Quantifying Framing in the 2024 MLB Season

Ben Ellman

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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 show-stopping catches in the outfield. They're relegated to a far less dynamic role on the surface. However, their leadership status is an easy indication of their importance to the defensive success of the team. Without a standard of comparison to determine the overall effect a player has on the game, it's easy to 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 prevalent way that perhaps any position player can make an impact defensively: receiving pitches.

I offer an updated statistic to determine runs saved through receiving pitches as well as an overview of framing in 2024. The goal is to supplement statistics like Defensive Runs Saved (DRS) to be more inclusive of the ways catchers influence each game on a pitch-by-pitch basis. Using pitch tracking data from Statcast, we assign an expected runs saved value to each pitch a catcher frames (misses) into a ball (strike) via receiving to arrive at a total runs saved statistic for each catcher in the 2024 MLB 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", or to present a pitch in a way that makes it appear more like a strike, can influence an umpire's decision when calling balls and strikes, as Jerry Weinstein points out in his Baseball Prospectus article. If a catcher is successful at framing, 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 the error associated with the umpire, 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" (balls) pitches and "in zone" (strikes) pitches, 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. This allowed me to create (Table 1) to rank catchers through frame and miss rates. Shown below are the top 20 catchers sorted by total number of frames:

Table 1: Top 20 Catchers by Total Frames

Catcher	Total Frames	Frame %	Miss %	Frames per Miss
Bailey, Patrick	1001	12.88	8.73	4.47
Raleigh, Cal	990	11.83	9.70	3.82
Contreras, William	967	11.25	10.63	3.12
O'Hoppe, Logan	921	10.35	10.47	3.27
Langeliers, Shea	872	9.57	12.25	2.44
Heim, Jonah	849	10.54	10.78	3.10
Naylor, Bo	827	11.51	9.96	3.61
Stephenson, Tyler	813	10.03	11.00	2.80
Wells, Austin	805	11.05	9.08	4.03
Kirk, Alejandro	773	12.38	8.81	4.44
Fortes, Nick	773	10.57	11.18	2.97
Ruiz, Keibert	770	9.95	11.58	2.71
Diaz, Yainer	742	9.77	12.54	2.47
Smith, Will	734	8.77	11.19	2.38
Amaya, Miguel	730	10.06	10.63	2.82
Rutschman, Adley	729	10.02	10.60	2.95
Rogers, Jake	703	12.28	7.60	4.82
Lee, Korey	682	9.08	12.42	2.42
Realmuto, J.T.	681	9.90	10.68	2.78
Perez, Salvador	677	10.58	10.46	3.12

The frames per miss ratio (number of framed pitches per missed strike), frame percentage (of the total called strikes and balls), and miss percentage are also shown. On average, catchers framed 10.4% of pitches and missed 11.1% of strikes. It's interesting to note that catchers miss more pitches than they frame on average. Minimizing mistakes is just as important as stealing 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

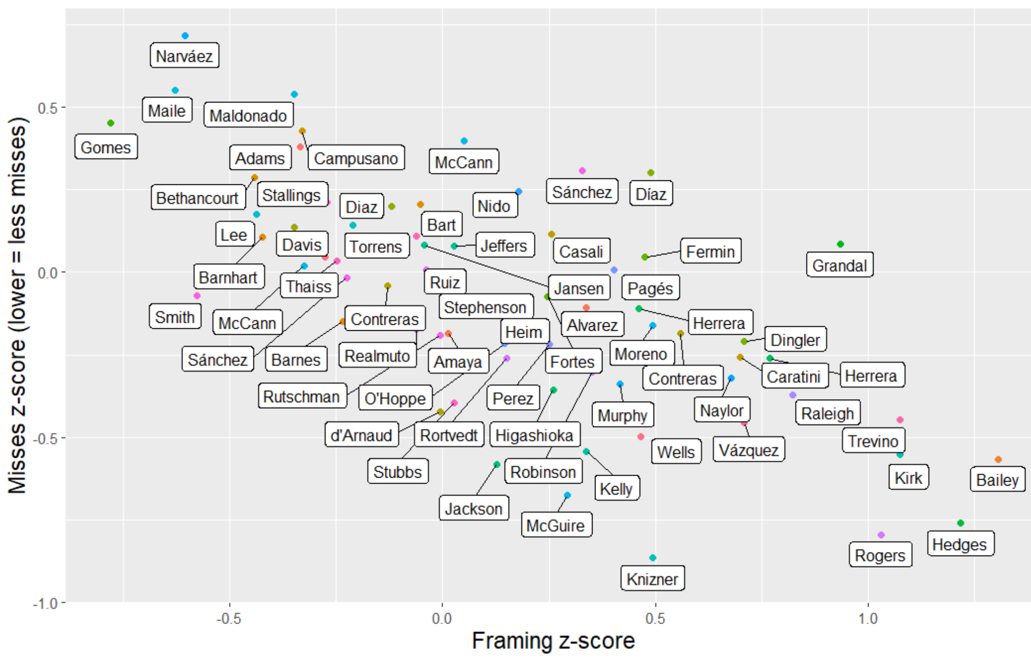
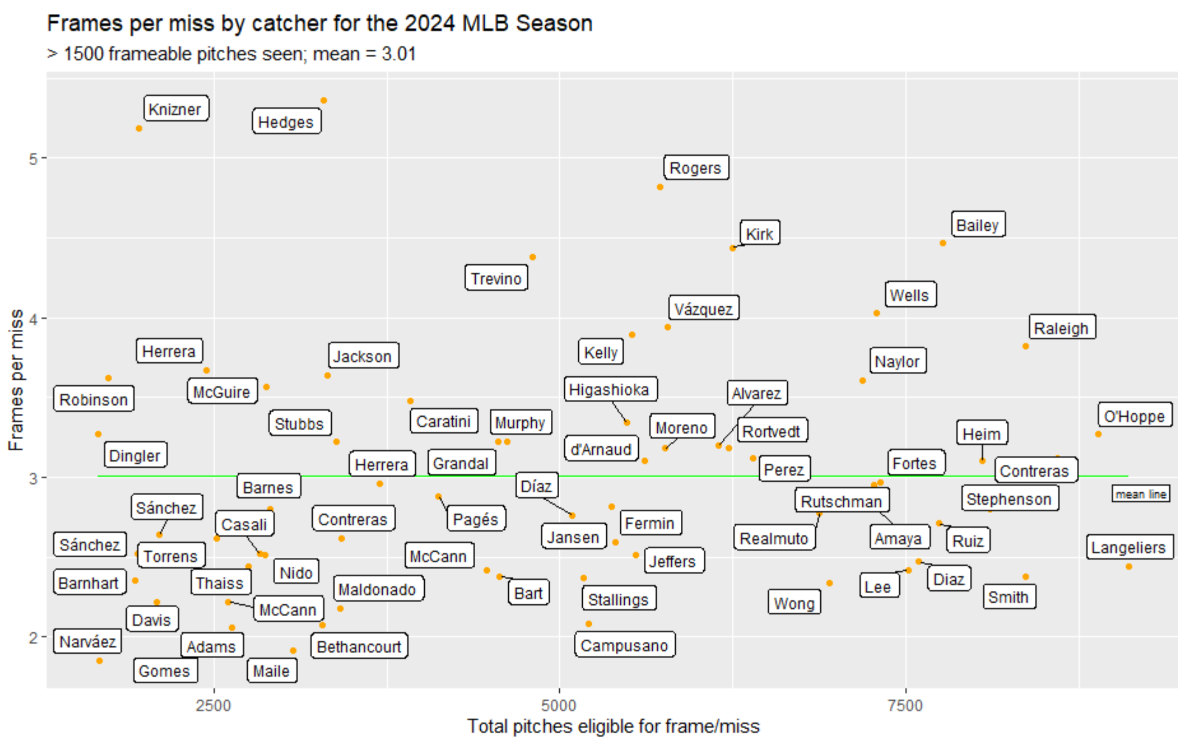


Figure 2 displays the total pitches seen vs. the frames per miss ratio, along with an average line for the frames per miss statistic (3.01):

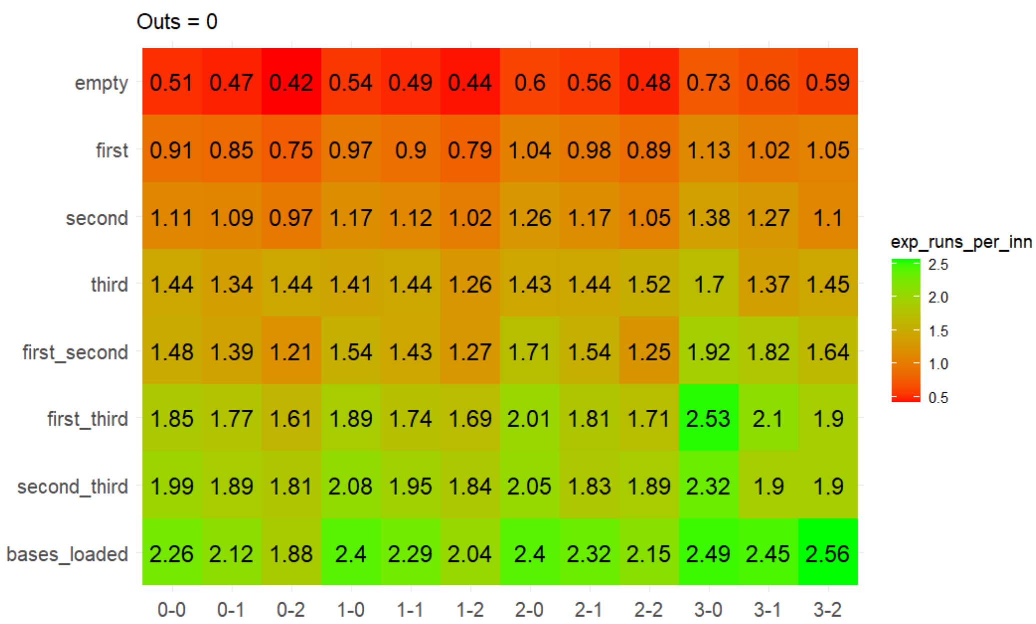
Figure 2: Total Pitches Seen vs Frames per Miss Ratio



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-base runner 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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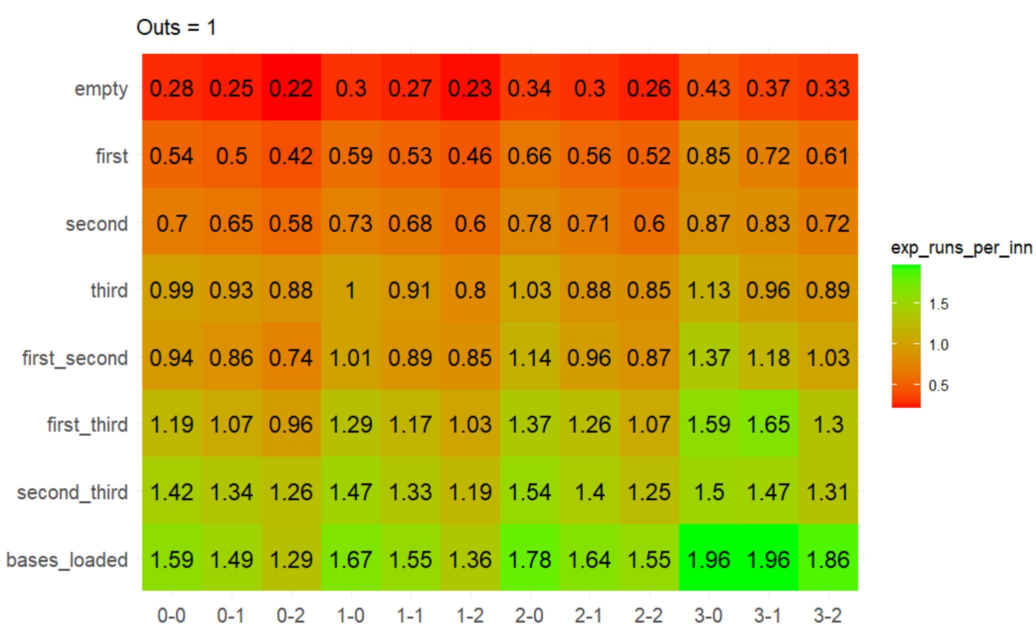
2.0
1.5
1.0
0.5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first 0.54 0.5 0.42 0.59 0.53 0.46 0.66 0.56 0.52 0.85 0.72 0.61
second 0.7 0.65 0.58 0.73 0.68 0.6 0.78 0.71 0.6 0.87 0.83 0.72
third 0.99 0.93 0.88 1 0.91 0.8 1.03 0.88 0.85 1.13 0.96 0.89
first_second 0.94 0.86 0.74 1.01 0.89 0.85 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
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1.0
0.5

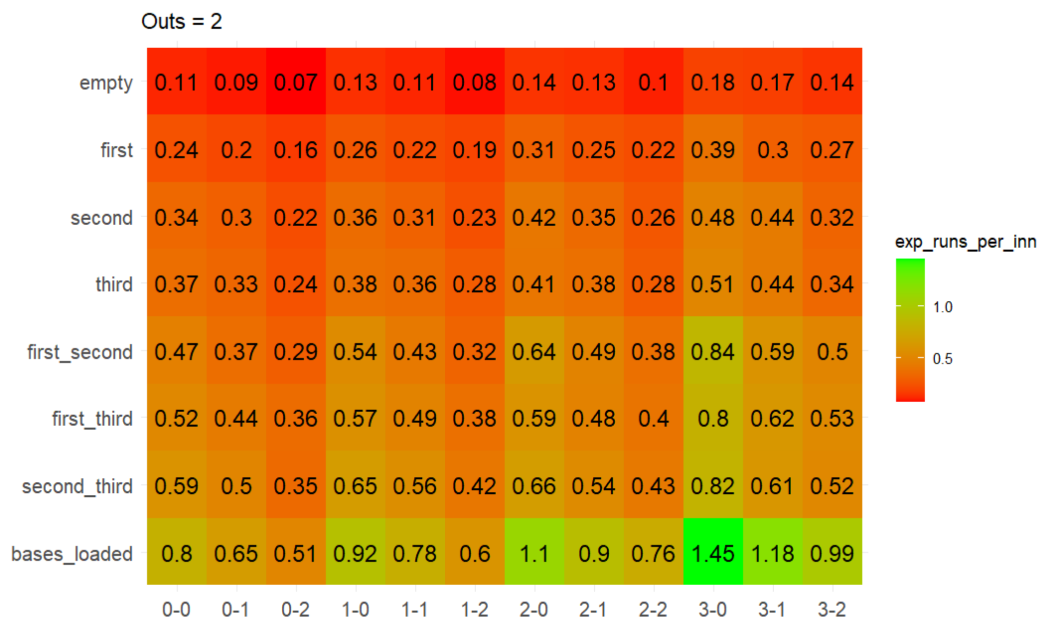

Figure 3: Run Expectancies per inning for each count-out-base state

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-base runner 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) had another catcher been receiving the pitch, and implies that a frame and a miss are essentially equally important when it comes to preventing runs.

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 saving 10 runs more than the average catcher (in the sample) through framing:

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

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 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 actual 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-base runner state.

To build our probability model, a training set of 2024 pitch data from Statcast was sampled, with zone location being the primary determinant in calling a pitch. After some fine tuning, the constructed strike probability model yielded 92% accuracy in our test data (n = 70,177). This gives us confidence that our model can accurately assign a probability to any given pitch.

Using the likelihood of a pitch being called a strike, our new expected runs saved statistic accounts for the relative difficulty of framing any given pitch. 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 in framing difficulty between catchers, such as variations in pitchers' ability to "paint" corners vs miss badly, by rewarding catchers more for difficult frames and less for easier ones.

Simultaneously, the accuracy of the runs saved statistic should be improved thanks to removing the binary condition where a catcher would receive the entire amount of runs saved had they framed or missed a pitch. A catcher should only receive the expected value of a frame above the performance of an average catcher. This prevents too much of the total change in expected runs being allocated on any given pitch. Table 3 shows the top 20 leaders in expected runs saved with the updated probability model incorporated:

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: Catcher runs saved above average based on probabilistic balls/strikes

Many of the top rated catchers – Patrick Bailey, Cal Raleigh, Alejandro Kirk to name a few – remain at the upper tier after applying the pitch probabilities to the runs saved per frame/miss.

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, which is significant for just being a receiving statistic, and is more reasonable than estimating a 6-7 win difference between the top guys and the average catcher.

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 (only 21 OPS+ !)

8 Impact of pitchers

The runs saved statistic calculated here is not meant to be an end-all-be-all determination of a catcher's framing abilities. Receiving outcomes are not entirely by 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 should 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.

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 4 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 markedly better than their peers are those with more negative run differentials, implying they performed markedly better at saving runs on a per pitch basis than their teammates with the same pitchers. To say for certain whether a catcher did not receive bias 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 biased against catchers on teams with superior backups, and merely act as a placeholder for future analysis on the subject.

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 4: Best catcher-pitcher run differentials

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.

Those catchers with high run differentials may be teammates with sub-par framers, their ineffective peers artificially inflating the comparison presented here.

Alternatively, guys with a negative run differential on this list are simply better at receiving than the average catcher, leading to both quality framing statistics and expected runs saved per pitch, relative to the league and their peers. Combined with the previous statistics measured, I think it's safe to say that guys like Cal Raleigh, Patrick Bailey, and Alejandro Kirk are truly high-quality framers who save their teams lots of runs.

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 5: Worst catcher-pitcher run differentials

On the flip side, guys 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 benefitted more from the quality of the pitchers than their own framing, or at least that their teammates performed better. For guys in starting roles who catch the same guys often, the former becomes even more compelling. Bo Naylor's positive run differential per pitch, for instance, shows his teammates were much 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.

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 compare catchers to so many 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 give us an idea of a catcher's relative quality compared to those who catch the same pitchers, and act as a check to ensure a catcher's value isn't solely from the pitchers they caught.

9 Other Considerations

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. A catcher may theoretically be better at receiving, but due to seeing a lower than average number of high-leverage pitches, their total runs saved wouldn't reflect their potential impact. Like most metrics, the runs saved statistic is a measure of the actual impact of a catcher's receiving in a season, rather than their expected performance all else being equal.

Catcher positioning caused by different base runner 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 hurt catchers on worse teams/with worse pitching who get more guys on base.

Catcher receiving should be as commonly discussed as any other defensive contribution. The runs saved metric indicates catchers saved on average 24.5 runs in 2024 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.

10 Works cited / acknowledgements

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. If you have any questions or comments, feel free to reach out to me via

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.