Is the Hot Hand Psychological?

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Background on The Hot Hand Literature

- Seminal Paper: GVT 1985
  - People believe in the hot hand, but the data does not support these beliefs.
  - Employed data from NBA shooting, and an experiment with Cornell players.
- Most of the work that followed GVT confirmed their findings
- This "hot hand fallacy" is frequently invoked as motivation for behavioral economics and behavioral finance
- Three drawbacks of this literature
  1. Endogeneity: defensive and offensive adjustments
  2. Statistical power
  3. Biased methodologies
     - E.g., using a fixed effect to control for player ability

Motivation

- After addressing these drawbacks, recent work suggests that a hot hand does in fact exist
  - Statistical power, equilibrium adjustments: Green and Zwiebel (2018)
  - Correcting for small sample bias: Miller and Sanjurjo (2018)

- The magnitude is economically meaningful
  - Being "hot" corresponds to a 0.5-1 s.d. increase in subsequent performance

- Our question: is the hot hand driven by psychological factors (e.g., confidence and motivation)? Or, is it purely a physiological phenomenon?
  - Does success breed success?
  - Or, is success merely indicative that the player is hot?

This Paper

- Methodology: An quasi-RDD using distance from outfield wall
  - Treated: batted balls that just barely cleared the outfield wall (just HRs)
  - Untreated: balls that just barely missed clearing the wall (almost HRs)

- Our Idea: Performance can affect psychology, but not physiology
  - Treated will have more confidence and motivation in subsequent attempts.
  - However, their physiological factors should be on average the same.

- Main Result: Treated significantly outperform untreated in subsequent performance (but look similar in prior performance)
  - Magnitude: $\approx$ 0.4-0.8 s.d.
  - Decomposition

Data

1. Statcast
   - Pitch-by-pitch level data
   - Contains batted ball characteristics
     - Launch angle, horizontal angle, launch speed, hit distance

2. Retrosheet
   - Plate-appearance level data
   - Used for calculating performance metrics

Identifying Neighbors

Goal: identify batted balls that are "close" to being a HR

Challenge: Distance to HR wall and wall height varies across park, horizontal angle, and time.

- Players know this and (may) adjust accordingly.
  - A 350 ft ball hit down the line is much better than 375 ft to center
- To our knowledge, a comprehensive database with detailed ball park dimensions is not available.

Stadiums dimensions are not uniform

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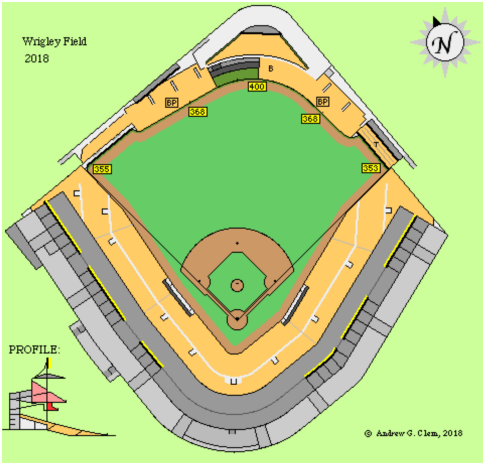
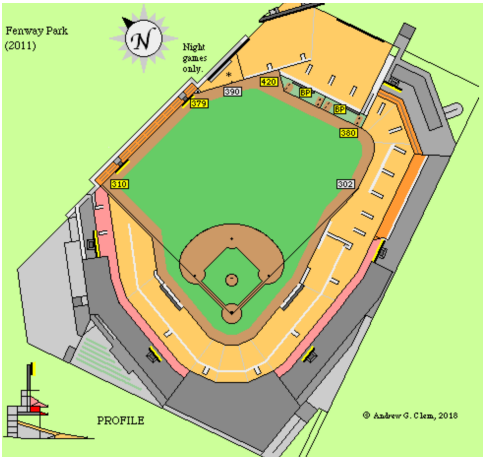


Stadiums dimensions are not uniform



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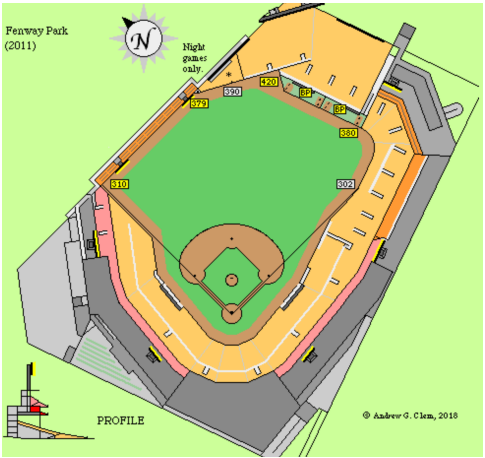

HR wall height is also not uniform

Identifying Neighbors: Distance Method

Step 1: Estimate wall distance

- For each park-year, break the field into six slices (15 degrees each)
- In each park-year-slice, estimate a logistic regression to predict home runs using distance as the sole explanatory variable.
- Estimate wall distance as the distance at which the probability of a home run equals 50%

Step 2: Compare hit distance to wall distance

- Assign each batted ball to its corresponding slice
- Estimate distance to wall = hit distance - wall distance

Step 3: Neighbors for a given margin (e.g., 10 feet)

- "Just enough" HRs $\equiv$ HRs & distance to wall<margin
- "Almost" HRs $\equiv$ non-HRs & distance to wall>-margin

Identifying Neighbors: Machine Learning (ML) Method

Step 1: Estimate probability of home run using random forest model

- Split the data into training and test subsamples
- Use training data to estimate a random forest model

$$\Pr(\text{HR}) = F(\text{h.angle, launch angle, launch speed, park-year, [hit distance]})$$

- Apply model to the test subsample

Step 2: Define neighbors in for a given margin (e.g., 0.1)

- Neighbors $\equiv$ All batted balls with RFP $\in$ (0.5-margin, 0.5+margin)
- Just enough HRs $\equiv$ HRs $\cap$ Neighbors
- Almost HRs $\equiv$ non-HRs $\cap$ Neighbors

Identifying Neighbors: Intersection Method

$$\text{Neighbor}_{\text{Inter}} = \text{Neighbor}_{\text{ML}} \cap \text{Neighbor}_{\text{Distance}}$$

- ML and Distance methods disagree primarily for balls:
  - At boundary of horizontal angle slices
  - With low launch angle that hit the wall

Example of Intersection Neighbor

Wilmer Flores facing Kelvin Herrera

- Juan Soto is in left field...
- Soto has since moved to right field

Our Question: Does Wilmer Flores perform better in his next few attempts than he would have performed if Soto had caught the ball?

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Results

Treatment Group	N	Prior	Post	Difference	P-value
Just Enough	4223	0.763	0.806	0.043***	0.002
				(0.014)	
Almost	3754	0.773	0.792	0.019	0.199
				(0.015)	
Diff-in-Diff				0.024	0.242
				(0.021)	

Performance measure is OPS $\equiv$ OBP+SLG

- Prior is average performance in the five attempts just before neighbor
- Post is average performance in the five attempts just after neighbor
- Just enough treatment effect corresponds ≈ 0.4 s.d. in the cross section

Decomposition

Treatment Group	N	Prior	Post	Difference	P-Value
Just Enough (Hr)	4223	0.763	0.806	0.043***	0.002
				(0.014)	
Almost (Hit)	2716	0.756	0.796	0.040**	0.022
				(0.017)	
Almost (Out)	1038	0.817	0.781	-0.036	0.203
				(0.028)	
Hr - Out				0.079**	0.013
				(0.032)	
Hr - Hit				0.003	0.892
				(0.021)	

Performance measure is OPS $\equiv$ OBP+SLG

Walks

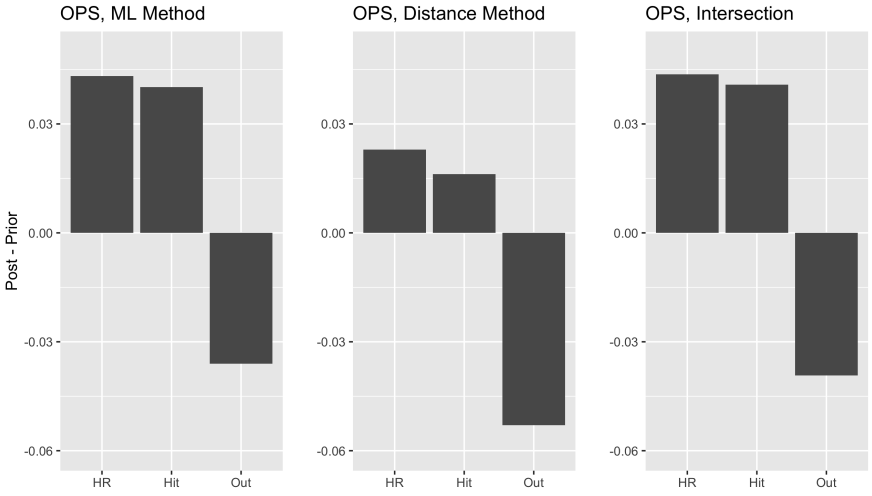
Treatment Group	N	Prior	Post	Difference	P-Value
Just Enough (Hr)	4223	0.085	0.094	0.009*** (0.003)	0.002
Almost (Hit)	2716	0.090	0.092	0.003 (0.004)	0.433
Almost (Out)	1038	0.091	0.090	-0.001 (0.006)	0.888
Hr - Out				0.010 (0.006)	0.138
Hr - Hit				0.006 (0.005)	0.200

Performance measure is BB% $\equiv$ BB / PA

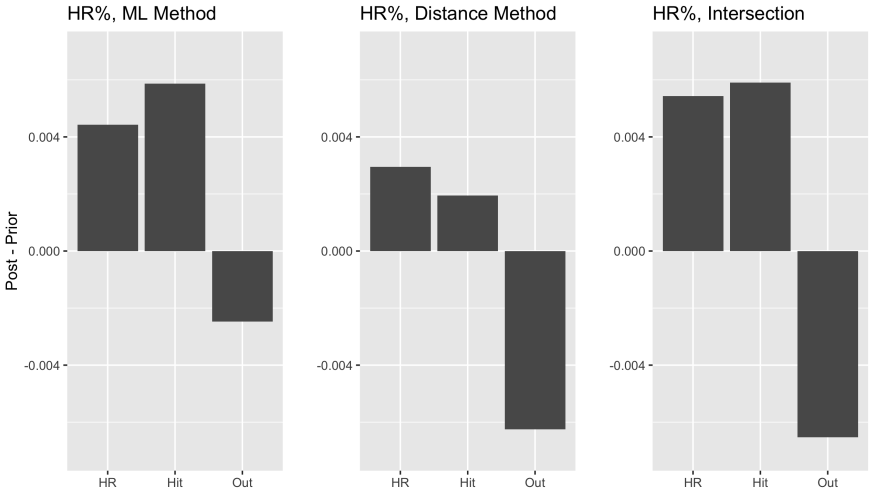
Robustness

- The results are largely similar across different performance measures
  - OPS, WOBA, HR/AB
- And across different methodologies for identifying neighbors
  - Distance, ML, Intersection
- It is stronger for shorter durations (3 and 5) than longer durations (10 and 20)

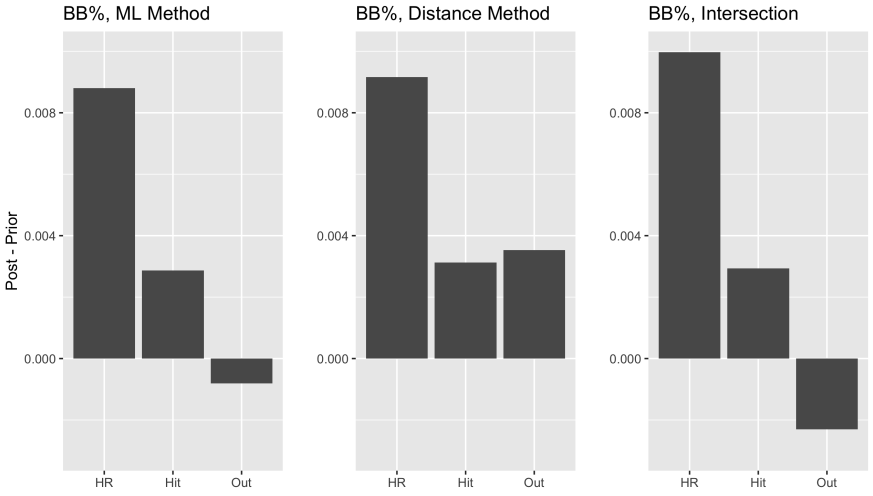
Robustness


OPS, ML Method
OPS, Distance Method
OPS, Intersection
Post - Prior
0.03
0.00
-0.03
-0.06
HR
Hit
Out

Robustness


HR%, ML Method
HR%, Distance Method
HR%, Intersection
Post - Prior
0.004
0.000
-0.004
HR
Hit
Out

Robustness


BB%, ML Method
BB%, Distance Method
BB%, Intersection
Post - Prior
0.008
0.004
0.000
HR
Hit
Out

Summary

- Investigate the mechanism for the hot hand effect
- Provide evidence that "success breeds success" using detailed data from Major League Baseball
- Our interpretation: success makes a player more confident and motivated thereby temporarily increasing her ability and therefore her success probability