# 5 Pythagorean expectation as predictor in MLB

September 4, 2025

## 1 Pythagorean expectation as predictor in Major League Baseball

One of the main reasons that people are interested in sports analytics is that they want to predict the outcome of events that have not yet occurred. Thus we want to go beyond "explanation" - finding the model that best fits the data (i.e. history) and to use our model to forecast the outcome of games in the future.

Pythagorean Expectation can be thought of as a forecast. At any point in the season, it can be calculated based on the games already played. Using it as a forecast would amount to saying that from that point onward the win percentage of the team would equal the Pythagorean Expectation to date.

In this notebook, we're going to see if it is a good forecasting model in the context of the MLB data we examined earlier. Specifically, we will take the Pythagorean expectation based on games already played up to the All-Star Game (which takes place roughly in the middle of the season) and then see how well it correlates with win percentage in the second half of the season. We also have a natural benchmark against which to evaluate this forecast. The simplest forecast of all is to assume that win percentage will stay the same. Hence we will compare Pythagorean Expectation before the All-Star Game to win percentage before the All-Star Game as forecast of win percentage in the second half of the season.

To implement this test we initially follow the same procedures as we used in the previous MLB notebook to measure team performance. But then we split the data at the All-Star Game and compare statistics for each half of the season.

In [7]:
```
# Import packages

import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Read in the data

MLB = pd.read_excel('../../Data/Week 1/Retrosheet MLB game log 2018.xlsx')
print(MLB.columns.tolist())
```

```
['Date', 'DoubleHeader', 'DayOfWeek', 'VisitingTeam', 'VisitingTeamLeague', 'VisitingTeamGameNu
```

In [3]:
```
# Create df containing only the variables we need
# Create a counter

MLB18 = MLB[['VisitingTeam','HomeTeam','VisitorRunsScored','HomeRunsScore','Date']]
MLB18 = MLB18.rename(columns={'VisitorRunsScored':'VisR','HomeRunsScore':'HomR'})
MLB18['count']=1
MLB18
```

Out[3]:

| | VisitingTeam | HomeTeam | VisR | HomR | Date | count |
|---|---|---|---|---|---|---|
| 0 | COL | ARI | 2 | 8 | 20180329 | 1 |
| 1 | PHI | ATL | 5 | 8 | 20180329 | 1 |
| 2 | SFN | LAN | 1 | 0 | 20180329 | 1 |
| 3 | CHN | MIA | 8 | 4 | 20180329 | 1 |
| 4 | SLN | NYN | 4 | 9 | 20180329 | 1 |
| ... | ... | ... | ... | ... | ... | ... |
| 2426 | CHA | MIN | 4 | 5 | 20180930 | 1 |
| 2427 | TEX | SEA | 1 | 3 | 20180930 | 1 |
| 2428 | TOR | TBA | 4 | 9 | 20180930 | 1 |
| 2429 | MIL | CHN | 3 | 1 | 20181001 | 1 |
| 2430 | COL | LAN | 2 | 5 | 20181001 | 1 |

[2431 rows x 6 columns]

In [4]:
```
# Create df recording team performance as home team
# We create an additional column 'home' which here has a value 1 to designate that the

MLBhome = MLB18[['HomeTeam','HomR','VisR','count','Date']].copy()
MLBhome['home']=1
MLBhome = MLBhome.rename(columns={'HomeTeam':'team','VisR':'RA','HomR':'R'})
MLBhome
```

Out[4]:

| | team | R | RA | count | Date | home |
|---|---|---|---|---|---|---|
| 0 | ARI | 8 | 2 | 1 | 20180329 | 1 |
| 1 | ATL | 8 | 5 | 1 | 20180329 | 1 |
| 2 | LAN | 0 | 1 | 1 | 20180329 | 1 |
| 3 | MIA | 4 | 8 | 1 | 20180329 | 1 |
| 4 | NYN | 9 | 4 | 1 | 20180329 | 1 |
| ... | ... | .. | .. | ... | ... | ... |
| 2426 | MIN | 5 | 4 | 1 | 20180930 | 1 |
| 2427 | SEA | 3 | 1 | 1 | 20180930 | 1 |
| 2428 | TBA | 9 | 4 | 1 | 20180930 | 1 |
| 2429 | CHN | 1 | 3 | 1 | 20181001 | 1 |
| 2430 | LAN | 5 | 2 | 1 | 20181001 | 1 |

[2431 rows x 6 columns]

In [5]:
```
# Create df recording team performance as visiting team
# As above, we create an additional column 'home', which now has a value 0 to designat
```

```
MLBaway = MLB18[['VisitingTeam','VisR','HomR','count','Date']].copy()
MLBaway['home']=0
MLBaway = MLBaway.rename(columns={'VisitingTeam':'team','VisR':'R','HomR':'RA'})
MLBaway
```

Out[5]:

| | team | R | RA | count | Date | home |
|---|---|---|---|---|---|---|
| 0 | COL | 2 | 8 | 1 | 20180329 | 0 |
| 1 | PHI | 5 | 8 | 1 | 20180329 | 0 |
| 2 | SFN | 1 | 0 | 1 | 20180329 | 0 |
| 3 | CHN | 8 | 4 | 1 | 20180329 | 0 |
| 4 | SLN | 4 | 9 | 1 | 20180329 | 0 |
| ... | ... | .. | .. | ... | ... | ... |
| 2426 | CHA | 4 | 5 | 1 | 20180930 | 0 |
| 2427 | TEX | 1 | 3 | 1 | 20180930 | 0 |
| 2428 | TOR | 4 | 9 | 1 | 20180930 | 0 |
| 2429 | MIL | 3 | 1 | 1 | 20181001 | 0 |
| 2430 | COL | 2 | 5 | 1 | 20181001 | 0 |

[2431 rows x 6 columns]

In [6]:
```
# Here is where the approach differs from the previous notebooks. Instead of taking su
# concatenate, meaning that we stack performances as home team and away team. This cre
# by each team across the season. The list is 4,862 rows long, which is twice the numb
# season.

MLB18 = pd.concat([MLBhome,MLBaway])
MLB18
```

Out[6]:

| | team | R | RA | count | Date | home |
|---|---|---|---|---|---|---|
| 0 | ARI | 8 | 2 | 1 | 20180329 | 1 |
| 1 | ATL | 8 | 5 | 1 | 20180329 | 1 |
| 2 | LAN | 0 | 1 | 1 | 20180329 | 1 |
| 3 | MIA | 4 | 8 | 1 | 20180329 | 1 |
| 4 | NYN | 9 | 4 | 1 | 20180329 | 1 |
| ... | ... | .. | .. | ... | ... | ... |
| 2426 | CHA | 4 | 5 | 1 | 20180930 | 0 |
| 2427 | TEX | 1 | 3 | 1 | 20180930 | 0 |
| 2428 | TOR | 4 | 9 | 1 | 20180930 | 0 |
| 2429 | MIL | 3 | 1 | 1 | 20181001 | 0 |
| 2430 | COL | 2 | 5 | 1 | 20181001 | 0 |

[4862 rows x 6 columns]

In [8]:
```
# We define a win

MLB18['win'] = np.where(MLB18['R']> MLB18['RA'],1,0)
MLB18
```

---

```
    KeyError                                  Traceback (most recent call last)

    /opt/conda/lib/python3.6/site-packages/pandas/core/indexes/base.py in get_loc(self, key
   2656             try:
-> 2657                 return self._engine.get_loc(key)
   2658             except KeyError:


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get


    KeyError: 'R'


During handling of the above exception, another exception occurred:


    KeyError                                  Traceback (most recent call last)

    <ipython-input-8-ec072d652993> in <module>
      1 # We define a win
      2
----> 3 MLB18['win'] = np.where(MLB18['R']> MLB18['RA'],1,0)
      4 MLB18


    /opt/conda/lib/python3.6/site-packages/pandas/core/frame.py in __getitem__(self, key)
   2925             if self.columns.nlevels > 1:
   2926                 return self._getitem_multilevel(key)
-> 2927             indexer = self.columns.get_loc(key)
   2928             if is_integer(indexer):
   2929                 indexer = [indexer]


    /opt/conda/lib/python3.6/site-packages/pandas/core/indexes/base.py in get_loc(self, key
   2657                 return self._engine.get_loc(key)
   2658             except KeyError:
-> 2659                 return self._engine.get_loc(self._maybe_cast_indexer(key))
```

```
2660         indexer = self.get_indexer([key], method=method, tolerance=tolerance)
2661         if indexer.ndim > 1 or indexer.size > 1:


pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get


pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get


KeyError: 'R'
```

In [8]:
```
# Now we define the season up to the All-Star Game (which was on July 17, 2018) as the
# We use .describe() to show the summary statistics. You can see this includes 2,886 r
# 1,443 games.

Half1 = MLB18[MLB18.Date < 20180717]
Half1.describe()
```

Out[8]:

| | R | RA | count | Date | home | win |
|---|---|---|---|---|---|---|
| count | 2886.000000 | 2886.000000 | 2886.0 | 2.886000e+03 | 2886.000000 | 2886.000000 |
| mean | 4.417533 | 4.417533 | 1.0 | 2.018054e+07 | 0.500000 | 0.500000 |
| std | 3.174305 | 3.174305 | 0.0 | 1.054102e+02 | 0.500087 | 0.500087 |
| min | 0.000000 | 0.000000 | 1.0 | 2.018033e+07 | 0.000000 | 0.000000 |
| 25% | 2.000000 | 2.000000 | 1.0 | 2.018043e+07 | 0.000000 | 0.000000 |
| 50% | 4.000000 | 4.000000 | 1.0 | 2.018052e+07 | 0.500000 | 0.500000 |
| 75% | 6.000000 | 6.000000 | 1.0 | 2.018062e+07 | 1.000000 | 1.000000 |
| max | 20.000000 | 20.000000 | 1.0 | 2.018072e+07 | 1.000000 | 1.000000 |

In [9]:
```
# Now we define the season after the All-Star Game (which was on July 17, 2018) as the
# We use .describe() to show the summary statistics. You can see this includes 1,976 r
```

```
# 988 games.


Half2 = MLB18[MLB18.Date > 20180717]
Half2.describe()
```

Out[9]:

| | R | RA | count | Date | home | win |
|---|---|---|---|---|---|---|
| count | 1976.000000 | 1976.000000 | 1976.0 | 1.976000e+03 | 1976.000000 | 1976.000000 |
| mean | 4.494433 | 4.494433 | 1.0 | 2.018084e+07 | 0.500000 | 0.500000 |
| std | 3.219870 | 3.219870 | 0.0 | 7.011522e+01 | 0.500127 | 0.500127 |
| min | 0.000000 | 0.000000 | 1.0 | 2.018072e+07 | 0.000000 | 0.000000 |
| 25% | 2.000000 | 2.000000 | 1.0 | 2.018081e+07 | 0.000000 | 0.000000 |
| 50% | 4.000000 | 4.000000 | 1.0 | 2.018082e+07 | 0.500000 | 0.500000 |
| 75% | 6.000000 | 6.000000 | 1.0 | 2.018091e+07 | 1.000000 | 1.000000 |
| max | 25.000000 | 25.000000 | 1.0 | 2.018100e+07 | 1.000000 | 1.000000 |

In [10]:
```
# We now use .groupby to sum the number of games, wins, runs and runs against for the

Half1perf = Half1.groupby('team')['count','win','R','RA'].sum().reset_index()
Half1perf = Half1perf.rename(columns={'count':'count1','win':'win1','R':'R1','RA':'RA
Half1perf
```

Out[10]:

| | team | count1 | win1 | R1 | RA1 |
|---|---|---|---|---|---|
| 0 | ANA | 97 | 49 | 425 | 401 |
| 1 | ARI | 97 | 53 | 421 | 378 |
| 2 | ATL | 94 | 52 | 456 | 388 |
| 3 | BAL | 97 | 28 | 345 | 504 |
| 4 | BOS | 98 | 68 | 530 | 367 |
| 5 | CHA | 95 | 33 | 384 | 510 |
| 6 | CHN | 93 | 55 | 476 | 362 |
| 7 | CIN | 96 | 43 | 461 | 493 |
| 8 | CLE | 95 | 52 | 487 | 405 |
| 9 | COL | 96 | 51 | 467 | 468 |
| 10 | DET | 98 | 41 | 386 | 456 |
| 11 | HOU | 99 | 64 | 500 | 312 |
| 12 | KCA | 95 | 27 | 337 | 530 |
| 13 | LAN | 96 | 53 | 453 | 371 |
| 14 | MIA | 98 | 41 | 376 | 491 |

```
15  MIL      98    55  426  377
16  MIN      94    44  424  447
17  NYA      95    62  493  362
18  NYN      94    39  363  431
19  OAK      97    55  449  425
20  PHI      95    53  411  393
21  PIT      97    48  425  450
22  SDN      99    40  365  465
23  SEA      97    58  412  414
24  SFN      98    50  399  425
25  SLN      94    48  413  402
26  TBA      96    49  401  381
27  TEX      97    41  424  487
28  TOR      95    43  423  467
29  WAS      96    48  417  387
```

In [11]:
```
# From these statistics we calculate win percentage and Pythagorean Expectation for t

Half1perf['wpc1'] = Half1perf['win1']/Half1perf['count1']
Half1perf['pyth1'] = Half1perf['R1']**2/(Half1perf['R1']**2 + Half1perf['RA1']**2)
Half1perf
```

Out[11]:

| | team | count1 | win1 | R1 | RA1 | wpc1 | pyth1 |
|---|---|---|---|---|---|---|---|
| 0 | ANA | 97 | 49 | 425 | 401 | 0.505155 | 0.529031 |
| 1 | ARI | 97 | 53 | 421 | 378 | 0.546392 | 0.553662 |
| 2 | ATL | 94 | 52 | 456 | 388 | 0.553191 | 0.580049 |
| 3 | BAL | 97 | 28 | 345 | 504 | 0.288660 | 0.319067 |
| 4 | BOS | 98 | 68 | 530 | 367 | 0.693878 | 0.675908 |
| 5 | CHA | 95 | 33 | 384 | 510 | 0.347368 | 0.361805 |
| 6 | CHN | 93 | 55 | 476 | 362 | 0.591398 | 0.633566 |
| 7 | CIN | 96 | 43 | 461 | 493 | 0.447917 | 0.466495 |
| 8 | CLE | 95 | 52 | 487 | 405 | 0.547368 | 0.591158 |
| 9 | COL | 96 | 51 | 467 | 468 | 0.531250 | 0.498930 |
| 10 | DET | 98 | 41 | 386 | 456 | 0.418367 | 0.417435 |
| 11 | HOU | 99 | 64 | 500 | 312 | 0.646465 | 0.719748 |
| 12 | KCA | 95 | 27 | 337 | 530 | 0.284211 | 0.287903 |
| 13 | LAN | 96 | 53 | 453 | 371 | 0.552083 | 0.598539 |
| 14 | MIA | 98 | 41 | 376 | 491 | 0.418367 | 0.369652 |
| 15 | MIL | 98 | 55 | 426 | 377 | 0.561224 | 0.560795 |
| 16 | MIN | 94 | 44 | 424 | 447 | 0.468085 | 0.473612 |
| 17 | NYA | 95 | 62 | 493 | 362 | 0.652632 | 0.649702 |
| 18 | NYN | 94 | 39 | 363 | 431 | 0.414894 | 0.414981 |
| 19 | OAK | 97 | 55 | 449 | 425 | 0.567010 | 0.527439 |
| 20 | PHI | 95 | 53 | 411 | 393 | 0.557895 | 0.522377 |
| 21 | PIT | 97 | 48 | 425 | 450 | 0.494845 | 0.471452 |
| 22 | SDN | 99 | 40 | 365 | 465 | 0.404040 | 0.381242 |
| 23 | SEA | 97 | 58 | 412 | 414 | 0.597938 | 0.497579 |
| 24 | SFN | 98 | 50 | 399 | 425 | 0.510204 | 0.468478 |

```
25  SLN      94    48  413  402  0.510638  0.513494
26  TBA      96    49  401  381  0.510417  0.525559
27  TEX      97    41  424  487  0.422680  0.431174
28  TOR      95    43  423  467  0.452632  0.450682
29  WAS      96    48  417  387  0.500000  0.537262
```

In [12]:
```
# As above we use .groupby to sum the number of games, wins, runs and runs against fo

Half2perf = Half2.groupby('team')['count','win','R','RA'].sum().reset_index()
Half2perf = Half2perf.rename(columns={'count':'count2','win':'win2','R':'R2','RA':'RA2
Half2perf
```

Out[12]:

| | team | count2 | win2 | R2 | RA2 |
|---|---|---|---|---|---|
| 0 | ANA | 65 | 31 | 296 | 321 |
| 1 | ARI | 65 | 29 | 272 | 266 |
| 2 | ATL | 68 | 38 | 303 | 269 |
| 3 | BAL | 65 | 19 | 277 | 388 |
| 4 | BOS | 64 | 40 | 346 | 280 |
| 5 | CHA | 67 | 29 | 272 | 338 |
| 6 | CHN | 70 | 40 | 285 | 283 |
| 7 | CIN | 66 | 24 | 235 | 326 |
| 8 | CLE | 67 | 39 | 331 | 243 |
| 9 | COL | 67 | 40 | 313 | 277 |
| 10 | DET | 64 | 23 | 244 | 340 |
| 11 | HOU | 63 | 39 | 297 | 222 |
| 12 | KCA | 67 | 31 | 301 | 303 |
| 13 | LAN | 67 | 39 | 351 | 239 |
| 14 | MIA | 63 | 22 | 213 | 318 |
| 15 | MIL | 65 | 41 | 328 | 282 |
| 16 | MIN | 68 | 34 | 314 | 328 |
| 17 | NYA | 67 | 38 | 358 | 307 |
| 18 | NYN | 68 | 38 | 313 | 276 |
| 19 | OAK | 65 | 42 | 364 | 249 |
| 20 | PHI | 67 | 27 | 266 | 335 |
| 21 | PIT | 64 | 34 | 267 | 243 |
| 22 | SDN | 63 | 26 | 252 | 302 |
| 23 | SEA | 65 | 31 | 265 | 297 |
| 24 | SFN | 64 | 23 | 204 | 274 |
| 25 | SLN | 68 | 40 | 346 | 289 |
| 26 | TBA | 66 | 41 | 315 | 265 |
| 27 | TEX | 65 | 26 | 313 | 361 |
| 28 | TOR | 67 | 30 | 286 | 365 |
| 29 | WAS | 66 | 34 | 354 | 295 |

In [13]:
```
# From these statistics we calculate win percentage and Pythagorean Expectation for t

Half2perf['wpc2'] = Half2perf['win2']/Half2perf['count2']
Half2perf['pyth2'] = Half2perf['R2']**2/(Half2perf['R2']**2 + Half2perf['RA2']**2)
Half2perf
```

Out[13]:

| | team | count2 | win2 | R2 | RA2 | wpc2 | pyth2 |
|---|---|---|---|---|---|---|---|
| 0 | ANA | 65 | 31 | 296 | 321 | 0.476923 | 0.459548 |
| 1 | ARI | 65 | 29 | 272 | 266 | 0.446154 | 0.511151 |
| 2 | ATL | 68 | 38 | 303 | 269 | 0.558824 | 0.559231 |
| 3 | BAL | 65 | 19 | 277 | 388 | 0.292308 | 0.337607 |
| 4 | BOS | 64 | 40 | 346 | 280 | 0.625000 | 0.604272 |
| 5 | CHA | 67 | 29 | 272 | 338 | 0.432836 | 0.393055 |
| 6 | CHN | 70 | 40 | 285 | 283 | 0.571429 | 0.503521 |
| 7 | CIN | 66 | 24 | 235 | 326 | 0.363636 | 0.341948 |
| 8 | CLE | 67 | 39 | 331 | 243 | 0.582090 | 0.649789 |
| 9 | COL | 67 | 40 | 313 | 277 | 0.597015 | 0.560791 |
| 10 | DET | 64 | 23 | 244 | 340 | 0.359375 | 0.339942 |
| 11 | HOU | 63 | 39 | 297 | 222 | 0.619048 | 0.641553 |
| 12 | KCA | 67 | 31 | 301 | 303 | 0.462687 | 0.496689 |
| 13 | LAN | 67 | 39 | 351 | 239 | 0.582090 | 0.683228 |
| 14 | MIA | 63 | 22 | 213 | 318 | 0.349206 | 0.309701 |
| 15 | MIL | 65 | 41 | 328 | 282 | 0.630769 | 0.574983 |
| 16 | MIN | 68 | 34 | 314 | 328 | 0.500000 | 0.478204 |
| 17 | NYA | 67 | 38 | 358 | 307 | 0.567164 | 0.576243 |
| 18 | NYN | 68 | 38 | 313 | 276 | 0.558824 | 0.562571 |
| 19 | OAK | 65 | 42 | 364 | 249 | 0.646154 | 0.681224 |
| 20 | PHI | 67 | 27 | 266 | 335 | 0.402985 | 0.386685 |
| 21 | PIT | 64 | 34 | 267 | 243 | 0.531250 | 0.546955 |
| 22 | SDN | 63 | 26 | 252 | 302 | 0.412698 | 0.410477 |
| 23 | SEA | 65 | 31 | 265 | 297 | 0.476923 | 0.443245 |
| 24 | SFN | 64 | 23 | 204 | 274 | 0.359375 | 0.356631 |
| 25 | SLN | 68 | 40 | 346 | 289 | 0.588235 | 0.589046 |
| 26 | TBA | 66 | 41 | 315 | 265 | 0.621212 | 0.585571 |
| 27 | TEX | 65 | 26 | 313 | 361 | 0.400000 | 0.429143 |
| 28 | TOR | 67 | 30 | 286 | 365 | 0.447761 | 0.380409 |
| 29 | WAS | 66 | 34 | 354 | 295 | 0.515152 | 0.590164 |

In [14]:
```
# Now we merge the two dfs

Half2predictor = pd.merge(Half1perf,Half2perf, on='team')
Half2predictor
```

Out[14]:

| | team | count1 | win1 | R1 | RA1 | wpc1 | pyth1 | count2 | win2 | R2 | RA2 | \ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ANA | 97 | 49 | 425 | 401 | 0.505155 | 0.529031 | 65 | 31 | 296 | 321 | |
| 1 | ARI | 97 | 53 | 421 | 378 | 0.546392 | 0.553662 | 65 | 29 | 272 | 266 | |
| 2 | ATL | 94 | 52 | 456 | 388 | 0.553191 | 0.580049 | 68 | 38 | 303 | 269 | |
| 3 | BAL | 97 | 28 | 345 | 504 | 0.288660 | 0.319067 | 65 | 19 | 277 | 388 | |
| 4 | BOS | 98 | 68 | 530 | 367 | 0.693878 | 0.675908 | 64 | 40 | 346 | 280 | |
| 5 | CHA | 95 | 33 | 384 | 510 | 0.347368 | 0.361805 | 67 | 29 | 272 | 338 | |
| 6 | CHN | 93 | 55 | 476 | 362 | 0.591398 | 0.633566 | 70 | 40 | 285 | 283 | |
| 7 | CIN | 96 | 43 | 461 | 493 | 0.447917 | 0.466495 | 66 | 24 | 235 | 326 | |
| 8 | CLE | 95 | 52 | 487 | 405 | 0.547368 | 0.591158 | 67 | 39 | 331 | 243 | |
| 9 | COL | 96 | 51 | 467 | 468 | 0.531250 | 0.498930 | 67 | 40 | 313 | 277 | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 10 | DET | 98 | 41 | 386 | 456 | 0.418367 | 0.417435 | 64 | 23 | 244 | 340 |
| 11 | HOU | 99 | 64 | 500 | 312 | 0.646465 | 0.719748 | 63 | 39 | 297 | 222 |
| 12 | KCA | 95 | 27 | 337 | 530 | 0.284211 | 0.287903 | 67 | 31 | 301 | 303 |
| 13 | LAN | 96 | 53 | 453 | 371 | 0.552083 | 0.598539 | 67 | 39 | 351 | 239 |
| 14 | MIA | 98 | 41 | 376 | 491 | 0.418367 | 0.369652 | 63 | 22 | 213 | 318 |
| 15 | MIL | 98 | 55 | 426 | 377 | 0.561224 | 0.560795 | 65 | 41 | 328 | 282 |
| 16 | MIN | 94 | 44 | 424 | 447 | 0.468085 | 0.473612 | 68 | 34 | 314 | 328 |
| 17 | NYA | 95 | 62 | 493 | 362 | 0.652632 | 0.649702 | 67 | 38 | 358 | 307 |
| 18 | NYN | 94 | 39 | 363 | 431 | 0.414894 | 0.414981 | 68 | 38 | 313 | 276 |
| 19 | OAK | 97 | 55 | 449 | 425 | 0.567010 | 0.527439 | 65 | 42 | 364 | 249 |
| 20 | PHI | 95 | 53 | 411 | 393 | 0.557895 | 0.522377 | 67 | 27 | 266 | 335 |
| 21 | PIT | 97 | 48 | 425 | 450 | 0.494845 | 0.471452 | 64 | 34 | 267 | 243 |
| 22 | SDN | 99 | 40 | 365 | 465 | 0.404040 | 0.381242 | 63 | 26 | 252 | 302 |
| 23 | SEA | 97 | 58 | 412 | 414 | 0.597938 | 0.497579 | 65 | 31 | 265 | 297 |
| 24 | SFN | 98 | 50 | 399 | 425 | 0.510204 | 0.468478 | 64 | 23 | 204 | 274 |
| 25 | SLN | 94 | 48 | 413 | 402 | 0.510638 | 0.513494 | 68 | 40 | 346 | 289 |
| 26 | TBA | 96 | 49 | 401 | 381 | 0.510417 | 0.525559 | 66 | 41 | 315 | 265 |
| 27 | TEX | 97 | 41 | 424 | 487 | 0.422680 | 0.431174 | 65 | 26 | 313 | 361 |
| 28 | TOR | 95 | 43 | 423 | 467 | 0.452632 | 0.450682 | 67 | 30 | 286 | 365 |
| 29 | WAS | 96 | 48 | 417 | 387 | 0.500000 | 0.537262 | 66 | 34 | 354 | 295 |

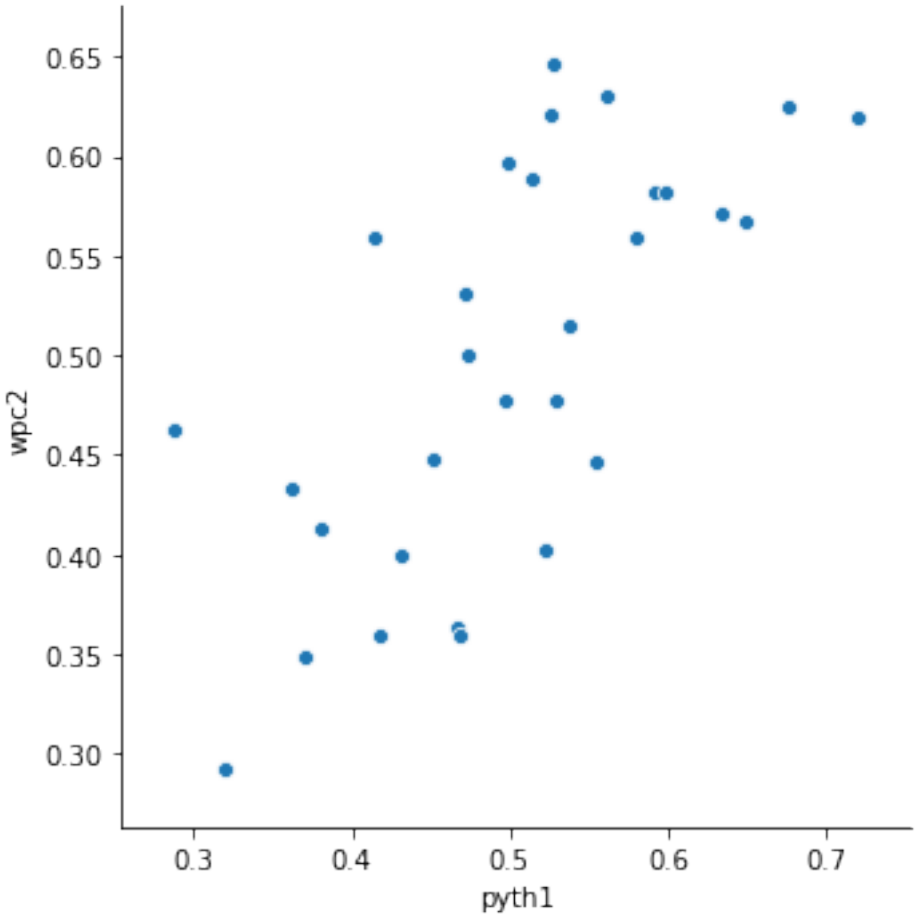
| | wpc2 | pyth2 |
|---|---|---|
| 0 | 0.476923 | 0.459548 |
| 1 | 0.446154 | 0.511151 |
| 2 | 0.558824 | 0.559231 |
| 3 | 0.292308 | 0.337607 |
| 4 | 0.625000 | 0.604272 |
| 5 | 0.432836 | 0.393055 |
| 6 | 0.571429 | 0.503521 |
| 7 | 0.363636 | 0.341948 |
| 8 | 0.582090 | 0.649789 |
| 9 | 0.597015 | 0.560791 |
| 10 | 0.359375 | 0.339942 |
| 11 | 0.619048 | 0.641553 |
| 12 | 0.462687 | 0.496689 |
| 13 | 0.582090 | 0.683228 |
| 14 | 0.349206 | 0.309701 |
| 15 | 0.630769 | 0.574983 |
| 16 | 0.500000 | 0.478204 |
| 17 | 0.567164 | 0.576243 |
| 18 | 0.558824 | 0.562571 |
| 19 | 0.646154 | 0.681224 |
| 20 | 0.402985 | 0.386685 |
| 21 | 0.531250 | 0.546955 |
| 22 | 0.412698 | 0.410477 |
| 23 | 0.476923 | 0.443245 |
| 24 | 0.359375 | 0.356631 |
| 25 | 0.588235 | 0.589046 |

```
26  0.621212  0.585571
27  0.400000  0.429143
28  0.447761  0.380409
29  0.515152  0.590164
```

In [15]:
```
# First, plot Pythagorean Expectation against win percentage in the second half of th

sns.relplot(x="pyth1", y="wpc2", data = Half2predictor)
```

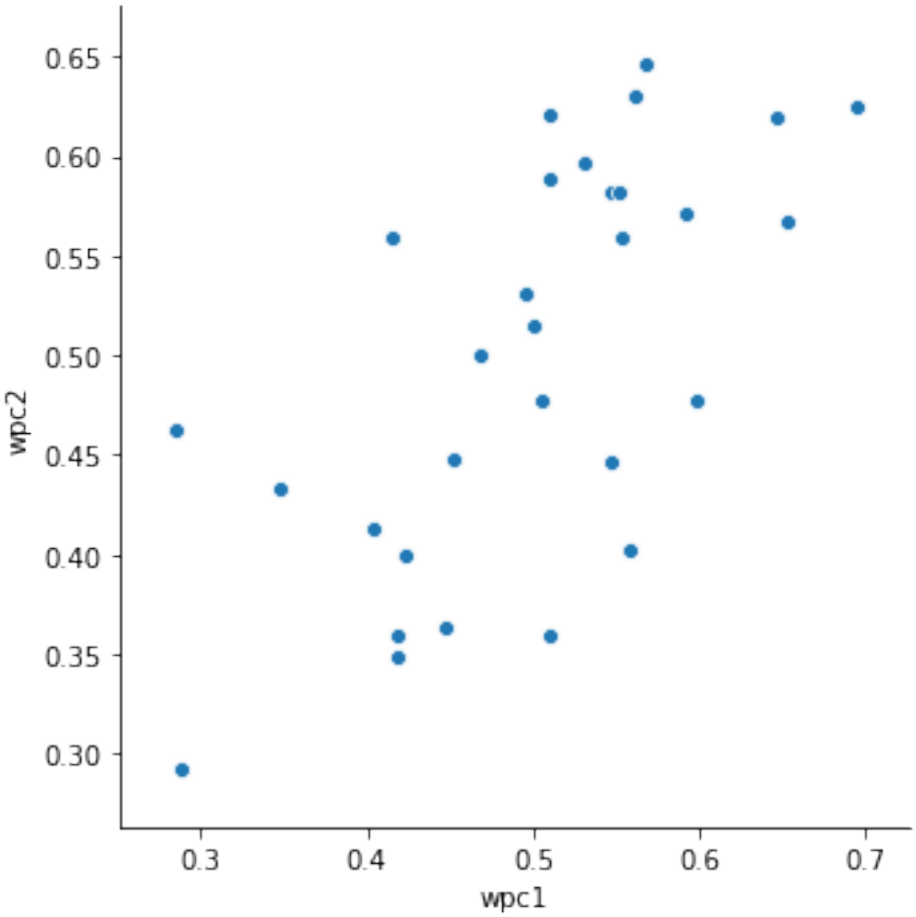
Out[15]:
```
<seaborn.axisgrid.FacetGrid at 0x21194672b08>
```




In [16]:
```
# Now, compare this with a plot of win percentage from the first half of the season a
#in the second half of the season


sns.relplot(x="wpc1", y="wpc2", data = Half2predictor)
```

Out[16]:
```
<seaborn.axisgrid.FacetGrid at 0x21195439188>
```




In [17]:
```
# The two plots look similar
# We can be more precise still if we compare the correlation coefficients. The first
# correlation of win percentage in second half of the season against itself, win perc
# Pythagorean Expectation in the first half of the season, and Pythagorean Expectatio
# Our focus is on comparing the second and third columns.

keyvars = Half2predictor[['team','wpc2','wpc1','pyth1','pyth2']]
keyvars.corr()
```

Out[17]:

| | wpc2 | wpc1 | pyth1 | pyth2 |
|---|---|---|---|---|
| wpc2 | 1.000000 | 0.652549 | 0.690752 | 0.924473 |
| wpc1 | 0.652549 | 1.000000 | 0.941082 | 0.577847 |
| pyth1 | 0.690752 | 0.941082 | 1.000000 | 0.659521 |
| pyth2 | 0.924473 | 0.577847 | 0.659521 | 1.000000 |

In [18]:
```
# We can also sort the variables to show for each club how close the relationships ar
# of the season
```

```
keyvars = keyvars.sort_values(by=['wpc2'],ascending=False)
keyvars
```

Out[18]:

| | team | wpc2 | wpc1 | pyth1 | pyth2 |
|---|---|---|---|---|---|
| 19 | OAK | 0.646154 | 0.567010 | 0.527439 | 0.681224 |
| 15 | MIL | 0.630769 | 0.561224 | 0.560795 | 0.574983 |
| 4 | BOS | 0.625000 | 0.693878 | 0.675908 | 0.604272 |
| 26 | TBA | 0.621212 | 0.510417 | 0.525559 | 0.585571 |
| 11 | HOU | 0.619048 | 0.646465 | 0.719748 | 0.641553 |
| 9 | COL | 0.597015 | 0.531250 | 0.498930 | 0.560791 |
| 25 | SLN | 0.588235 | 0.510638 | 0.513494 | 0.589046 |
| 8 | CLE | 0.582090 | 0.547368 | 0.591158 | 0.649789 |
| 13 | LAN | 0.582090 | 0.552083 | 0.598539 | 0.683228 |
| 6 | CHN | 0.571429 | 0.591398 | 0.633566 | 0.503521 |
| 17 | NYA | 0.567164 | 0.652632 | 0.649702 | 0.576243 |
| 2 | ATL | 0.558824 | 0.553191 | 0.580049 | 0.559231 |
| 18 | NYN | 0.558824 | 0.414894 | 0.414981 | 0.562571 |
| 21 | PIT | 0.531250 | 0.494845 | 0.471452 | 0.546955 |
| 29 | WAS | 0.515152 | 0.500000 | 0.537262 | 0.590164 |
| 16 | MIN | 0.500000 | 0.468085 | 0.473612 | 0.478204 |
| 23 | SEA | 0.476923 | 0.597938 | 0.497579 | 0.443245 |
| 0 | ANA | 0.476923 | 0.505155 | 0.529031 | 0.459548 |
| 12 | KCA | 0.462687 | 0.284211 | 0.287903 | 0.496689 |
| 28 | TOR | 0.447761 | 0.452632 | 0.450682 | 0.380409 |
| 1 | ARI | 0.446154 | 0.546392 | 0.553662 | 0.511151 |
| 5 | CHA | 0.432836 | 0.347368 | 0.361805 | 0.393055 |
| 22 | SDN | 0.412698 | 0.404040 | 0.381242 | 0.410477 |
| 20 | PHI | 0.402985 | 0.557895 | 0.522377 | 0.386685 |
| 27 | TEX | 0.400000 | 0.422680 | 0.431174 | 0.429143 |
| 7 | CIN | 0.363636 | 0.447917 | 0.466495 | 0.341948 |
| 10 | DET | 0.359375 | 0.418367 | 0.417435 | 0.339942 |
| 24 | SFN | 0.359375 | 0.510204 | 0.468478 | 0.356631 |
| 14 | MIA | 0.349206 | 0.418367 | 0.369652 | 0.309701 |
| 3 | BAL | 0.292308 | 0.288660 | 0.319067 | 0.337607 |

## 2 Conclusion

We can see from the correlation matrix that win percentage in the second half of the season is correlated with win percentage in the first half of the season - the correlation coefficient is +0.653. It's not surprising that performance in the first half of the season is to an extent predictive of performance in the second half. But there are also clearly things that can change.

When we sort the teams from highest to lowest send half of season win percentage, we find a mixed picture. Some clubs perform with less than one percentage point difference in each half, e.g. The Brave (ATL), the Padres (SDN) or the Orioles (BAL), while others differed by more than ten percentage points, e.g. the Rays (TBA), the Mets (NYN) or the Mariners (SEA).

We could simply use first half win percentage as a predictor of second half win percentage, but when we look at the correlation matrix we can see that the Pythagorean Expectation is an even

better forecast - the correlation coefficient is higher, at +0.691. To be sure, the difference is not large, but it is slightly better. This was, in fact, the initial impetus for Bill James when introducing the statistic. He argued that a win could ride on lucky hit and the difference of just one run, which made wins a less reliable predictor than the aggregate capacity to produce runs and limit conceding runs. As in many aspects of baseball analysis, our data show that James was quite right.

In [ ]: