Performance Analysis: OGS Go 9x9

In [1]:
```
import numpy as np
import pandas as pd
import requests
import json
import time
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Data Acquisition

In [2]:
```
my_id = "*******"
url = f"https://online-go.com/api/v1/players/{my_id}/games/"
games = []

while url:
    response = requests.get(url)
    data = response.json()

    games.extend(data['results'])
    url = data.get('next')

    time.sleep(0.3)

raw_df = pd.DataFrame(games)
raw_df.to_csv("my_ogs_games.csv", index=False)
```

In [3]:
```
raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 157 entries, 0 to 156
Data columns (total 43 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   related                   157 non-null    object
 1   players                   157 non-null    object
 2   id                        157 non-null    int64
 3   name                      157 non-null    object
 4   creator                   157 non-null    int64
 5   mode                      157 non-null    object
 6   source                    157 non-null    object
 7   black                     157 non-null    int64
 8   white                     157 non-null    int64
 9   width                     157 non-null    int64
 10  height                    157 non-null    int64
 11  rules                     157 non-null    object
 12  ranked                    157 non-null    bool
 13  handicap_rank_difference  157 non-null    object
 14  handicap                  157 non-null    int64
 15  komi                      157 non-null    object
 16  time_control              157 non-null    object
 17  black_player_rank         157 non-null    int64
 18  black_player_rating       157 non-null    object
 19  white_player_rank         157 non-null    int64
 20  white_player_rating       157 non-null    object
 21  time_per_move             157 non-null    int64
 22  time_control_parameters   157 non-null    object
 23  disable_analysis          157 non-null    bool
 24  tournament                0 non-null      object
 25  tournament_round          157 non-null    int64
 26  ladder                    0 non-null      object
 27  pause_on_weekends         157 non-null    bool
 28  outcome                   157 non-null    object
 29  black_lost                157 non-null    bool
 30  white_lost                157 non-null    bool
 31  annulled                  157 non-null    bool
 32  started                   157 non-null    object
 33  ended                     157 non-null    object
 34  sgf_filename              0 non-null      object
 35  historical_ratings        157 non-null    object
 36  rengo                     157 non-null    bool
 37  rengo_black_team          0 non-null      object
 38  rengo_white_team          0 non-null      object
 39  rengo_casual_mode         157 non-null    bool
 40  flags                     0 non-null      object
 41  bot_detection_results     0 non-null      object
 42  bot_parameters            0 non-null      object
dtypes: bool(8), int64(11), object(24)
memory usage: 44.3+ KB
```

In [4]:
```
raw_df['id'].nunique() # Expected 150 games
```

Out[4]: 157

In [5]:
```
raw_df['outcome'].value_counts()
```

Out[5]:
```
outcome
Resignation     48
3.5 points      11
8.5 points      10
1.5 points       9
Timeout          7
0.5 points       7
Cancellation     6
5.5 points       6
2.5 points       5
4.5 points       5
7.5 points       5
11.5 points      5
16.5 points      4
13.5 points      3
6.5 points       2
9.5 points       2
19.5 points      2
20.5 points      2
14.5 points      2
87.5 points      2
23.5 points      2
30.5 points      1
21.5 points      1
24.5 points      1
39.5 points      1
54.5 points      1
10.5 points      1
31.5 points      1
28.5 points      1
47.5 points      1
18.5 points      1
33.5 points      1
26.5 points      1
Name: count, dtype: int64
```

2. Data Cleaning & Filtering

In [6]:
```
# Filtering out cancelled and annulled games
df = raw_df[(raw_df['outcome'] != "Cancellation") & (raw_df['annulled'] != True)
```

In [7]:
```
df['id'].nunique()
```

Out[7]:
```
150
```

3. Feature Engineering

In [8]:
```
df['is_win'] = ((df['black'] == int(my_id)) & (df['black_lost'] == False)) | ((d

df['is_win'] = df['is_win'].astype(int)
```

In [9]:
```
df['time_control_parameters'].value_counts()
```

Out[9]:
```
time_control_parameters
{"system": "fischer", "speed": "rapid", "pause_on_weekends": false, "initial_ti
me": 120, "time_increment": 7, "max_time": 1200, "time_control": "fischer"}
75
{"system": "byoyomi", "speed": "rapid", "pause_on_weekends": false, "main_tim
e": 120, "periods": 5, "period_time": 30, "time_control": "byoyomi"}
61
{"system": "fischer", "speed": "blitz", "pause_on_weekends": false, "initial_ti
me": 30, "time_increment": 5, "max_time": 300, "time_control": "fischer"}
7
{"system": "byoyomi", "speed": "blitz", "pause_on_weekends": false, "main_tim
e": 30, "periods": 5, "period_time": 10, "time_control": "byoyomi"}
7
Name: count, dtype: int64
```

In [10]:
```
params_list = [json.loads(x) for x in df['time_control_parameters']]

temp_df = pd.DataFrame(params_list, index=df.index)

df['game_mode'] = temp_df['system'] + " " + temp_df['speed']
```

In [11]:
```
df['game_mode'].value_counts()
```

Out[11]:
```
game_mode
fischer rapid    75
byoyomi rapid    61
fischer blitz     7
byoyomi blitz     7
Name: count, dtype: int64
```

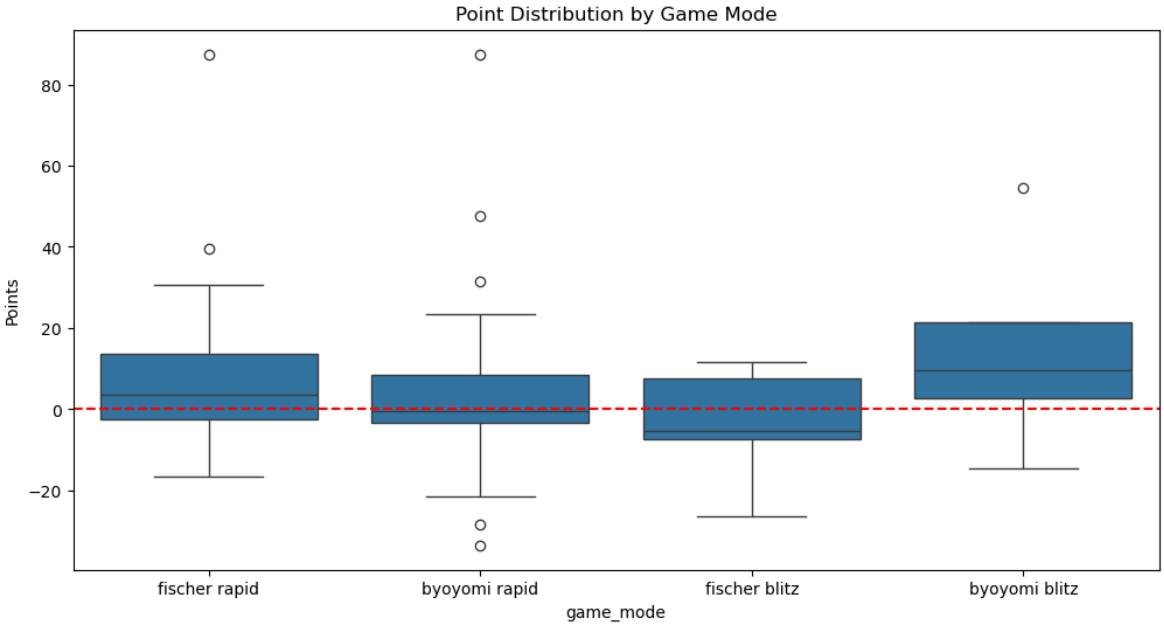
In [12]:
```
first_word = df['outcome'].str.split().str[0]

df['points'] = pd.to_numeric(first_word, errors='coerce')
```

In [13]:
```
df['outcome_type'] = 'Points'
df.loc[df['outcome'] == 'Resignation', 'outcome_type'] = 'Resign'
df.loc[df['outcome'] == 'Timeout', 'outcome_type'] = 'Timeout'
```

In [14]:
```
df['signed_points'] = np.where(df['is_win'], df['points'], -df['points'])
```

4. Exploratory Data Analysis: Game Modes

In [15]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(data=df[df['outcome_type'] == 'Points'], x='game_mode', y='signed_po
plt.axhline(0, color='red', linestyle='--')
plt.title('Point Distribution by Game Mode')
plt.ylabel('Points')
plt.show()
```



In [16]:
```
print("Type of Outcome Distribution by Game Mode (%):")
(pd.crosstab(df['game_mode'], df['outcome_type'], normalize='index') * 100).roun
```

```
Type of Outcome Distribution by Game Mode (%):
```

Out[16]:

game_mode	outcome_type	Points	Resign	Timeout
byoyomi blitz		57.1	28.6	14.3
byoyomi rapid		68.9	31.1	0.0
fischer blitz		71.4	0.0	28.6
fischer rapid		60.0	36.0	4.0

In [17]:
```
analysis_table = df.groupby('game_mode').agg(
    games_count=('id', 'count'),
    win_rate=('is_win', 'mean'),
    avg_score=('signed_points', 'mean'),
    median_score=('signed_points', 'median'),
    std_score=('signed_points', 'std'),
    min_score=('signed_points', 'min'),
    max_score=('signed_points', 'max')
).reset_index()

analysis_table['win_rate'] = (analysis_table['win_rate'] * 100).round(1)
analysis_table = analysis_table.round(2)

print("Metrics by Game Mode:")
analysis_table
```

```
Metrics by Game Mode:
```

Out[17]:

	game_mode	games_count	win_rate	avg_score	median_score	std_score	min_score
0	byoyomi blitz	7	85.7	14.75	9.5	28.83	-14.5
1	byoyomi rapid	61	55.7	3.38	-0.5	19.65	-33.5
2	fischer blitz	7	28.6	-4.10	-5.5	14.94	-26.5
3	fischer rapid	75	64.0	7.48	3.5	16.63	-16.5

The "Fischer" Boost: My win rate is 9% higher with an increment. Cumulative time provides a safety net that stabilizes my play

Pressure Factor: Under the "beep of Byoyomi", my blunder rate (Score < -30) doubles. I perform significantly better when I don't feel rushed by a sound timer

5. Time-of-Day Dynamics

In [18]:
```
df['started'] = pd.to_datetime(df['started'])

df['local_time'] = (df['started'].dt.hour + 5) % 24 # Converting UTC to local ti

bins = [0, 6, 12, 18, 23, 24]
labels = ['4. Night', '1. Morning', '2. Afternoon', '3. Evening', '4. Night']

df['day_period'] = pd.cut(df['local_time'], bins=bins, labels=labels, right=Fals

df.drop(columns=['local_time'], inplace=True)
```

In [19]:
```
time_analysis = df.groupby('day_period', observed=False).agg(
    games_count=('id', 'count'),
    win_rate=('is_win', 'mean'),
    avg_score=('signed_points', 'mean'),
    median_score=('signed_points', 'median'),
    std_score=('signed_points', 'std'),
    min_score=('signed_points', 'min'),
    max_score=('signed_points', 'max')
).reset_index()

time_analysis['win_rate'] = (time_analysis['win_rate'] * 100).round(1)

print("Metrics by Day Period:")
time_analysis
```

```
Metrics by Day Period:
```

Out[19]:

	day_period	games_count	win_rate	avg_score	median_score	std_score	min_score
0	1. Morning	39	71.8	15.023810	7.5	27.253659	-5.5
1	2. Afternoon	107	56.1	2.666667	1.5	14.501093	-33.5
2	3. Evening	3	33.3	-3.500000	-3.5	1.414214	-4.5
3	4. Night	1	100.0	16.500000	16.5	NaN	16.5

In [20]:
```
print("Game Mode Preference by Time of Day:")
pd.crosstab(df['day_period'], df['game_mode'])
```

```
Game Mode Preference by Time of Day:
```

Out[20]:

game_mode	byoyomi blitz	byoyomi rapid	fischer blitz	fischer rapid
day_period				
1. Morning	3	17	1	18
2. Afternoon	4	43	6	54
3. Evening	0	1	0	2
4. Night	0	0	0	1

Morning Aggression: My early sessions (5:00–12:00) are my most successful. I play a high-variance, bold style that leads to dominant wins

Afternoon Slump: During the day, my play becomes too "cautious." This lack of initiative leads to lower win rates despite smaller margins of loss

6. Competitive Analysis: Rating & Difficulty

In [21]:
```
df['black_rating'] = [x['black']['ratings']['overall']['rating'] for x in df['hi
df['white_rating'] = [x['white']['ratings']['overall']['rating'] for x in df['hi

# Calculating rating difference from my perspective
df['rating_delta'] = np.where(
    df['black'] == int(my_id),
    df['black_rating'] - df['white_rating'],
    df['white_rating'] - df['black_rating']
)

df.drop(columns=['black_rating', 'white_rating'], inplace=True)
```

In [22]:
```
bins = [-float('inf'), -50, -15, 15, 50, float('inf')]
labels = ['Much Stronger', 'Slightly Stronger', 'Equal', 'Slightly Weaker', 'Muc

df['difficulty'] = pd.cut(df['rating_delta'], bins=bins, labels=labels, right=Fa

df['is_resign'] = (df['outcome_type'] == 'Resign').astype(int)

quality_analysis = df.groupby('difficulty', observed=False).agg(
```

```
    games_count=('id', 'count'),
    win_rate=('is_win', 'mean'),
    avg_margin=('signed_points', 'mean'),
    std_margin=('signed_points', 'std'),
    resign_rate=('is_resign', 'mean')
).reset_index()

quality_analysis['win_rate'] = (quality_analysis['win_rate'] * 100).round(1)
quality_analysis['resign_rate'] = (quality_analysis['resign_rate'] * 100).round(

print("Metrics based on Opponent Difficulty:")
quality_analysis
```

```
Metrics based on Opponent Difficulty:
```

Out[22]:

	difficulty	games_count	win_rate	avg_margin	std_margin	resign_rate
0	Much Stronger	18	66.7	14.071429	32.903177	61.1
1	Slightly Stronger	24	45.8	-1.312500	11.184625	25.0
2	Equal	28	50.0	3.738095	14.070909	21.4
3	Slightly Weaker	24	58.3	0.954545	12.209534	45.8
4	Much Weaker	56	69.6	8.548780	20.493842	25.0

My progress stalls against the 'Minor Underdog' segment. Even though I keep games close, my win rate drops below 50%

Yose Deficit: An average margin of only -1.3 points identifies a clear technical gap: I am losing games in the endgame (Yose). I need to focus on final point-counting to break this ceiling

7. Strategic Analysis: Color & Komi Effect

In [23]:
```
# Note: The abnormally high win rate against "Much Stronger" opponents
# is due to the "Cold Start" period. At the beginning,
# the system matched me with high-rated players to calibrate my true rating fast

df['is_black'] = (df['black'] == int(my_id)).astype(int)
df['color'] = df['is_black'].map({1: 'Black', 0: 'White'})

komi_analysis = df.groupby(['color', 'difficulty'], observed=False).agg(
    games_count=('id', 'count'),
    win_rate=('is_win', 'mean'),
    avg_margin=('signed_points', 'mean'),
    std_margin=('signed_points', 'std')
).reset_index()

komi_analysis['win_rate'] = (komi_analysis['win_rate'] * 100).round(1)
```

In [24]:
```
komi_pivot = komi_analysis.pivot(index='color', columns='difficulty', values='wi
print("Win Rate (%) by Stone Color and Opponent Difficulty:")
komi_pivot
```

```
Win Rate (%) by Stone Color and Opponent Difficulty:
```

Out[24]:

difficulty	Much Stronger	Slightly Stronger	Equal	Slightly Weaker	Much Weaker
color					
Black	64.7	46.7	46.7	77.8	100.0
White	100.0	44.4	53.8	46.7	69.1

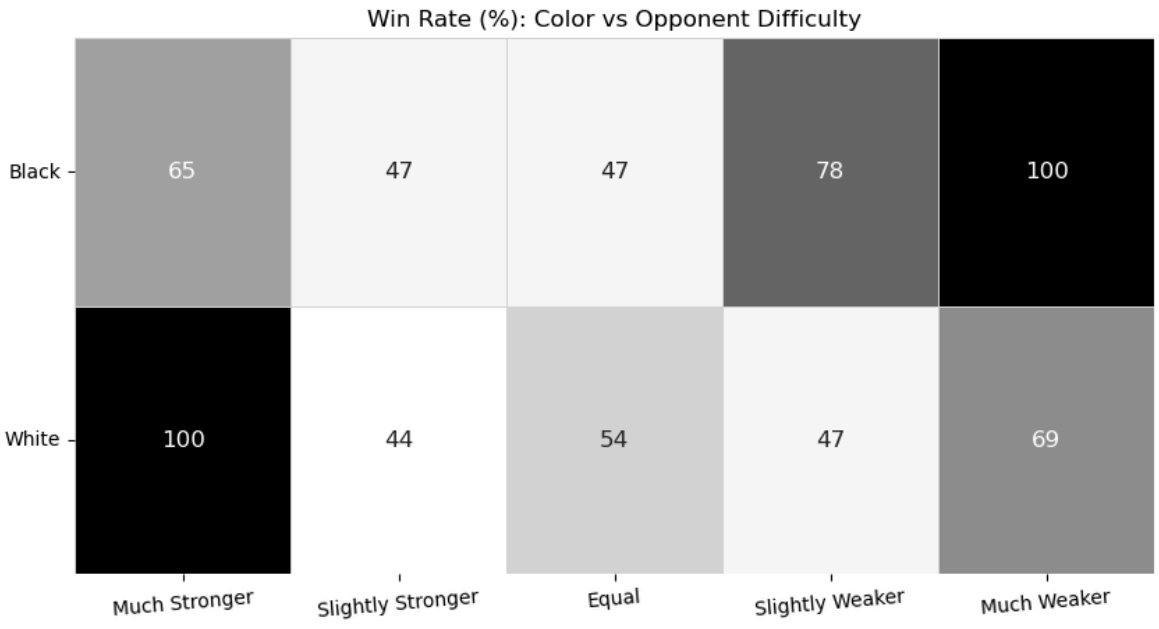
In [25]:
```
margin_pivot = komi_analysis.pivot(index='color', columns='difficulty', values='
print("Point Differential by Stone Color and Opponent Difficulty:")
margin_pivot.round(2)
```

```
Point Differential by Stone Color and Opponent Difficulty:
```

Out[25]:

difficulty	Much Stronger	Slightly Stronger	Equal	Slightly Weaker	Much Weaker
color					
Black	1.83	-2.59	1.96	2.50	NaN
White	87.50	1.50	6.62	0.38	8.55

In [26]:
```
plt.figure(figsize=(10, 5))
sns.heatmap(komi_pivot,cbar=False, cmap='binary', annot=True, fmt=".0f", linewid
plt.ylabel('')
plt.xlabel('')
plt.xticks(rotation=5)
plt.yticks(rotation=0)
plt.title('Win Rate (%): Color vs Opponent Difficulty')
plt.show()
```



Defensive Stability: I am highly efficient at punishing mistakes (as White) but struggle to dictate the game pace as Black

The Goal: My next evolution is to learn how to force opponent errors without the psychological "insurance" of Komi

In [ ]: