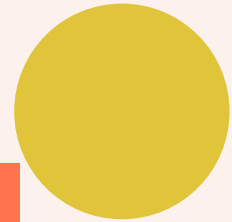
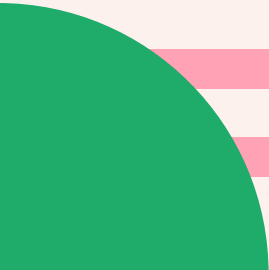
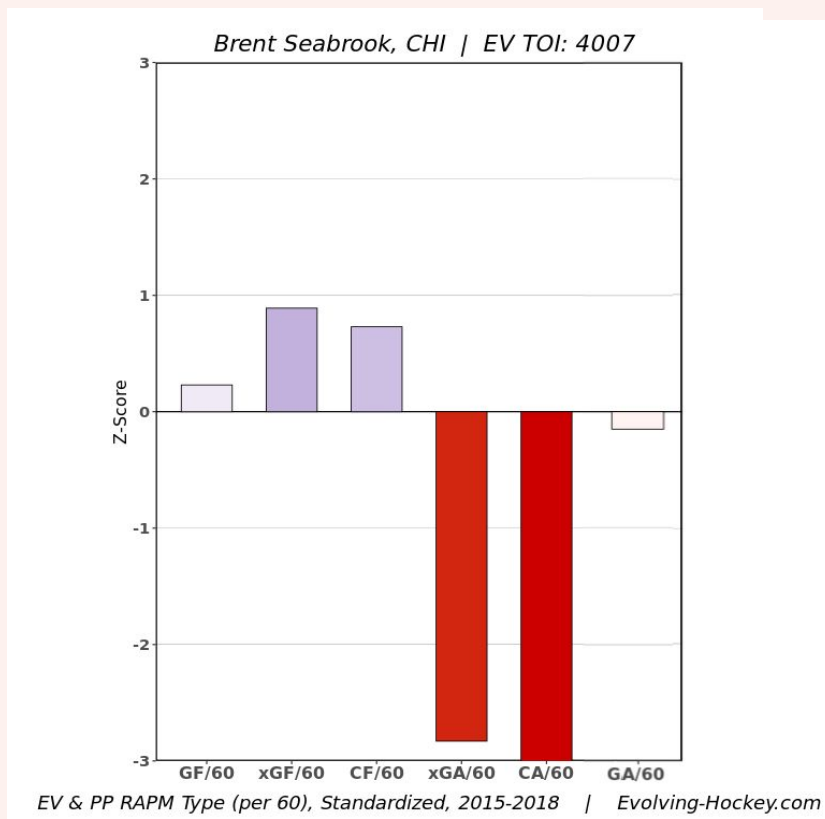


Can Skaters Impact Goaltending Metrics?

By CJ Turtoro



Brent Seabrook SUCKED at the end ... or did he?



Brent Seabrook SUCKED at the end ... or did he?

- According to Alex Novet's merged data from NHL pbp and Sznajder's tracking...
 - Of 337 skaters with 500+ FA tracked, Seabrook allowed the 16th most dangerous average shot with a xFSh% of 6.14
 - When we incorporated our tracking data, the xFSh% went down to 5.88% and his shots became the 87th most dangerous
 - He had the 44th largest shift in average shot danger when moving from public pbp data to Sznajder's tracking data

Brent Seabrook SUCKED at the end ... or did he?

- Entering 2019, Brent Seabrook's career, had been *reliably* getting better "goals against" impacts than "expected goals against" impacts.
- Seabrook was the league's worst even-strength defender (+0.226 xGA/60) in terms of RAPM xGA.
- But he was slightly better than neutral (-0.018 xGA/60) in RAPM GA

Season	GP	TOI	GA/60	xGA/60	xGA/60 - GA/60
2008	81	1289.13	-0.033	-0.064	-0.031
2009	82	1412.38	-0.074	-0.068	0.006
2010	78	1441.5	-0.01	-0.054	-0.044
2011	82	1538.3	0.025	-0.096	-0.121
2012	78	1520.42	0.05	-0.082	-0.132
2013	47	811.97	-0.014	0.087	0.101
2014	82	1481.78	0.054	0.001	-0.053
2015	82	1441.62	0.022	0.094	0.072
2016	81	1424.1	0	0.337	0.337
2017	79	1329.15	0.016	0.187	0.171
2018	81	1253.77	-0.075	0.141	0.216
2019	78	1171.93	0.055	0.179	0.124
2020	32	503.1	-0.062	0.133	0.195

#1 differential
in the NHL

Brent Seabrook SUCKED at the end ... or did he?

The "Crawford Effect"?

Corey Crawford was the #2 goalie in the NHL during that 2015-2018 stretch by GSAX

Season	GP	TOI	GA/60	xGA/60	xGA/60 - GA/60	Crawford GSAX
2008	81	1289.13	-0.033	-0.064	-0.031	
2009	82	1412.38	-0.074	-0.068	0.006	
2010	78	1441.5	-0.01	-0.054	-0.044	
2011	82	1538.3	0.025	-0.096	-0.121	7.7
2012	78	1520.42	0.05	-0.082	-0.132	-20.04
2013	47	811.97	-0.014	0.087	0.101	7.1
2014	82	1481.78	0.054	0.001	-0.053	-2.55
2015	82	1441.62	0.022	0.094	0.072	8.6
2016	81	1424.1	0	0.337	0.337	21.65
2017	79	1329.15	0.016	0.187	0.171	10.21
2018	81	1253.77	-0.075	0.141	0.216	13.8
2019	78	1171.93	0.055	0.179	0.124	1.11
2020	32	503.1	-0.062	0.133	0.195	7.44

Brent Seabrook SUCKED at the end ... or did he?

- If the “Crawford Effect” exists, it’s suspiciously absent for the other Chicago defencemen *nearly* this size discrepancy.
- In fact, removing Seabrook, the Chicago blueline actually allowed .02 *more* goals per hour than expected.

Player	Season	TOI	GA/60	xGA/60	xGA/60 - GA/60
Brent Seabrook	15-18	4007.02	-0.018	0.226	0.244
Brian Campbell	16-17	1325.88	-0.075	0.059	0.134
Gustav Forsling	16-18	1144.62	0.017	0.139	0.122
Duncan Keith	15-18	4316.98	0.002	0.101	0.099
David Rundblad	15-16	109.47	-0.034	0.057	0.091
Michal Rozsival	15-17	1069.9	-0.003	0.068	0.071
Trevor Daley	15-16	374.38	-0.015	0.038	0.053
Viktor Svedberg	15-16	392.62	0.055	0.093	0.038
Erik Gustafsson (D)	15-18	1138.4	0.002	0.037	0.035
Blake Hillman	17-18	65.63	-0.019	0.007	0.026
Christian Ehrhoff	15-16	124.18	0.006	0.006	0
Cody Franson	17-18	325.08	-0.083	-0.094	-0.011
Carl Dahlstrom	17-18	175.53	0.066	0.052	-0.014
Jan Rutta	17-18	927.52	0.071	0.042	-0.029
Connor Murphy	17-18	1142.02	-0.03	-0.067	-0.037
Rob Scuderi	15-16	184.8	0.057	0.02	-0.037
Johnny Oduya	16-17	246.42	-0.028	-0.083	-0.055
Michal Kempny	16-18	1143.7	-0.042	-0.179	-0.137
Trevor Van Riemsdyk	15-17	2405.42	0.007	-0.135	-0.142
Jordan Oesterle	17-18	1013.97	0.094	-0.066	-0.16
Niklas Hjalmarsson	15-17	2869.7	-0.021	-0.22	-0.199

Brent Seabrook SUCKED at the end ... or did he?

Seabrook improved in this “skill” of limiting GAs from xGAs even in games in which Crawford wasn’t playing.

Season	Together		Just Seabrook		Just Crawford		GSAx per 100 xG			
	xGA	GA	xGA	GA	xGA	GA	Crawford	Seabrook	Together	
20102011	35.74	41	19.34	25	58.96	55	6.7	-29.3	-14.7	
20112012	35.14	41	21.23	27	61.24	66	-7.8	-27.2	-16.7	
20122013	16.98	14	13.22	13	30.98	28	9.6	1.7	17.6	
20132014	35.69	36	21.41	28	57.42	58	-1.0	-30.8	-0.9	
20142015	40.68	40	22.84	18	66.25	58	12.5	21.2	1.7	
20152016	42.39	31	25.24	26	70.33	64	9.0	-3.0	26.9	
20162017	39.4	36	25.57	22	68.89	64	7.1	14.0	8.6	
20172018	17.32	11	46.23	50	36.78	34	7.6	-8.2	36.5	
20182019	27.44	29	34.54	30	53.13	56	-5.4	13.1	-5.7	
20192020	13.81	10	12.71	9	74.85	72	3.8	29.2	27.6	

Who Gets Credit for the Defensive Overachievement?

- Use 3 years of player's GSAX (dGA/60) for predict year 4 (Marcel borrowed from Tom Tango)
- Add up the roster TOIs of year 4 and apply a weighted average of the rosters' predicted GSAXs to get team-level estimates
- Use 3 years of goalie's GSAX (dGA/60) for predict year 4
- Compare the goalie model vs the skater-roster model in ability to predict year 4 goalie performance

Gaps between xGA and GA RAPMs are “repeatable”

- Previous year has t-value of 11.6 (*highly* significant) in predicting current year RAPM gap.
- In total, about 1.8% of the variance can be “explained” by 3-year skater history.

```
Call:
lm(formula = `Year 4` ~ `Year 1` + `Year 2` + `Year 3`, data = skater_rapms,
  weights = TOI)

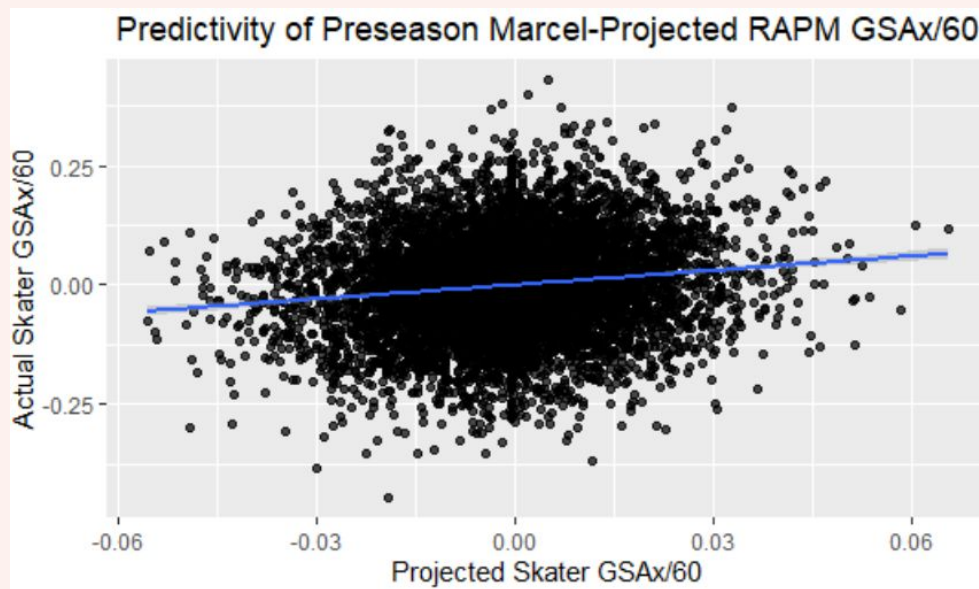
Weighted Residuals:
    Min       1Q   Median       3Q      Max
-12.5059  -1.0644  -0.0129   1.0267  13.5888

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0004843  0.0008471  -0.572   0.567
`Year 1`     0.0774180  0.0114697   6.750 1.54e-11 ***
`Year 2`     0.0701312  0.0102539   6.839 8.27e-12 ***
`Year 3`     0.1066327  0.0092156  11.571 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.444 on 14345 degrees of freedom
Multiple R-squared:  0.01809,    Adjusted R-squared:  0.01788
F-statistic: 88.07 on 3 and 14345 DF,  p-value: < 2.2e-16
```

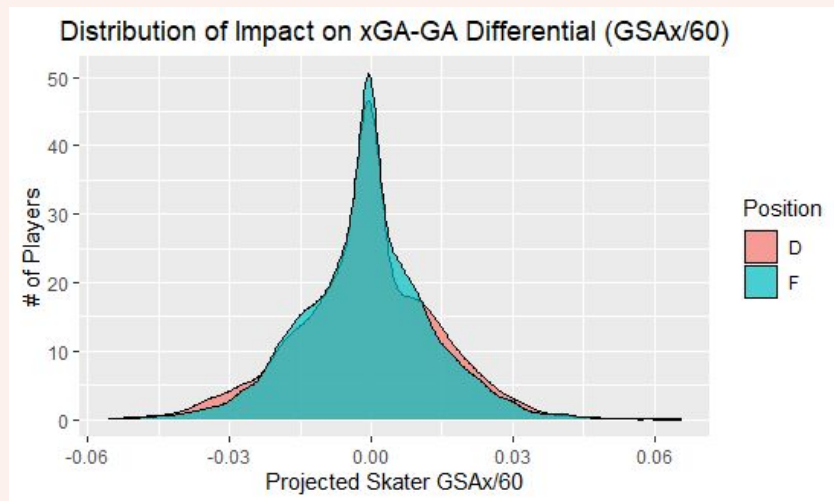
Gaps between xGA and GA RAPMs are “repeatable”

- *Some* consistency in a player's ability have defensive goal impacts over/underachieve their defensive xG impacts.
- Relatively small (correlation of +0.114)
- Limited range – the IQR of the predicted values (0.011) is about a tenth the size of the true numbers (0.103)



Gaps between xGA and GA RAPMs are “repeatable”

- The range of impacts for defenders is *slightly* (though, negligibly) wider than that of forwards.
- We'd expect a bigger difference between positions, so lurking goaltender or team impact seems likely.



Comparing Skater GSAx to Goalie GSAx

Marcel projection for goaltenders has slightly *lower* adjusted r-squared than skaters (1.4% vs 1.8%)

```
Call:
lm(formula = `Year 4` ~ `Year 1` + `Year 2` + `Year 3`, data = gdf_time,
    weights = TOI)

Weighted Residuals:
    Min       1Q   Median       3Q      Max
-115.070  -24.486   -2.313   18.130   93.154

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.059639   0.025959  -2.297  0.02174 *
`Year 1`     0.006485   0.019625   0.330  0.74111
`Year 2`     0.052079   0.021447   2.428  0.01529 *
`Year 3`     0.078672   0.020697   3.801  0.00015 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 32.22 on 1441 degrees of freedom
Multiple R-squared:  0.01586,    Adjusted R-squared:  0.01381
F-statistic: 7.739 on 3 and 1441 DF,  p-value: 3.964e-05
```

Comparing Skater GSAx to Goalie GSAx

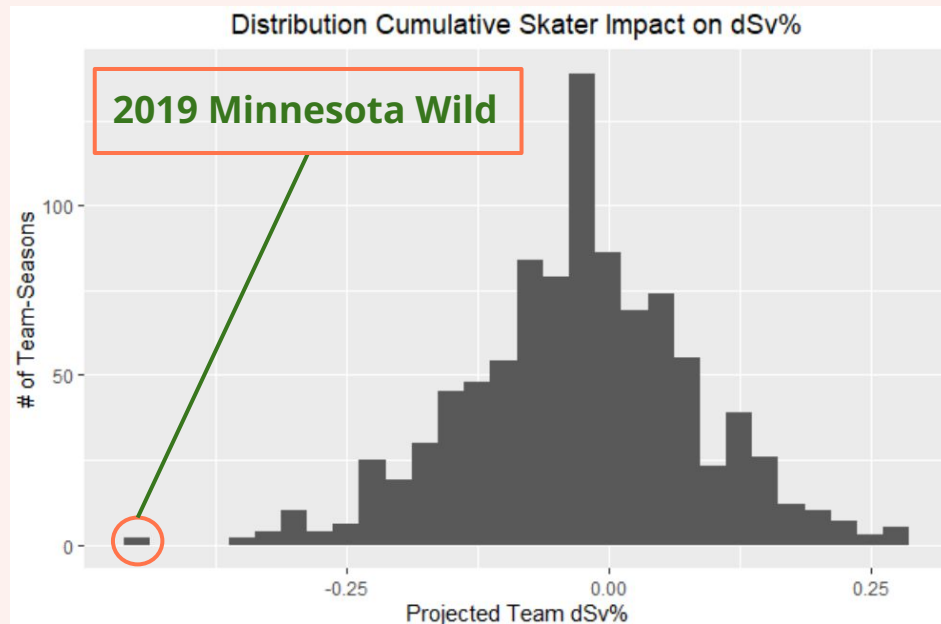
```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
`goalie-based_proj`    0.7983     0.1773   4.503 7.24e-06 ***
`skater-based_proj`   5.7024     1.2988   4.391 1.21e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 31.99 on 1443 degrees of freedom
Multiple R-squared:  0.03567,    Adjusted R-squared:  0.03433
F-statistic: 26.69 on 2 and 1443 DF,  p-value: 4.153e-12
```

If we try to predict a goalie's dSv% using the skater-based GSAx/60 Marcel projection AND the goalie-based dSv% Marcel projection, BOTH are significant predictors!

How Much Does it Matter?

- In the distribution of team-level cumulative skater impacts, ~90% of team-seasons are in the -0.2 to +0.2 range of dSv% impacts.
- That's a difference of 1 GSAX every 250 shots between the 5th and 95th percentiles.



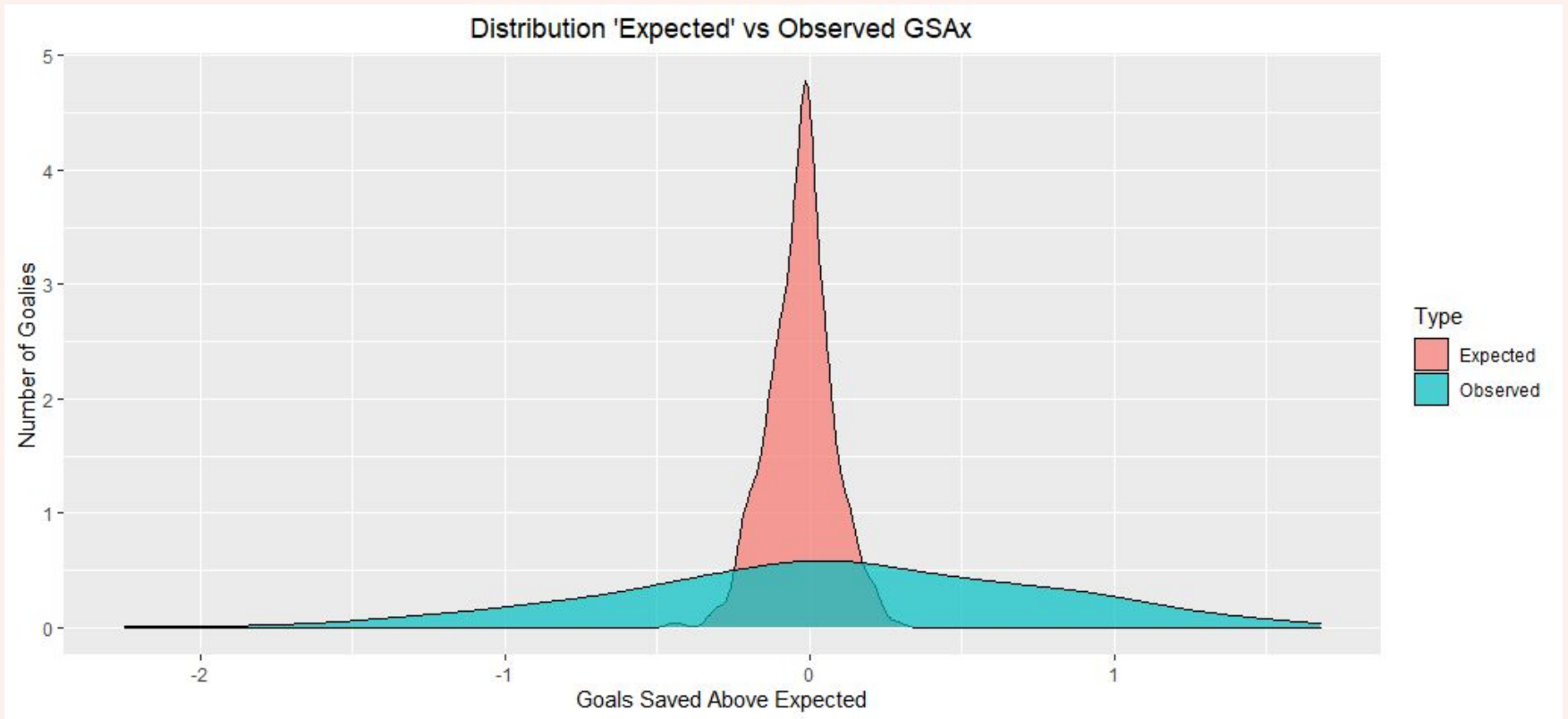
How Much Does it Matter?

Team	# of Skaters with dGA/60 under -0.1
MIN	7
PHI	6
VGK	5
CHI	4
COL	3
CAR	3
FLA	3
OTT	3
DAL	3
ARI	2
WPG	2
S.J	2
N.J	2
PIT	2
DET	2
BUF	2
STL	2
L.A	2
TOR	2

Player	Season	Position	GP	TOI	GA/60	xGA/60	dGA/60
Marcus Foligno	17-19	L	159	1632.47	-0.068	-0.264	-0.196
Greg Pateryn	18-19	D	80	1218.17	-0.018	-0.199	-0.181
Jonas Brodin	16-19	D	223	3892.77	-0.029	-0.156	-0.127
Mikko Koivu	16-19	C	210	2925.3	-0.103	-0.23	-0.127
Ryan Suter	16-19	D	242	5005.58	0.002	-0.107	-0.109
Marco Scandella	16-17	D	71	1144.27	0.134	0.031	-0.103
Jared Spurgeon	16-19	D	219	4135.2	-0.031	-0.132	-0.101

***Skaters on one team could all benefit from rink bias**

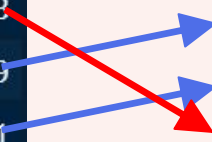
How Much Does it Matter?



How Much Does it Matter?

	Player	GP	dSv
1	Alex Nedeljkovic	23	1.55
2	Juuse Saros	36	1.39
3	Chris Driedger	23	1.24
4	Marc-Andre Fleury	36	1.08
5	Andrei Vasilevskiy	42	0.87
6	Connor Hellebuyck	45	0.83
7	Thatcher Demko	35	0.75
8	Igor Shesterkin	35	0.68
9	Semyon Varlamov	36	0.59
10	Jack Campbell	22	0.51

	Player	GP	ddSv
1	Alex Nedeljkovic	23	1.63
2	Juuse Saros	36	1.40
3	Marc-Andre Fleury	36	1.20
4	Chris Driedger	23	1.18
5	Andrei Vasilevskiy	42	1.07
6	Connor Hellebuyck	45	0.82
7	Thatcher Demko	35	0.74
8	Semyon Varlamov	36	0.66
9	Jack Campbell	22	0.52
10	Igor Shesterkin	35	0.50



Big Takeaways

- 1) Skaters seem to exhibit repeatable defensive over- and under-achievement in terms of their defensive expected goal impacts.
- 2) When summed up at the team-level and placed into a model with goaltender predictions, the team-level predictions retain statistical significance comparable to that of the goalies
- 3) The differentials are minor, worth only about 1 goal every ~10 games in even the most extreme cases.

Where From Here?

1) Improved Data

- a) Game- or shift-level rosters, not season-level
- b) Use per-shot data for skaters rather than per60
- c) Use rink-adjustments
- d) Include goalies in directly in impact models like RAPMs
- e) Include skaters in impact on goal odds similar to goalies

2) Improved Models

- a) Bayesian posterior calculation at player-level
- b) More years / recency weighting
- c) Split forwards / defenders