mWAR: a Bayesian Estimator of Manager Value

Supplemental Information

1. mWAR Estimator learning curve

The mWAR Estimator measures managers' latent skill, a quality that they are presumed to possess from the beginning of their careers. It forms that estimate via a Bayesian process: a prior estimate—uniformly zero for all managers—is combined with data generated on a season-by-season basis over every manager's career. Indeed, even after a manager retires, his $mw162$ could in theory be updated insofar as both β_{wpg}, the team WAR parameter, and τ, the individual manager heterogeneity parameter (3), are re-estimated whenever a new season of data is entered. In truth, though, after 125 seasons of updating, those contributions to any manager's score are by now effectively fixed in stone .

Although the Estimator will never stop updating, manager $mw162$s can be expected to settle down to a fairly stable value once some critical quantum of data accumulates. The Estimator in this sense can be said to exhibit a "learning curve" that consists in the amount of data, accumulated over successive seasons, that it requires to form a stable estimate of any manager's latent skill. It is important for any user of the Estimator to understand the speed of this learning curve, particularly if he or she is evaluating managers who are relatively early on in their careers. And it is important for any reflective person who is trying to learn about or from the Estimator to understand how the learning curve was determined.

a. Speed. Although there is variability and outliers, the Estimator generally can be expected to settle down to a stable estimate—one that is unlikely to move substantially in either direction thereafter—in about 900 games or just under 6 modern seasons (Figure SI 1). It takes substantially less data, however, for it to determine whether a managers' MAP $mw162$ exceeds a threshold of practical consequence, such as ± 2.0: the median number of games it took the Estimator to recognize that a manger had a $|mw162|$ of ≥ 2 was 522 games, or 3.25 seasons. Of course, the confidence reflected in such an estimate can still be expected to evolve over the longer period it takes the Estimator to form a mature (i.e., stable) skill level estimate. For example, to determine that a manager possessed a posterior mass 70% of which included an $|mw162|$ of ≥ 2, the median number of games was again about 900 games. The number of games for determining such a manager's attainment of intermediate benchmark $mw162$ scores are reported in Figure SI 2.

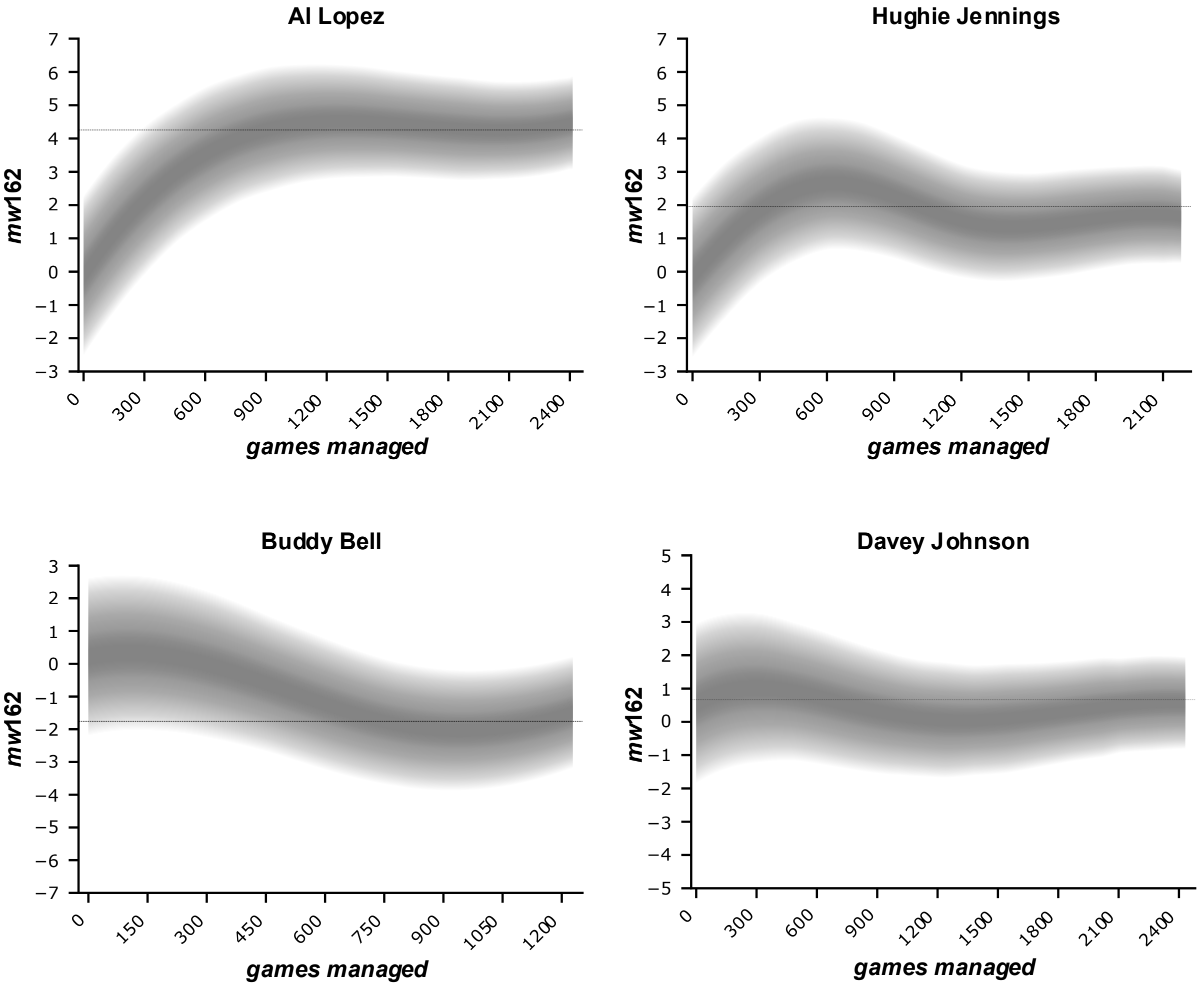

Figure SI 1. Select *mw*162 measurement histories. Gray bands reflect 0.67 HDI estimation of indicated manager's *mw*162 at number of games managed.

b. Measuring its speed. As the paper makes clear, the Estimator was formed by fitting the mWAR Model to manager performance data over a 125-season period—from 1901 to 2025—and then using empirical Bayesian methods to extract the information necessary to form *mw*162 posteriors. Accordingly, the Estimator learned everything there was to know in a matter of minutes.

The "learning curve" is thus a constructive one designed to gauge the pace at which the Estimator *would* have formed its estimates had it been run in "real time"—as data accumulated season-by-season. The purpose was to form a reasonable understanding of how quickly the Estimator's measurement of individual manager latent skill levels can be expected to take shape going forward as it is applied to still active and new managers.

The method for achieving this aim had elements of a historical "what if" simulation. In it, the hierarchical Bayes mWAR Model (2) was fit 125 times—once after each season *to all the manager data that had accumulated through that season*. After each successive model was fit, the posteriors of the managers who had served at any time *up to that that point* were estimated *based on all the information the Estimator used to form posterior estimates of all managers in 2025.*

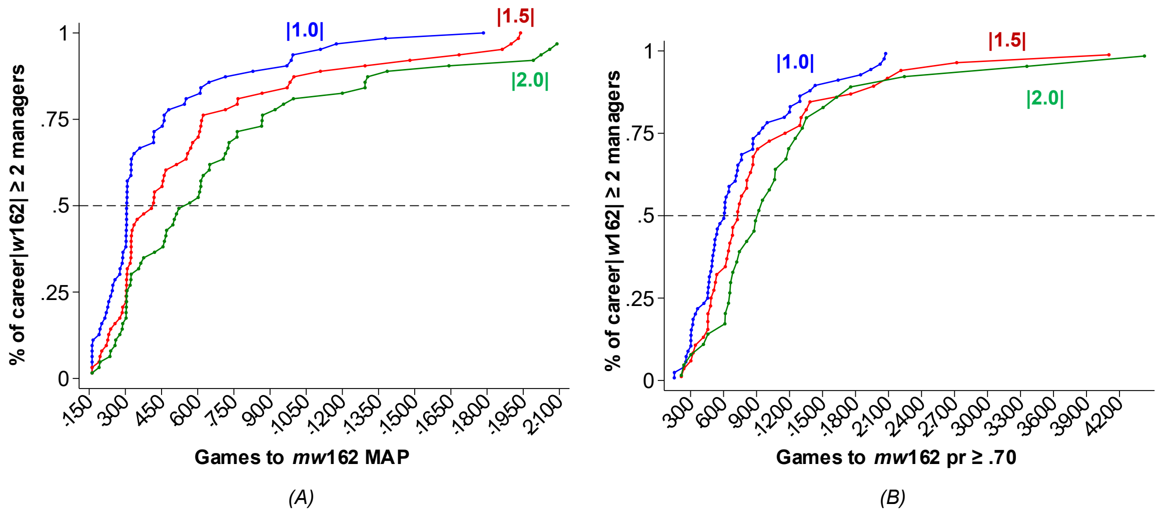

Figure SI 2. mWAR. Estimator learning curve for career $|mw162| \geq 2$ managers. Panels (A) and (B) plot the number of games required for managers with career $|mw162s| \geq 2$ to reach MAP $mw162 = |1.0|/|1.5|/|2.0|$ and $mw162$ with 0.70 posterior masses at those values respectively. For details on how the Estimator's updating speed was determined, see the Supplemental Information (SI).

The latter information reflects nothing in particular about individual managers (if it had, the whole exercise would have been circular). Rather it consists in everything there is to know now—which is a lot—about how managers in general affect team records and about how θ varies in general across the manager population. That information is encapsulated, first, in the parameter estimate for *zWPG*, the team WAR predictor, and in τ^2, the population variance term that defines the spread or scale of the manger-impact prior. Accordingly, the simulation generated a recreation of the *historical* trajectory of managers' *mw*162 scores using *timeless* (really, contemporary) estimates of those two quantities.

Put differently, the goal of the "what if" simulation was not to discover how quickly the mWAR Estimator would have learned about the *weight* to afford season-level data. It was to determine, given what the Estimator *now* knows about *that*, how quickly the Estimator would have formed stable estimates of past managers' innate skill via the Bayesian updating. The answer to that question is the best estimate of how rapidly the Estimator can be expected to form stable estimates of managers' *mw*162s today.

2. Additional *mw*162 scores

The paper identifies the managers with the 39 highest and 39 lowest *mw*162s over the history of the American and National Leagues (Table 2). SI Table 1 and SI Table 2 present the *mw*162 scores of Hall of Fame managers and of managers active since 2000, respectively. A complete list of all evaluated managers can be downloaded from the supporting materials page.

rank	Manager	G	W%	*mw*162	data_162
1	John McGraw	4439	.590	6.4	7.8
4	Joe McCarthy	3426	.615	4.5	5.8
5	Al Lopez	2414	.584	4.4	6.1
13	Wilbert Robinson	2827	.499	2.7	3.2
17	Tony LaRussa	5356	.535	2.4	2.4
22	Casey Stengel	3732	.509	2.3	2.3
22	Bobby Cox	4490	.555	2.3	2.4
31	Miller Huggins	2550	.554	2.1	2.6
39	Bill McKechnie	3619	.524	1.9	2.2
46	Jim Leyland	3489	.507	1.8	1.7
52	Whitey Herzog	2406	.532	1.7	2.2
76	Billy Southworth	1748	.597	1.2	1.7
93	Dick Williams	3010	.519	1.0	1.0
118	Sparky Anderson	4001	.544	0.8	0.8
118	Leo Durocher	3645	.539	0.8	0.8
151	Walter Alston	3632	.559	0.5	0.3
194	Joe Torre	4276	.538	0.2	-0.1
194	Earl Weaver	2518	.582	0.2	0.2
194	Tom Lasorda	3034	.527	0.2	-0.1
280	Bucky Harris	4379	.493	-0.3	1.8
377	Connie Mack	7386	.485	-0.8	-1.4

SI Table 1. Hall of Fame managers (post 1900). "Rank" refers to *mw*162 rank for all rated managers; "g" career games; "W%" career winning percentage; "HDI" the densest portion of the manager's posterior mass that includes 95% of the manager's *mw*162 distribution; and "data" the manager's mWAR Model *mw*162 score prior to Bayesian shrinkage.

	manager	G	W%	*mw*162	data
1	Felipe Alou	2050	.503	4.0	6.1
2	Fredi González	1411	.507	3.0	4.8
2	Dave Roberts	1516	.619	3.0	5.1
4	Craig Counsell	1653	.532	2.8	4.5
5	Cecil Cooper	344	.506	2.7	11.7
5	Stephen Vogt	323	.557	2.7	12.4
7	Dusty Baker	4016	.539	2.4	2.7
7	Tony LaRussa	5356	.535	2.4	2.4
7	Bruce Bochy	4512	.498	2.4	2.8
7	Jim Tracy	1738	.493	2.4	3.6
11	Bobby Cox	4490	.555	2.3	2.4
11	Buddy Black	2583	.460	2.3	2.7
13	Kirk Gibson	730	.485	2.2	4.9
13	Mike Shildt	775	.561	2.2	5.1
15	Jim Fregosi	2121	.485	2.0	2.1
16	Clint Hurdle	2595	.486	1.9	2.5
16	Brian Snitker	1478	.548	1.9	3.0
18	Ron Roenicke	740	.504	1.8	4.5
18	Jim Leyland	3489	.507	1.8	1.7
18	Pete Mackanin	525	.436	1.8	5.2
18	Art Howe	2263	.498	1.8	2.3
18	Gabe Kapler	867	.526	1.8	4.1
23	Bobby Valentine	2347	.504	1.7	2.4
24	Don Baylor	1321	.477	1.6	2.6
24	Jack McKeon	2037	.514	1.6	2.1
24	Aaron Boone	1191	.584	1.6	2.8
24	Andy Green	650	.431	1.6	4.1
28	John Boles	432	.461	1.5	6.1
28	Dave Miley	289	.433	1.5	7.8
28	Terry Collins	2002	.494	1.5	1.6
31	Mike Quade	199	.477	1.3	8.5
32	Cookie Rojas	158	.487	1.2	6.6
32	John Russell	488	.381	1.2	3.5
32	Jim Riggleman	1630	.445	1.2	1.9
32	Scott Servais	1313	.514	1.2	1.7
36	Bill Russell	330	.539	1.1	4.0
36	Jeff Banister	637	.512	1.1	2.4
38	Bob Brenly	562	.537	1.0	2.0
38	Rene Lachemann	995	.435	1.0	1.5
38	Dan Wilson	196	.566	1.0	4.1
38	Oliver Marmol	646	.502	1.0	2.6
38	Frank Robinson	2219	.476	1.0	1.3
38	Tim Bogar	24	.583	1.0	29.0
44	Charlie Manuel	1790	.547	0.9	1.3
44	Ken Macha	972	.540	0.9	1.6
44	Bob Boone	791	.459	0.9	1.5
44	Lloyd McClendon	1109	.451	0.9	0.7
44	Brad Mills	462	.387	0.9	0.8
49	Skip Schumaker	324	.448	0.8	1.1
49	Davey Johnson	2432	.562	0.8	0.9
51	Pat Murphy	420	.552	0.7	2.6
51	A. J. Hinch	1831	.526	0.7	0.9
51	Paul Molitor	647	.471	0.7	1.5
51	Ryne Sandberg	278	.428	0.7	3.0
55	Tom Trebelhorn	930	.505	0.6	1.4
55	Pat Corrales	1212	.475	0.6	0.6
55	Ray Knight	260	.477	0.6	2.0
55	Larry Dierker	781	.556	0.6	1.6
59	Tony Pérez	158	.468	0.5	3.3
59	Larry Bowa	847	.491	0.5	0.5
61	Carlos Mendoza	324	.531	0.4	-0.4
61	Miguel Cairo	107	.449	0.4	7.1
61	Davey Lopes	336	.429	0.4	0.8
61	Mike Matheny	1449	.522	0.4	0.2

	manager	G	w%	*mw*162	data
65	Derek Shelton	747	.410	0.3	-0.2
65	Tom Lawless	24	.458	0.3	6.5
67	Manny Acta	894	.417	0.2	-0.5
67	Demarlo Hale	82	.488	0.2	-0.6
67	John Schneider	562	.541	0.2	0.6
67	Edwin Rodríguez	162	.475	0.2	1.7
67	Joe Torre	4276	.538	0.2	-0.1
67	Sandy Alomar	52	.577	0.2	10.1
67	Tony DeFrancesco	41	.390	0.2	7.9
74	Grady Sizemore	45	.289	0.1	-4.2
74	David Bell	862	.470	0.1	-0.5
74	Robby Thompson	29	.483	0.1	6.1
74	Tom Runnells	152	.454	0.1	-0.8
74	Chris Speier	19	.737	0.1	32.2
74	Bob Melvin	3253	.513	0.1	-0.5
74	Jamie Quirk	21	.333	0.1	-15.8
74	Joe Nossek	14	.429	0.1	-23.8
82	Bob Schaefer	22	.364	0.0	1.9
82	Joey Cora	16	.500	0.0	1.3
82	Jerry Royster	150	.353	0.0	-5.1
82	Dan Jennings	124	.444	0.0	0.7
82	David Ross	536	.478	0.0	-0.8
87	Scott Ullger	18	.500	-0.1	-6.2
87	Willie Randolph	556	.545	-0.1	-0.1
87	Bryan Price	665	.420	-0.1	-0.7
87	Daren Brown	50	.380	-0.1	-7.6
87	Joel Skinner	77	.468	-0.1	1.0
92	John McLaren	174	.460	-0.2	-1.8
92	Mickey Callaway	324	.503	-0.2	-1.5
92	Buck Showalter	3379	.510	-0.2	-0.5
92	Bill Virdon	1942	.519	-0.2	-0.9
92	Ozzie Guillén	1435	.514	-0.2	-0.2
92	Bucky Dent	95	.411	-0.2	-1.8
92	Jeff Torborg	1351	.469	-0.2	-1.0
99	Jerry Manuel	1376	.507	-0.3	-1.1

	manager	G	w%	*mw*162	data
99	Rich Renteria	700	.436	-0.3	-2.0
99	Phil Garner	2018	.483	-0.3	-1.2
99	Matt Williams	324	.552	-0.3	-2.4
99	Jerry Narron	633	.463	-0.3	-1.7
105	Carlos Tosca	384	.490	-0.4	-3.1
105	Phil Nevin	257	.451	-0.4	-2.7
105	Torey Lovullo	1401	.492	-0.4	-1.3
105	Bo Porter	300	.367	-0.4	-2.2
105	Rocco Baldelli	1021	.509	-0.4	-0.8
105	Trey Hillman	357	.429	-0.4	-2.0
111	Bruce Kimm	78	.423	-0.5	-5.2
111	Grady Little	675	.554	-0.5	-1.4
111	Kevin Cash	1678	.533	-0.5	-1.4
111	Al Pedrique	84	.274	-0.5	-10.3
111	Alex Cora	1128	.540	-0.5	-1.5
116	Mike Scioscia	3064	.534	-0.6	-1.2
116	Chip Hale	328	.454	-0.6	-3.7
116	Robin Ventura	804	.466	-0.6	-2.2
116	Tony Beasley	48	.354	-0.6	-17.6
116	Jayce Tingler	228	.522	-0.6	-2.9
116	Mike Redmond	371	.426	-0.6	-2.9
122	Rob Thomson	602	.578	-0.7	-1.9
122	Toby Harrah	80	.412	-0.7	-12.4
122	Don Wakamatsu	301	.452	-0.7	-3.5
125	Luis Pujols	155	.355	-0.8	-5.4
125	Terry Francona	3648	.538	-0.8	-1.5
125	Joe Maddon	2606	.533	-0.8	-1.3
125	Ron Washington	1598	.500	-0.8	-1.6
125	Walt Weiss	646	.438	-0.8	-2.6
125	Brad Ausmus	805	.477	-0.8	-2.9
125	Dale Sveum	336	.399	-0.8	-4.0
132	Joe Espada	330	.542	-0.9	-2.3
132	Don Mattingly	1826	.484	-0.9	-1.9
132	Tony Peña	483	.410	-0.9	-3.9
132	Ned Yost	2542	.473	-0.9	-1.6

	manager	G	w%	*mw*162	data
132	Luis Rojas	220	.464	-0.9	-5.8
132	Sam Perlozzo	300	.420	-0.9	-5.7
138	Ron Gardenhire	2464	.484	-1.0	-1.7
138	Juan Samuel	51	.333	-1.0	-18.3
138	Matt Quatraro	485	.464	-1.0	-4.3
138	Joe Kerrigan	43	.395	-1.0	-21.4
138	Lee Mazzilli	269	.483	-1.0	-5.5
138	Pedro Grifol	278	.317	-1.0	-6.3
144	Buck Martinez	212	.467	-1.1	-8.0
145	Will Venable	168	.363	-1.2	-10.8
150	John Farrell	1073	.515	-1.5	-3.4
152	Tony Muser	763	.421	-1.6	-5.9
152	Hal McRae	872	.458	-1.6	-4.2
154	Charlie Montoyo	471	.501	-1.8	-5.7
154	Dave Trembley	465	.396	-1.8	-7.2
154	Buddy Bell	1228	.418	-1.8	-3.9
157	Larry Rothschild	494	.407	-1.9	-7.0
158	Mike Hargrove	2343	.504	-2.0	-3.2
158	Bob Geren	714	.475	-2.0	-5.3
160	Lou Piniella	3524	.517	-2.1	-3.1
157	Larry Rothschild	494	.407	-1.9	-7.0

	manager	G	w%	*mw*162	data
158	Mike Hargrove	2343	.504	-2.0	-3.2
158	Bob Geren	714	.475	-2.0	-5.3
160	Lou Piniella	3524	.517	-2.1	-3.1
150	John Farrell	1073	.515	-1.5	-3.4
152	Tony Muser	763	.421	-1.6	-5.9
152	Hal McRae	872	.458	-1.6	-4.2
154	Charlie Montoyo	471	.501	-1.8	-5.7
154	Dave Trembley	465	.396	-1.8	-7.2
154	Buddy Bell	1228	.418	-1.8	-3.9
157	Larry Rothschild	494	.407	-1.9	-7.0
158	Mike Hargrove	2343	.504	-2.0	-3.2
158	Bob Geren	714	.475	-2.0	-5.3
160	Lou Piniella	3524	.517	-2.1	-3.1
161	Johnny Oates	1539	.517	-2.2	-4.1
162	Tom Kelly	2375	.478	-2.3	-3.8
163	Alan Trammell	498	.382	-2.4	-9.9
163	Jimy Williams	1697	.535	-2.4	-4.4
165	John Gibbons	1580	.501	-3.3	-6.0
166	Eric Wedge	1587	.476	-3.5	-6.5
167	Cito Gaston	1726	.516	-3.8	-6.5

SI Table 2. Manager *mw*162s since 2000. List includes every manager who has managed since 2000. Ranks are post-2000 only; games managed and *mw*162s are regardless of when career started. “Data” refers to MLE mWAR (1) score.

3. mWAR Estimator_*p*

The paper proposes a provisional variant of the mWAR Estimator, the mWAR Estimator_*p*, for single-season use. Calculation of the Estimator_*p* scores is straightforward. As indicated in the paper, the scores are formed by awarding 24% of the residuals of a model that predicts team wins on the basis of team WAR (5). The required data are the wins, the games played, and the standardized season WAR per game for all teams in the relevant season. After the model is fit, the residuals for each team (which will consist in win counts over the number of games played in a season) should be predicted or otherwise calculated and then multiplied by 0.24. These are the manager *mw*162*p*s realized by each team. Where a team was managed by one person the entire season, that individual is awarded that score. Where a team used more than one manager in a season, each can be awarded the fraction of the *mw*162*p* total corresponding to the fraction of total games that he (or once this gender barrier gives way, she) managed. Alternatively, one could split the team into two separate observations if one has access to the WAR per game data corresponding to the portions of the season overseen by each manager.

The data necessary to generate the season *w*162*p*s for every season since 1901 (including a file that identifies the manager and number of games managed per team per season) are available for download in the supporting materials page. A file reporting Estimator_p scores—referred to as w162ps—from 1901 to 2025 also can be found there.

4. Asymmetric loss function

The paper illustrates how the mWAR Estimator can be conformed to a user-specific loss function. The default loss function maximizes accuracy by minimizing mean squared error (MSE). It can be represented as

$$L(\emptyset, \widehat{\emptyset}) = (\emptyset - \widehat{\emptyset})^2 \,. \tag{SI.1}$$

Simply put, the penalty for any discrepancy between the true value of θ (understood as managerial skill level) at any particular point in the distribution at which it is being estimated and the reported value, $\hat{\theta}$ is the magnitude of the difference squared.

That default loss function can be adjusted at will:

$$L(\emptyset, \widehat{\emptyset}) = f[(\emptyset - \widehat{\emptyset})^2]. \tag{SI.2}$$

Here *f* stands for any set of operations performed on the MSE loss function to conform it to an alternative decision theory or utilitarian loss function (Berger, 1985).

In the paper, *an asymmetric loss function* was posited. For reasons explored in the paper, it was suggested that a team front office might adopt the position that the mistake of estimating a manager's *mw*162 to be < 2 when it is in fact ≥ 2 is *more costly* than the mistake of erroneously estimating that his *mw*162 is ≥ 2 when in fact it is < 2. A team front office might similarly deem the mistake of erroneously estimating that a manager's *mw*162 is > -2 when in fact it is ≤ -2 to be more costly than the mistake of erroneously estimating that his *mw*162 is ≤ -2 when in fact it is > -2.

One could then represent, *f*, the adjustment being imposed on the MSE default loss function, this way,

$$L(\theta_i,\hat{\theta}_i)=\begin{cases} w_1\left(\theta_i-\hat{\theta}_i\right)^2, & \theta_i \le s, \\ w_2\left(\theta_i-\hat{\theta}_i\right)^2, & \theta_i \ge t, \\ \left(\theta_i-\hat{\theta}_i\right)^2, & s<\theta_i<t. \end{cases} \quad \text{(SI.3)}$$

Where *s* and *t* are, respectively, *mw*162 = - 2 and *mw*162 = 2, the region in between -2 and 2 is governed by the conventional MSE loss function. Errors are penalized by weights w_1 and w_2 for the regions of *mw*162 at or below -2 and at or above 2, respectively. In the paper, the special loss penalties for both of the specified type II errors in question were 2x; in that case $w_1 = w_2$. But the front office could vary w_1 and w_2 if it regarded one of the disfavored error types as even more costly than the other.

The Estimator can be programmed to generate the *mw*162 estimates that reflect this asymmetric loss function rather than the MSE one (Elliott & Timmerman, 2008, 2016; Patton & Timmerman, 2007). Under *f*, loss comprises the sum of $(\theta_j - \widehat{\theta}_j)^2$ across the three demarcated *mw*162 regions *weighted by* the fraction of a manger's posterior mass within each of those regions:

$$\sum_{\theta_i\le s} w_1\left(\theta_i-\hat{\theta}_i\right)^2 p(\theta_i \mid \text{data}_i) + \sum_{\theta_i\ge t} w_2\left(\theta_i-\hat{\theta}_i\right)^2 p(\theta_i \mid \text{data}_i) + \sum_{s<\theta_i<t} \left(\theta_i-\hat{\theta}_i\right)^2 p(\theta_i \mid \text{data}_i). \rightarrow \quad \text{(S1.4)}$$

Minimizing expected loss thus requires integrating this sum over the posterior of each manager. The resulting collection of estimates—not the MSE MAPs—are now reported as the managers' *mw*162s (SI Table 3).

Two consequences mentioned in the paper bear restating. First, the effects will be felt not only by some small select group of managers highly proximate to the *s* and *t* cutoffs but across the entire *mw*162 frontier depending on how much of each manager's posterior mass straddles one of the two error thresholds (Figure 8). Second, the effects will not be monotonic: all else equal, managers with relatively low individual variances will be affected less since the precision of their *mw*162s implies the probability of error associated with their MSE value is small; managers with higher variances will be affected more, since the uncertainty associated with their MSE *mw*162 scores will involve higher risks of error. As a result, the re-calculation of the manager *mw*162 point estimates can result in reordering of managers relative to their MAP baselines (SI Table 3).

These are exactly the effects that the front office management's valuations demand. To start, the impact of the re-calculations will always be *unidirectional* in relation to the stipulated *s* and *t* thresholds (Figure 8; SI Table 3). Managers with MSE MAPs above the *mw*162 > -2 threshold (to use the paper example) might be moved toward or over it depending on what fraction of their posterior mass lies below that threshold. Those with MSE MAPs below the *mw*162 < -2 threshold likewise might be pushed even further down depending on how much of their posterior mass straddles it. But managers with MSE MAPs below < -2 will *never* be moved upward, much less above, the ≤ -2 threshold—for by hypothesis, the readjustment of the manager's *mw*162 in that case would be *increasing* the probability of a *higher* error cost. Likewise, managers with MSE MAPs below the *mw*162 ≥2 threshold (again to use the paper example) might be moved up toward or over it. But those with MSE MAPs *above* the *mw*162 ≥ 2 threshold will *never* be moved downward: such a readjustment can, by hypothesis, *only* increase the risk of the higher-cost error.

In addition, any readjustments relative to the MSE MAPs will always be proportional to the front office's specified risk preference. All else equal, managers closer to *s* and *t* will be pushed harder. But importantly and as mentioned, when θ uncertainty for a manger is *low*, his adjusted *mw*162 will be adjusted less dramatically relative to his MSE MAP than it will be when his θ uncertainty is *high*: this is exactly in line with the *risk aversion* that the front office decisionmakers are posited as experiencing for retaining managers who might have true *mw*162s ≤ -2 and the risk *preference* they are posited as experiencing for retaining managers who might have true *mw*162s ≥ 2.

It bears re-emphasis, too, that this is just an illustration of this feature of the Hybrid Estimator. Its estimates can be made responsive not only to this non-MSE loss function but to any decision theory loss function a user chooses.

Managers in vicinity of MSE *mw162* = 2 threshold				
Manger	**adj. 162**	**MSE 162**	**var.**	**ROPE**
Joe Gordon	2.5	2.1	3.8	0.51
George Gibson	2.5	2.0	3.4	0.51
Miller Huggins	2.5	2.1	1.9	0.53
Chuck Dressen	2.4	2.1	2.2	0.52
Paul Richards	2.4	2.0	2.3	0.50
Bob Swift	2.4	1.9	5.5	0.49
Dick Howser	2.4	1.9	3.2	0.48
George Stallings	2.4	2.0	2.4	0.49
Jim Fregosi	2.3	2.0	2.0	0.49
Lum Harris	2.3	1.9	3.2	0.48
Brian Snitker	2.3	1.9	2.6	0.47
Ron Roenicke	2.3	1.8	3.7	0.47
Clint Hurdle	2.3	1.9	1.8	0.48
Pete Mackanin	2.3	1.8	4.1	0.47
Pinky Higgins	2.3	1.8	2.9	0.46
Bill McKechnie	2.3	1.9	1.4	0.48
Hughie Jennings	2.3	1.9	2.0	0.47
Gabe Kapler	2.2	1.8	3.4	0.45
Jim Leyland	2.2	1.8	1.5	0.44
Greg Riddoch	2.2	1.7	4.3	0.45
Art Howe	2.1	1.8	2.0	0.44
Ossie Vitt	2.1	1.7	4.2	0.44
Gabby Street	2.1	1.7	3.6	0.43
Bobby Valentine	2.1	1.7	2.0	0.42
Joe Cronin	2.0	1.7	2.0	0.41
Whitey Herzog	2.0	1.7	1.9	0.41
Don Baylor	2.0	1.6	2.7	0.41
Frank Selee	2.0	1.6	3.8	0.41
Aaron Boone	2.0	1.6	2.8	0.40
Andy Green	2.0	1.6	3.7	0.41
Jack McKeon	2.0	1.6	2.1	0.39
John Boles	2.0	1.5	4.3	0.41
Cookie Lavagetto	2.0	1.5	3.6	0.41
Dave Miley	2.0	1.5	4.8	0.42
Lefty Phillips	2.0	1.5	4.2	0.41
Vern Rapp	2.0	1.5	4.7	0.41
Terry Collins	1.9	1.5	2.1	0.37
Kerby Farrell	1.8	1.4	5.3	0.40

Managers in vicinity of MSE *mw162* = - 2 threshold				
manger	**adj. 162**	**MSE 162**	**var.**	**ROPE**
Bob Geren	-2.5	-2.0	3.6	0.51
Heinie Wagner	-2.5	-2.0	5.2	0.50
Stan Hack	-2.4	-2.0	4.1	0.50
Tom Loftus	-2.4	-2.0	4.5	0.49
Dan Howley	-2.4	-2.0	3.3	0.49
Mike Hargrove	-2.4	-2.0	1.9	0.51
Lou Piniella	-2.4	-2.1	1.5	0.52
Bill Donovan	-2.4	-1.9	4.2	0.48
Larry Rothschild	-2.4	-1.9	4.1	0.48
Bill Dahlen	-2.3	-1.9	3.9	0.48
Billy Herman	-2.3	-1.9	4.2	0.48
Freddie Fitzsimmons	-2.3	-1.9	4.5	0.47
Dave Trembley	-2.3	-1.8	4.2	0.46
Buddy Bell	-2.2	-1.8	2.8	0.46
Charlie Montoyo	-2.2	-1.8	4.1	0.46
Hugh Duffy	-2.2	-1.8	2.9	0.46
Preston Gómez	-2.2	-1.8	3.3	0.45
Shano Collins	-2.1	-1.7	5.0	0.45
Ray Schalk	-2.1	-1.7	5.0	0.44
Jimmy Callahan	-2.1	-1.7	3.4	0.43
Tris Speaker	-2.1	-1.7	3.1	0.42
Bucky Walters	-2.0	-1.6	5.1	0.43
Jimmy Burke	-2.0	-1.6	4.2	0.42
Hal McRae	-2.0	-1.6	3.4	0.42
Tony Muser	-2.0	-1.6	3.5	0.42
Chuck Tanner	-2.0	-1.6	1.7	0.39
Ned Hanlon	-2.0	-1.5	3.1	0.40
Bob Scheffing	-2.0	-1.5	3.4	0.40
Eddie Sawyer	-1.9	-1.5	3.4	0.40
Solly Hemus	-1.9	-1.5	4.4	0.41
John Farrell	-1.9	-1.5	3.1	0.39
Roy Hartsfield	-1.9	-1.5	4.1	0.40
Brandon Hyde	-1.9	-1.5	3.3	0.39
George Stovall	-1.8	-1.4	4.4	0.39
Ray Miller	-1.8	-1.4	3.9	0.38
Mark Kotsay	-1.8	-1.4	3.6	0.38
Bill Carrigan	-1.8	-1.4	3.2	0.37
Chris Woodward	-1.7	-1.3	4.0	0.37

SI Table 3. Asymmetric loss function adjustments. "Adj 162" and "MSE 162" refer respectively to the *mw*162 scores with and without the asymmetric-loss-function adjustment; "var" refers to the variance associated with the Estimator score; and "ROPE" the proportion of posterior mass outside the relevant border of |MSE *mw*162| = 2. Highlighted cells identify managers whose adjusted *mw*162s moved from below to above the +2 or from above to below the -2 thresholds, respectively.

Supplemental Information references

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