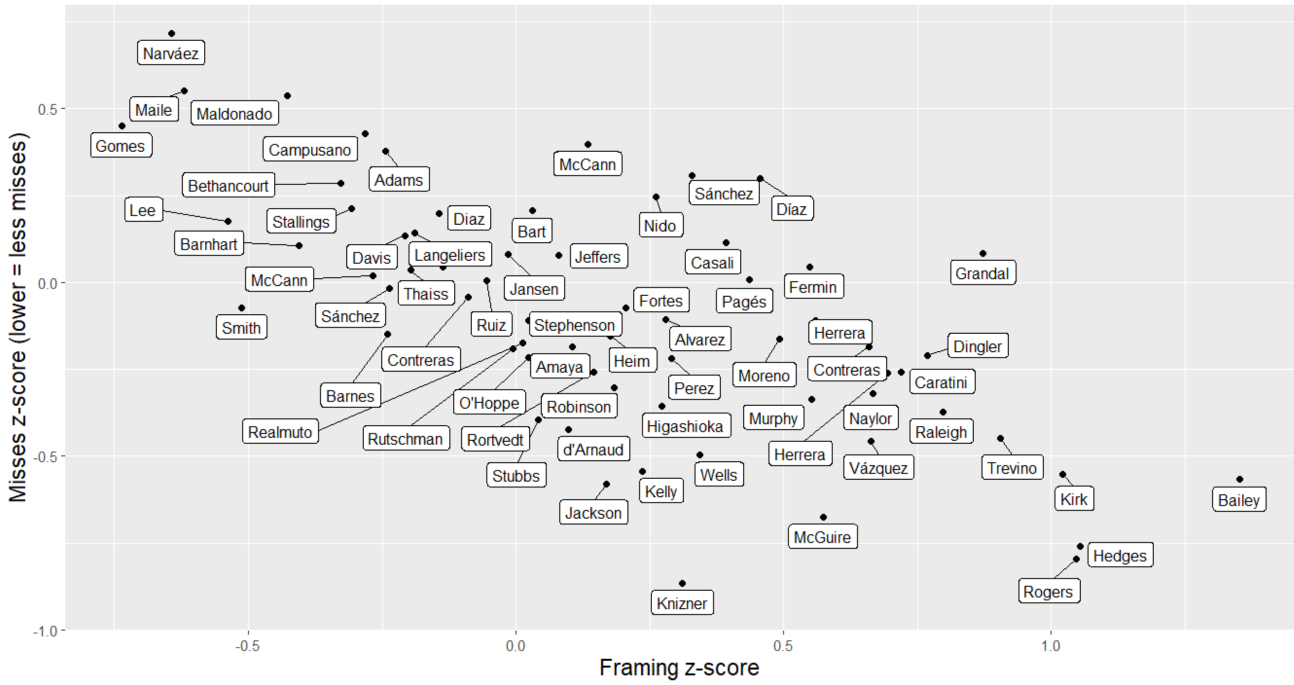
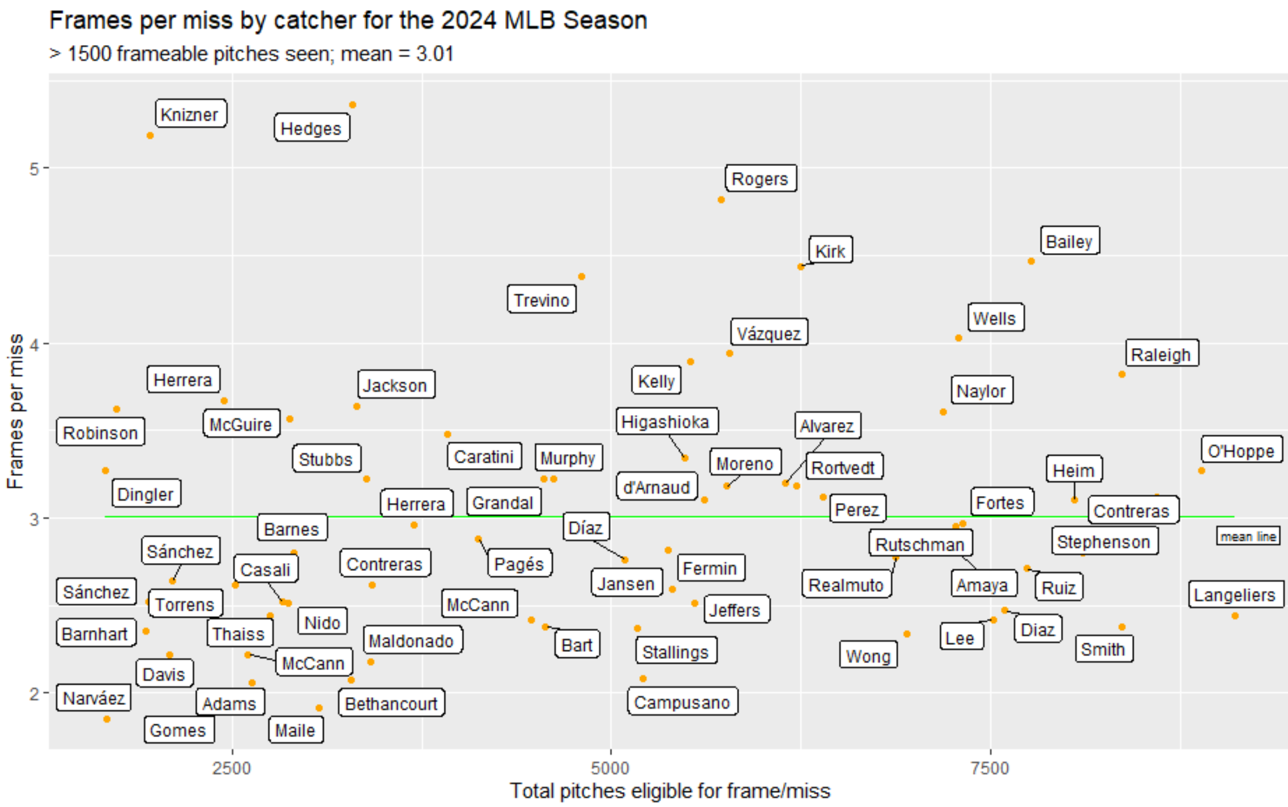


Figure 2 displays the total pitches seen vs. the frames per miss ratio, along with an average line for the frames per miss statistic (3.01):

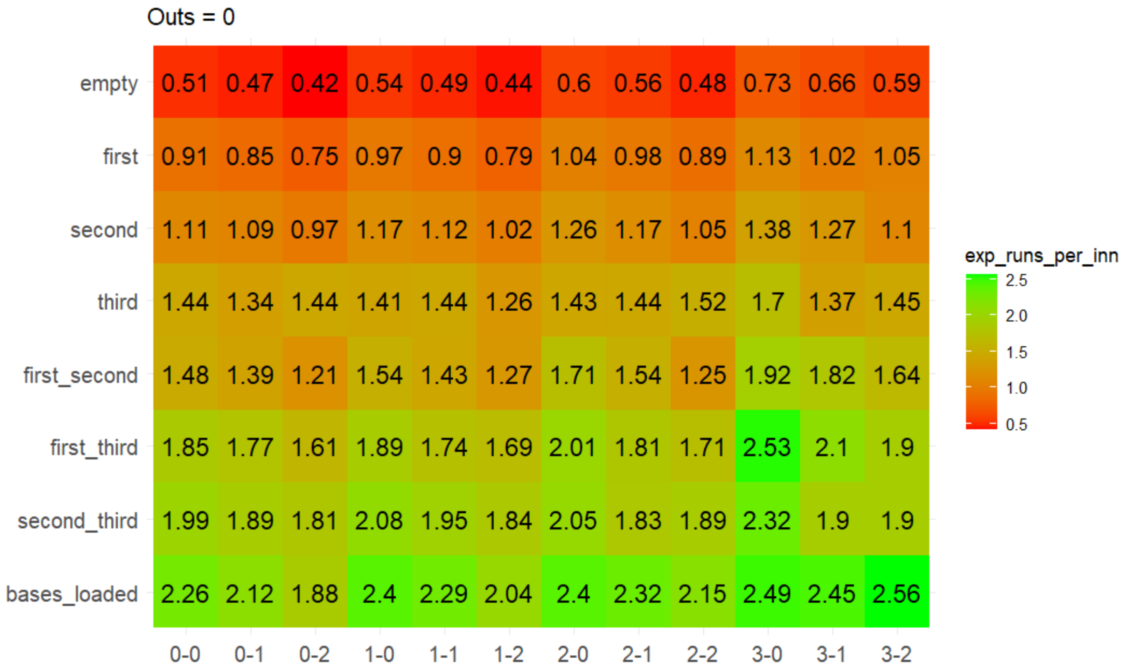
Figure 2: Total Pitches Seen vs Frames per Miss Ratio



5 Run expectancy and runs saved

Translating the impact of getting a called strike or ball requires an understanding of how run expectancy varies across different situations. A frame or miss in an 0-0 count with nobody on seems relatively low stakes compared with 3-2 bases loaded. Framing/missing a pitch in a higher stakes scenario would have a larger impact on a team's ability to score runs. Therefore, catchers who performed better in those higher leverage situations will have had a greater impact on the number of runs saved defensively.

I gathered data on all plays in 2023 and 2024 from Statcast, obtained using the baseballr package in R, to determine run probabilities for an inning in every given count-out-baserunner state, inspired by Tom Tango's run expectancy matrix and Greg Stoll's Win Expectancy model. These are rough estimates, given the sample size for each state can vary greatly, especially for higher counts and more baserunners. However, they should provide an idea of how many runs an average team should score from any point in an inning.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first 0.91 0.85 0.75 0.97 0.9 0.79 1.04 0.98 0.89 1.13 1.02 1.05
second 1.11 1.09 0.97 1.17 1.12 1.02 1.26 1.17 1.05 1.38 1.27 1.1
third 1.44 1.34 1.44 1.41 1.44 1.26 1.43 1.44 1.52 1.7 1.37 1.45
first_second 1.48 1.39 1.21 1.54 1.43 1.27 1.71 1.54 1.25 1.92 1.82 1.64
first_third 1.85 1.77 1.61 1.89 1.74 1.69 2.01 1.81 1.71 2.53 2.1 1.9
second_third 1.99 1.89 1.81 2.08 1.95 1.84 2.05 1.83 1.89 2.32 1.9 1.9
bases_loaded 2.26 2.12 1.88 2.4 2.29 2.04 2.4 2.32 2.15 2.49 2.45 2.56
0-0 0-1 0-2 1-0 1-1 1-2 2-0 2-1 2-2 3-0 3-1 3-2
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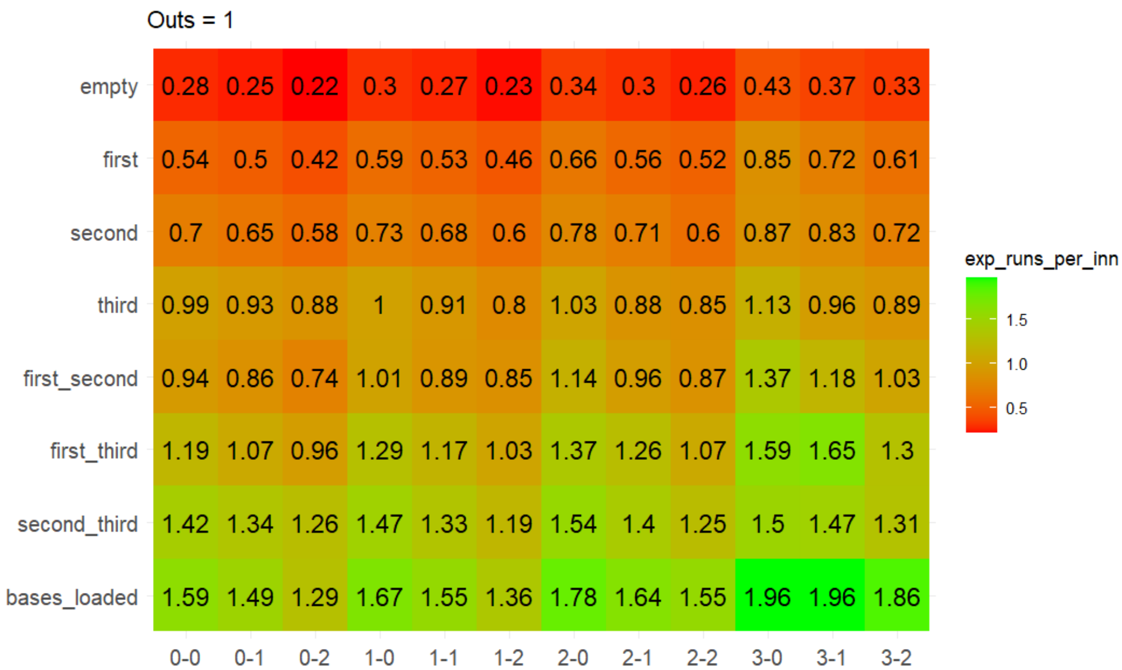
2.0
1.5
1.0
0.5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first 0.54 0.5 0.42 0.59 0.53 0.46 0.66 0.56 0.52 0.85 0.72 0.61
second 0.7 0.65 0.58 0.73 0.68 0.6 0.78 0.71 0.6 0.87 0.83 0.72
third 0.99 0.93 0.88 1 0.91 0.8 1.03 0.88 0.85 1.13 0.96 0.89
first_second 0.94 0.86 0.74 1.01 0.89 0.85 1.14 0.96 0.87 1.37 1.18 1.03
first_third 1.19 1.07 0.96 1.29 1.17 1.03 1.37 1.26 1.07 1.59 1.65 1.3
second_third 1.42 1.34 1.26 1.47 1.33 1.19 1.54 1.4 1.25 1.5 1.47 1.31
bases_loaded 1.59 1.49 1.29 1.67 1.55 1.36 1.78 1.64 1.55 1.96 1.96 1.86
0-0 0-1 0-2 1-0 1-1 1-2 2-0 2-1 2-2 3-0 3-1 3-2
exp_runs_per_inn
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1.0
0.5

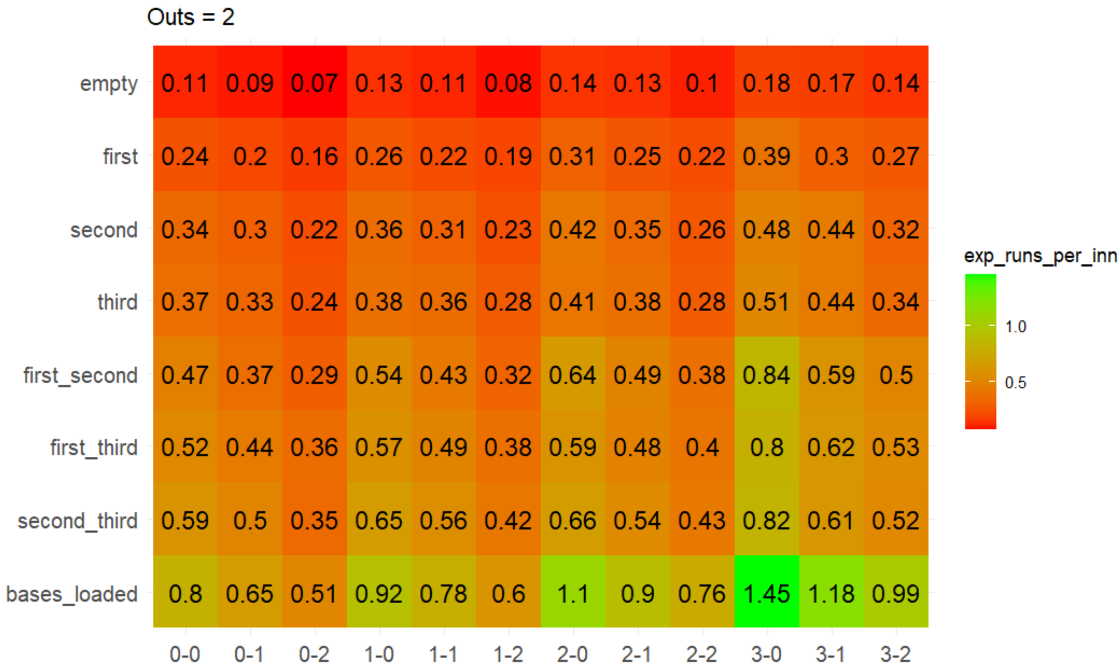

Figure 3: Run Expectancies per inning for each count-out-base state

The matrices show an average run expectancy of 0.51 runs at the start of each inning. We see this run expectancy fall approximately 50% after each out, given the bases are empty. Unsurprisingly, a 3-0 count with 0 outs and bases loaded produces the highest run expectancy for the inning, with an average of 2.49 runs expected for the inning from that state. The minimum run expectancy for the remainder of an inning is 0.07 runs and occurs at a 0-2 count, 2 outs, and bases empty. We can use these numbers to assess the expected change in runs scored for the remainder of an inning given a change in state.

Applying these run expectancies to the framing data, I was able to sum the "runs saved" for each catcher based on their frames and misses in each count-out-baserunner state. For example, if a catcher frames a pitch in a 0-0 count, 0 outs, nobody on, they are rewarded with 0.07 runs saved. This is the difference between the run expectancy for a 1-0, 0 outs, bases empty state and a 0-1, 0 outs, bases empty state. Conversely, if a catcher misses a strike in the same scenario, they are penalized with -0.07 runs saved. In other words, the difference in expected runs between if the pitch were called a ball vs a strike. This approach assumes any given frame (miss) would have resulted in a ball (strike) given no catcher influence on the pitch.

The approach also implies a fundamental difference between frame values across count-out-baserunner states. Applying discrete run expectancies based on each state rather than assigning value independent of the state they occurred, I assume that:

i. Catchers experience a similar allocation of states given a reasonable number of appearances

ii. There are meaningful differences between framing a crucial pitch in a high leverage situation (e.g., 3-2 bases loaded) compared with low leverage ones (e.g., 0-0 bases empty)

Assumption (i) is explored in a later section and quantified through Table 9.

Assumption (ii) describes the goal of creating a statistic that accurately captures the dynamics of run expectancy across inning states. Given the current scope is not to create a predictive statistic, but rather one to evaluate framing in a given period, I find it more informative in this context to assess catchers based on measured performance rather than normalizing each catcher to a single count-out-baserunner state mix.

Table 2: Catcher Totals for Runs Saved in 2024

Catcher	Runs saved above avg	Runs saved per pitch	Runs saved z-score
Bailey, Patrick	62.35	0.0119	0.700
Raleigh, Cal	56.02	0.0103	0.405
Kirk, Alejandro	47.17	0.0123	0.786
Contreras, William	46.36	0.0089	0.148
O'Hoppe, Logan	45.67	0.0085	0.078
Naylor, Bo	43.31	0.0102	0.390
Heim, Jonah	39.81	0.0086	0.106
Perez, Salvador	36.26	0.0103	0.417
Stephenson, Tyler	35.97	0.0081	0.010
Alvarez, Francisco	35.57	0.0106	0.476
Trevino, Jose	35.35	0.0135	1.012
Fortes, Nick	34.35	0.0088	0.130
Rogers, Jake	33.70	0.0111	0.559
Langeliers, Shea	33.59	0.0070	-0.203
Wells, Austin	33.58	0.0087	0.117
Amaya, Miguel	32.69	0.0086	0.101
Vázquez, Christian	32.06	0.0107	0.378
Moreno, Gabriel	31.76	0.0107	0.483
Rutschman, Adley	27.87	0.0079	-0.024
Kelly, Carson	27.61	0.0104	0.430

Table 2 shows the top 20 catchers by runs saved for the season. Note the statistic is calculated as “runs saved above average”, signifying that 10 is equivalent to preventing 10 runs more than the average catcher (in the sample) through framing.

6 Probabilistic model

The previous model calculated runs saved assuming that if a pitch was framed, a catcher was responsible for all the estimated runs saved associated with that pitch being framed or missed, regardless of the true ”difficulty” of the frame. Inspired by Dan Brooks and Harry Pavlidis at Baseball Prospectus, I remove this assumption by applying the percent chance a pitch was called a strike to the total run value measured for each frame and miss. For example, if a catcher framed a pitch that's called a ball 60% of the time across the league, then that catcher's expected runs saved on that framed pitch is 60% of the total run value of the frame; if a catcher misses a strike on a pitch called a strike 70% of the time, they receive 70% of the total run differential on that pitch. Run differential is again calculated using the expected runs per inning in each count-out-baserunner state.

To build our probability model, a training set of 2024 pitch data from Statcast was sampled, with zone location from Statcast being the primary determinant in calling a pitch. After some fine tuning, the constructed strike probability model yielded 92% accuracy with our test data ($n = 70{,}177$).

Using the calculated probabilities, our new expected runs saved statistic rewards higher difficulty frames and punishes easy misses. If a pitch was called a ball at a relatively higher percentage (based on location), then it should be theoretically more difficult to frame. This helps to limit potential bias arising from any systematic differences between each catcher's framing opportunities, such as variations in pitchers' ability to ”paint” corners vs miss badly, by rewarding catchers for such challenges.

Simultaneously, the statistic improves in accuracy by establishing an average catcher's performance as a baseline. Given each pitch has some percentage it would have been a ball or strike regardless of catcher behavior, using this probability as a weight proxies the contribution of each individual catcher to a frame or miss. Thus, a catcher only receives the portion of the run value of a frame above what an average catcher would have provided. Table 3 shows the top 20 leaders in expected runs saved with the updated probability model incorporated.

We also see the expected runs saved totals for the season fall down to Earth a bit compared to the first model. A maximum of 25 runs saved per year equates to about 2.5 wins above average, more reasonable than estimating a 6-7 win difference between the top and average catchers.

Catcher	Expected runs saved above avg	Runs saved per pitch
Bailey, Patrick	23.05	0.0033
Raleigh, Cal	16.55	0.0023
Kirk, Alejandro	16.37	0.0031
Trevino, Jose	15.02	0.0037
Naylor, Bo	11.93	0.0021
Alvarez, Francisco	11.29	0.0023
Wells, Austin	11.14	0.0019
Díaz, Elias	10.77	0.0027
Hedges, Austin	10.40	0.0041
Vázquez, Christian	10.40	0.0023
Perez, Salvador	9.78	0.0020
Rogers, Jake	9.26	0.0021
Moreno, Gabriel	7.62	0.0018
Grandal, Yasmani	7.22	0.0022
Rortvedt, Ben	5.82	0.0014
Fortes, Nick	5.35	0.0011
Heim, Jonah	4.74	0.0010
Jackson, Alex	4.50	0.0023
Herrera, Jose	4.42	0.0030
Caratini, Victor	4.37	0.0019

Table 3: Framing runs saved above average based on probabilistic balls/strikes

As a check, our runs saved above average metric has a correlation of 0.77 with each catcher's ratio of frames to misses. It's not surprising then that many of the top rated catchers – e.g., Patrick Bailey, Cal Raleigh, Alejandro Kirk – are highly rated in this statistic. Catchers who measurably frame much more often than they miss pitches should prevent more runs.

7 Player highlights

- **Patrick Bailey**
  - 23 runs saved above average (∼2.5 wins above average)
  - Highest frame percentage (12.88%), as well as most total frames (1001)
  - Fourth highest frames per miss (4.47)
  - >7700 pitches seen
- **Cal Raleigh**
  - Second highest number of runs saved above average (16.55) (∼1.5 wins above average)
  - Seventh highest frame percentage (11.83%)
  - Tenth highest frames-per-miss ratio (3.82)
  - High number of pitches seen (>8300 pitches)

- **Alejandro Kirk**
  - 16.37 runs saved above average (∼1.5 wins above average)
  - Fifth highest runs saved per pitch
  - T-third highest frame percentage (12.38%)
  - Seventh lowest miss percentage (8.81%)
  - 6244 pitches seen
- **Jose Trevino**
  - Second highest runs saved per pitch
  - T-third highest frame percentage (12.38%)
  - Sixth in frames per miss ratio (4.38)
  - Only 4807 frame-able pitches seen
  - Played behind rookie Austin Wells
- **Austin Hedges**
  - Highest runs saved per pitch
  - Highest frames per miss ratio (5.36)
  - Second highest frame percentage (12.69%)
  - Third lowest miss percentage (7.77%)
  - Only ∼3000 pitches seen

We further apply the same methodology to each team to arrive at their framing runs saved above average. This helps to understand how each team was impacted by their receiving [1].

Cleveland is a good example of a team that enjoyed huge success up until the ALCS, despite an essentially league-average offense. Their catchers were able to generate over 2 wins above average through framing, helping a solid pitching staff achieve the third-lowest ERA and fifth-lowest WHIP among all teams. Their success could also help reconcile their over-performance relative to preseason projections. Given framing is such an overlooked skill, perhaps a small market team like Cleveland looking for an edge has seen the value in taking catchers who are quality receivers.

The reigning champion Dodgers seem to have taken an alternative approach, surprisingly falling third to last in the team rankings. Will Smith, their primary starter, was responsible for a whopping -9 runs saved below average over the course of the season, with backup Austin Barnes not faring a whole lot better. Despite obvious success in the postseason last year, it will be interesting to see how they address this issue in the long-term, especially given Smith's 10-year contract extension at the beginning of the '24 season. Looking at high-quality defensive backups to balance the lackluster glove of Smith might be a prudent move for baseball's defending champions.

8 Normalizing states

To investigate potential bias from variation in count-out-baserunner state, I mapped each catcher's results to a standardized state mix. This was taken as the average proportion of count-out-baserunner states for each qualifying catcher over the 2024 season. I multiplied the average proportion of each state by each catcher's frame (miss) rate and probability of a pitch being called a ball (strike) in that state. This was finally multiplied by the expected runs saved for each frame (miss) in that state, giving us the expected runs saved per frame (miss)

[1] See Table 8.

for that catcher had they experienced the average count-out-baserunner state mix. This will allow us to observe how each catcher would have performed had they experienced identical game situations.

For each catcher c:

$$n \sum_{i \in I} (f_{i,c} \cdot p_i \cdot r_{f_i} \cdot (1 - k_{i,c})) - n \sum_{i \in I} (m_{i,c} \cdot p_i \cdot r_{m_i} \cdot k_{i,c})$$

, where:

- **n = number of frame/miss eligible pitches, defaulted to 7500**
- **i = each unique count-out-baserunner state**
- $f_{i,c}$ **= frame rate in each i for catcher c**
- r_{f_i} **= runs saved per frame in each i**
- $k_{i,c}$ **= probability of pitch being a strike in each i for catcher c**
- p_i **= proportion of total appearances in each i**
- $m_{i,c}$ **= miss rate in each i for catcher c**
- r_{m_i} **= runs saved per miss in each i**

Shown below are the resulting top 20 catchers by normalized runs saved above average. I also calculated the implied bias each catcher received from seeing different proportions of states relative to average by subtracting the normalized runs saved from a catcher's original runs saved, available in the appendix[2]. It's important to note these numbers are for the sake of comparison of how state mix impacts framing runs saved rather than a reinterpretation of the statistic.

Player	**Normalized Runs Saved**
Hedges, Austin	27.13
Trevino, Jose	22.09
Kirk, Alejandro	20.17
Bailey, Patrick	18.92
Raleigh, Cal	14.17
Alvarez, Francisco	13.14
Grandal, Yasmani	12.29
Perez, Salvador	12.27
Naylor, Bo	11.97
Díaz, Elias	11.21
Knizner, Andrew	10.86
Rogers, Jake	10.35
Vázquez, Christian	9.79
Rortvedt, Ben	7.83
Kelly, Carson	7.72
Moreno, Gabriel	7.68
Nido, Tomás	6.11
Caratini, Victor	5.98
Heim, Jonah	5.83
Wells, Austin	5.16

Table 4: Normalized runs saved by catcher, defaulted to 7,500 pitches seen

[2] See Table 9.

On a per pitch basis, we can examine how much each catcher's expected runs saved changed between their own state's seen vs the normalized state mix. Some players remained relatively unchanged by this, while others experienced dramatic shifts to their expected runs saved. Those most impacted likely saw a relatively high or low proportion of high-leverage states, leading to differences in their runs saved metrics despite potentially framing at a higher rate.

While the normalized statistic has its uses as a way to compare catcher's more directly, the original statistic is a better representation of how each catcher affected the games they played in. Understanding that this bias exists is important to arrive at better statistics for framing in the future, but it will require more disentanglement of the influence of catcher behavior on inning-state changes. Using a variation of this normalizing technique while retaining meaningful variables unique to each catcher, such as frame rates, could help to build better framing models without confounding effects outside the catcher's control.

9 Impact of pitchers

As much work as I spend emphasizing the contribution of catchers, receiving outcomes are not based on catcher skill alone. A pitcher first has to throw a "frameable" pitch. The quality of a catcher's pitchers, whether or not they consistently hit spots, or the difficulty in framing their pitches relative to others', may influence the ability of their catcher to frame.

To understand the potential impacts of pitchers on framing, I investigated each *pitcher*'s relative ability to generate frames, again compiled from 2024 Statcast pitch data. The idea is that pitchers who were able to generate more frames and less misses regardless of catcher inflate their catchers' runs saved estimation. If catchers are truly quality framers, they should perform statistically better than other catchers under similar conditions; in this case, their battery mate(s).

Grouping Statcast pitching data by pitcher and the catcher they were throwing to, I analyzed the expected runs added per pitch for each pitcher, grouped by the catcher they were throwing to. Table 5 looks at the expected runs added when each catcher was excluded from their teammates' receiving totals. I excluded batteries that did not have at least 150 pitches together to avoid small sample size bias, although the nature of catching means most pitchers don't have an even split between catchers. Catchers who performed better than their peers are those with more negative run differentials, implying their teammates saved relatively less framing runs with the same pitchers.

Catcher	**z-score**	**Run differential**
Raleigh, Cal	-1.3804	-0.00733
Amaya, Miguel	-1.0445	-0.00559
Bailey, Patrick	-1.0238	-0.00548
Trevino, Jose	-1.0090	-0.00540
Higashioka, Kyle	-0.9867	-0.00528
Fortes, Nick	-0.9305	-0.00499
Vázquez, Christian	-0.9277	-0.00498
Kirk, Alejandro	-0.8226	-0.00443
Nido, Tomás	-0.8065	-0.00435
O'Hoppe, Logan	-0.7800	-0.00421
Robinson, Chuckie	-0.7690	-0.00415
McGuire, Reese	-0.6914	-0.00375
Grandal, Yasmani	-0.6561	-0.00357
Hedges, Austin	-0.6235	-0.00340
Stephenson, Tyler	-0.6068	-0.00331
Knizner, Andrew	-0.5955	-0.00325
Rutschman, Adley	-0.5315	-0.00292
Jackson, Alex	-0.5178	-0.00285
Rogers, Jake	-0.4035	-0.00225
Murphy, Sean	-0.3874	-0.00217
Langeliers, Shea	-0.3368	-0.00191
Contreras, William	-0.3174	-0.00181
Ruiz, Keibert	-0.2956	-0.00169
Heim, Jonah	-0.2906	-0.00167
Herrera, Iván	-0.2629	-0.00152

Table 5: Best catcher-pitcher run differentials

To say for certain whether a catcher did not receive assistance from their pitchers would rely on the assumption that the rest of the team's catchers are close to "average" receivers. We will have to make do with the knowledge that these figures are likely skewed for catchers on teams with backups whose defensive abilities deviate from the mean significantly, and merely act as a placeholder for future analysis on the subject. Lack of available data such as catcher positioning relative to pitch location makes it difficult to determine how frame-able certain pitchers are compared to others.

Viewing the top 25 catchers by the z-score for the mean expected run differential, which is the difference in the mean expected runs saved per pitch when that catcher was excluded and the catcher's expected runs saved per pitch they received, we see some familiar faces. Cal Raleigh tops the list with a whopping .007 runs saved per pitch above his peers when catching the same pitchers. Patrick Bailey is third on this list with .0055 runs saved per pitch, while Alejandro Kirk falls slightly lower, and Austin Hedges below him. It's interesting to note Hedges placing lower than the aforementioned trio despite his domination in our earlier measurements of framing quality. Hedges may be the benefactor of higher quality pitching than the others.

On the flip side, catchers with positive run differentials are measured to have a negative impact relative to their peers catching the same pitchers. As a result, we can infer that they benefited more from the quality of the pitchers than their own framing, or at least that their teammates performed better.

For everyday players who catch the same pitchers often, the former becomes even more compelling. Bo Naylor's positive run differential per pitch, for instance, shows his teammates were more capable receiving the same pitchers he was. Thus, his framing numbers, though good on the surface, could be biased by the quality pitching he received all year. That being said, his competition mostly being Austin Hedges, a receiving specialist, is likely a big reason why Bo looks bad here, and also explains Hedges relative lack of dominance compared with his other framing statistics.

These run differential comparisons are by no means a sure-fire approach to determining catcher-receiving quality ceteris paribus. The lack of sufficient sample sizes necessitated by MLB roster constraints mean that we can only directly compare catchers to so few other catchers. It's lucky if a pitcher throws to more than a few catchers in a given year, let alone more than 150 pitches. However, it can act as a sanity check of a catcher's relative quality compared to those who catch the same pitchers.

Catcher	**z-score**	**Run differential**
Campusano, Luis	1.0944	0.00554
Davis, Henry	0.9579	0.00483
Wells, Austin	0.8973	0.00451
Sánchez, Gary	0.8456	0.00424
Narváez, Omar	0.7843	0.00392
Stallings, Jacob	0.7813	0.00391
Jeffers, Ryan	0.7745	0.00387
Naylor, Bo	0.7673	0.00383
Maile, Luke	0.7330	0.00366
Gomes, Yan	0.7278	0.00363
Casali, Curt	0.7191	0.00358
Jansen, Danny	0.6739	0.00335
Bethancourt, Christian	0.6498	0.00322
Torrens, Luis	0.6485	0.00322
Barnhart, Tucker	0.6231	0.00308
Adams, Riley	0.5333	0.00262
Diaz, Yainer	0.5081	0.00249
Wong, Connor	0.5052	0.00247
McCann, Kyle	0.4028	0.00194
Thaiss, Matt	0.3918	0.00188
Smith, Will	0.3906	0.00188
Contreras, Willson	0.3898	0.00187
Fermin, Freddy	0.3884	0.00187
Bart, Joey	0.2772	0.00129
Stubbs, Garrett	0.2233	0.00101

Table 6: Worst catcher-pitcher run differentials

10 Other Considerations

Catcher receiving should be as commonly discussed as any other defensive contribution. The runs saved metric indicates catchers saved multiple wins through stealing strikes and avoiding misses. This doesn't even factor in the impacts of blocking or caught stealing. It's easy for catchers to get overlooked by diving catches, double plays, and robbed home runs. Their contributions are much less obvious, but certainly no less important. Hopefully, this is a start to understanding their true value and importance to team success.

There are a number of potential improvements that could be made to refine the runs saved model. Differences in the sample of states each catcher faces may lead to certain catchers facing more high-leverage situations, as discussed earlier. With this in mind, the runs saved statistic is a measure of the realized impact of a catcher's receiving in a season, rather than their expected performance given a standardized set of opportunities.

Catcher positioning caused by different baserunner states may also bias results. If catchers face more stealing situations, it could cause them to move out of more comfortable receiving positions, leading to more frames and misses. This would tend to negatively impact catchers on worse teams or with worse pitching who tend to face more baserunners.

11 Acknowledgements

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All datasets displayed and used in this paper are available upon request. You can find most of the work associated with this, including R code, on my github /bellman123.

All of the pitch-level data was gathered from MLB's Statcast data platform and accessed through the "baseballr" package by Bill Petti and Saiem Gilani in R. I give full credit to MLB for ownership of the underlying data downloaded from the Statcast platform.

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13 Appendix

Team	Runs Saved	Frames per Miss
NYY	21.85	4.09
CLE	21.38	4.08
TOR	14.55	3.61
SF	14.26	3.60
SEA	10.46	3.56
DET	9.92	4.23
NYM	8.24	2.72
AZ	7.26	2.68
KC	6.62	2.97
TB	5.68	3.23
TEX	4.95	3.42
COL	3.17	2.78
HOU	0.73	2.87
MIN	-1.12	3.11
PHI	-2.23	2.92
STL	-3.94	3.02
ATL	-3.15	3.22
CHC	-3.40	2.59
LAA	-3.69	3.04
STL	-4.30	2.83
PIT	-4.62	2.66
CWS	-5.82	2.48
BAL	-6.62	2.74
MIA	-7.04	2.64
MIL	-7.29	3.05
CIN	-10.63	2.52
SD	-11.37	2.54
BOS	-12.80	2.61
LAD	-13.23	2.50
WSH	-13.79	2.53
OAK	-17.89	2.36

Table 8: Framing runs saved by team, 2024

	Player	Runs saved	Frames / miss	Frame rate	Miss rate	Runs saved per pitch	Total pitches
1	Bailey, Patrick	23.05	4.47	17.38	8.73	0.00262	7771
2	Raleigh, Cal	16.55	3.82	15.82	9.70	0.00161	8367
3	Kirk, Alejandro	16.37	4.44	16.45	8.81	0.00237	6244
4	Trevino, Jose	15.02	4.38	16.12	9.32	0.00301	4807
5	Naylor, Bo	11.93	3.61	15.45	9.96	0.00135	7183
6	Alvarez, Francisco	11.29	3.20	14.36	11.02	0.00159	6144
7	Wells, Austin	11.14	4.03	14.54	9.08	0.00121	7287
8	Díaz, Elias	10.77	2.76	14.86	13.04	0.00197	5088
9	Hedges, Austin	10.40	5.36	16.54	7.77	0.00333	3294
10	Vázquez, Christian	10.40	3.94	15.44	9.28	0.00159	5776
11	Perez, Salvador	9.78	3.12	14.39	10.46	0.00127	6397
12	Rogers, Jake	9.26	4.82	16.52	7.60	0.00141	5723
13	Moreno, Gabriel	7.62	3.18	14.96	10.74	0.00111	5761
14	Grandal, Yasmani	7.22	3.22	16.03	11.97	0.00151	4556
15	Rortvedt, Ben	5.82	3.18	13.98	10.26	0.00069	6223
16	Fortes, Nick	5.35	2.97	14.15	11.18	0.00041	7315
17	Heim, Jonah	4.74	3.10	14.07	10.78	0.00023	8057
18	Jackson, Alex	4.50	3.64	14.05	8.66	0.00152	3317
19	Herrera, Jose	4.42	3.67	15.53	10.25	0.00230	2443
20	Caratini, Victor	4.37	3.48	15.60	10.27	0.00115	3918
21	O'Hoppe, Logan	4.35	3.27	13.64	10.47	0.00010	8895
22	Knizner, Andrew	3.81	5.19	14.45	7.25	0.00273	1962
23	Nido, Tomás	3.69	2.51	14.31	12.77	0.00159	2869
24	Kelly, Carson	3.56	3.89	14.24	8.85	0.00045	5523
25	Amaya, Miguel	3.01	2.82	13.87	10.63	0.00010	7258
26	Stephenson, Tyler	2.72	2.80	13.64	11.00	-0.00003	8104
27	Rutschman, Adley	1.83	2.95	13.56	10.60	-0.00007	7272
28	Higashioka, Kyle	1.60	3.34	14.34	9.78	0.00011	5480
29	Contreras, William	0.96	3.12	15.43	10.63	-0.00027	8594
30	Fermin, Freddy	0.80	2.82	15.12	11.77	-0.00002	5374
31	Pagés, Pedro	0.65	2.88	14.80	11.59	0.00015	4125
32	d'Arnaud, Travis	0.15	3.10	13.85	9.45	-0.00017	5610
33	Stubbs, Garrett	0.06	3.22	13.69	9.58	0.00017	3381
34	Robinson, Chuckie	-0.76	3.62	14.09	10.04	0.00054	1741
35	Realmuto, J.T.	-0.78	2.78	13.61	10.68	-0.00041	6877
36	Barnhart, Tucker	-1.00	2.35	12.43	12.08	0.00029	1933
37	Maldonado, Martín	-1.02	2.18	12.37	14.22	-0.00016	3408
38	McGuire, Reese	-1.16	3.57	15.19	8.19	-0.00010	2877
39	Herrera, Iván	-1.30	2.96	15.15	11.00	-0.00028	3694
40	Dingler, Dillon	-1.63	3.27	15.74	10.50	0.00008	1667
41	Barnes, Austin	-1.65	2.80	12.90	10.81	-0.00027	2909
42	Sánchez, Ali	-1.96	2.64	12.91	11.46	-0.00025	2107
43	Jansen, Danny	-2.19	2.59	13.53	11.95	-0.00058	5400
44	Murphy, Sean	-2.28	3.22	15.13	9.87	-0.00058	4615
45	Diaz, Yainer	-2.39	2.47	13.17	12.54	-0.00065	7597
46	Contreras, Willson	-2.65	2.62	13.32	11.34	-0.00063	3417
47	Ruiz, Keibert	-2.89	2.71	13.42	11.58	-0.00072	7736
48	Narváez, Omar	-2.97	1.85	11.76	15.11	-0.00073	1676
49	Lee, Korey	-3.03	2.42	12.06	12.42	-0.00074	7515
50	Torrens, Luis	-3.54	2.62	13.33	12.09	-0.00095	2515
51	Bart, Joey	-4.01	2.38	13.66	12.57	-0.00096	4567
52	Thaiss, Matt	-4.07	2.44	13.02	11.72	-0.00113	2751
53	Langeliers, Shea	-4.33	2.44	13.04	12.25	-0.00088	9110
54	McCann, James	-4.47	2.42	12.82	11.64	-0.00106	4474
55	Gomes, Yan	-5.39	1.85	11.50	13.79	-0.00196	1957
56	Casali, Curt	-5.62	2.52	14.68	12.12	-0.00166	2834
57	Davis, Henry	-6.42	2.22	12.99	12.22	-0.00239	2083
58	Sánchez, Gary	-6.43	2.52	14.50	13.07	-0.00251	1945
59	Stallings, Jacob	-6.99	2.37	12.71	12.60	-0.00151	5172
60	Wong, Connor	-7.23	2.34	13.19	11.77	-0.00134	6949

Table 7: Framing runs saved by catcher, 2024

	Player	Norm runs saved	Run bias pct
1	Hedges, Austin	27.13	10.84
2	Trevino, Jose	22.09	21.38
3	Kirk, Alejandro	20.17	13.23
4	Bailey, Patrick	18.92	24.49
5	Raleigh, Cal	14.17	18.86
6	Alvarez, Francisco	13.14	24.55
7	Grandal, Yasmani	12.29	26.82
8	Perez, Salvador	12.27	18.06
9	Naylor, Bo	11.97	23.14
10	Díaz, Elias	11.21	44.80
11	Knizner, Andrew	10.86	58.16
12	Rogers, Jake	10.35	35.56
13	Vázquez, Christian	9.79	43.64
14	Rortvedt, Ben	7.83	26.19
15	Kelly, Carson	7.72	12.69
16	Moreno, Gabriel	7.68	44.08
17	Nido, Tomás	6.11	65.06
18	Caratini, Victor	5.98	57.65
19	Heim, Jonah	5.83	18.82
20	Wells, Austin	5.16	64.56
21	Herrera, Jose	4.97	77.97
22	Stephenson, Tyler	4.90	7.12
23	Robinson, Chuckie	3.55	62.29
24	Amaya, Miguel	3.18	48.53
25	Jackson, Alex	3.15	81.27
26	Rutschman, Adley	3.12	36.39
27	O'Hoppe, Logan	2.85	53.45
28	Fortes, Nick	2.42	71.24
29	Barnes, Austin	2.32	30.82
30	Higashioka, Kyle	2.30	63.60
31	Fermin, Freddy	1.54	71.19
32	Pagés, Pedro	1.25	80.91
33	Contreras, William	0.98	72.13
34	Stubbs, Garrett	0.48	92.67
35	Langeliers, Shea	-1.08	0.00
36	Ruiz, Keibert	-1.76	2393.98
37	Contreras, Willson	-1.89	372.65
38	Realmuto, J.T.	-2.05	184.98
39	d'Arnaud, Travis	-2.17	151.22
40	Bart, Joey	-2.25	-30.62
41	McGuire, Reese	-2.67	157.06
42	Lee, Korey	-3.16	-5006.69
43	Diaz, Yainer	-4.01	803.39
44	Torrens, Luis	-4.24	-150.81
45	Barnhart, Tucker	-5.15	167.51
46	Herrera, Iván	-5.57	263.79
47	Jansen, Danny	-5.92	639.83
48	Jeffers, Ryan	-6.34	-4.96
49	Smith, Will	-6.74	-23.30
50	McCann, James	-6.80	-169.71

Table 9: Normalized runs saved, default 7,500 pitches