DSO 585 PROJECT PRESENTATION

TWITCH GAME

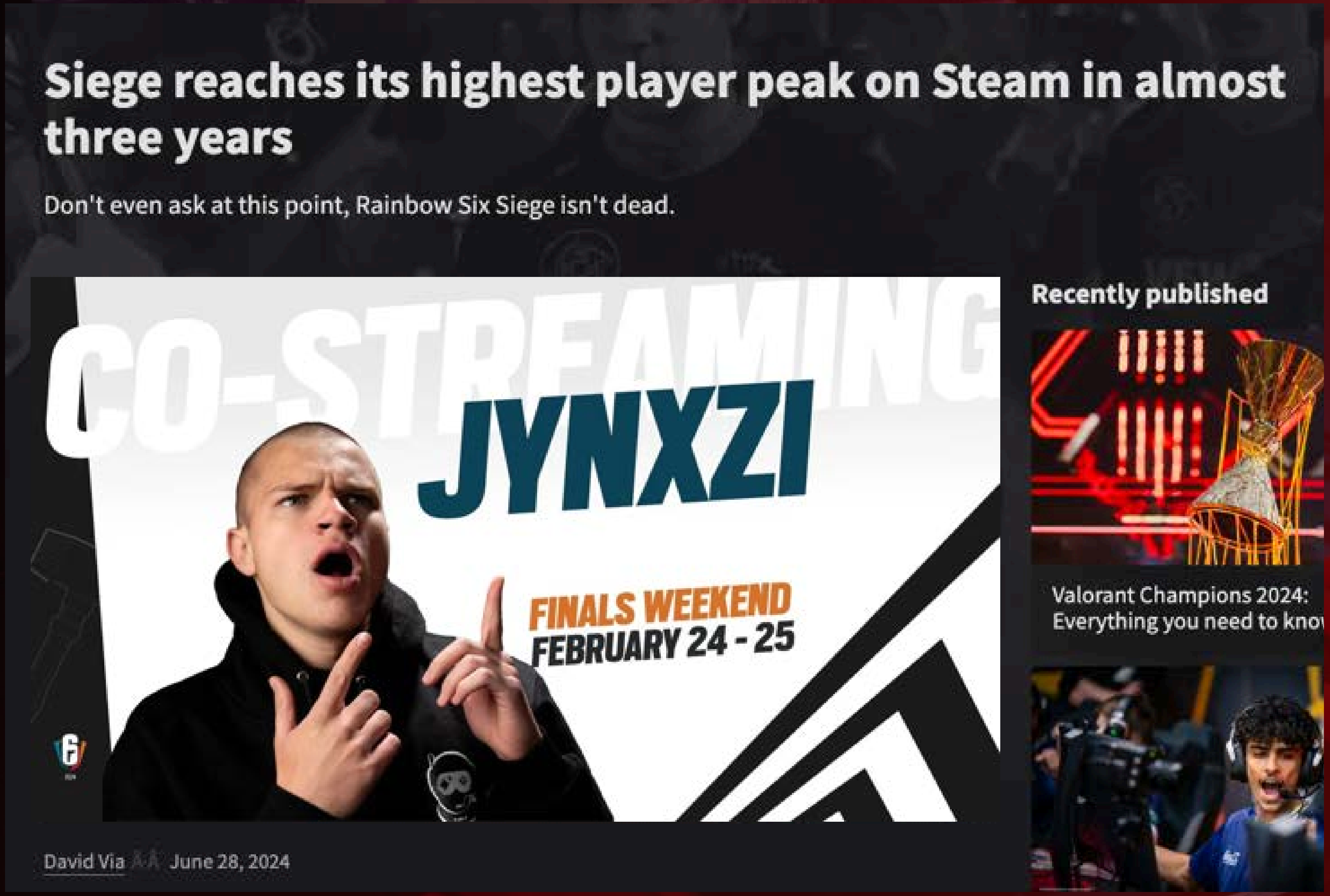
How does a game's Twitch Viewership influence its number of Active Players?

Inspiration

Start

Team2： Ethan Liu, Jeco Cheung, Sherry Shi

GAME NEWS



Read More

PROJECT INSPIRATION & HYPOTHESIS

Six Invitational 2024:

- Co-streamed by Twitch's most subbed channel Jynxzi.
- 521,349 peak viewers (the most-watched Six Invitational in the game's history).
- > 60,000 average players in June for the first time since April 2021.
- Hypothesis:

Viewership CAUSE ? Players

POTENTIAL BUSINESS OPPORTUNITIES

THOUGHT PROCESS

WHY DOES IT MATTER?

- A fast growing trend in the live-streaming industry led by Twitch and Youtube. (Stats)
- How does it impact the gamer's community and the industry in general?
- Potential business opportunities:
  - Could collaborating with streamers be a new channel to promote a game? More collaborations with Twitch?
- Project Direction:
  a. Start with Rainbow Six Siege data
  b. Use other games' data as a reference / to validate the idea

DATA SOURCE

GATHERING THE DATA

APIs:

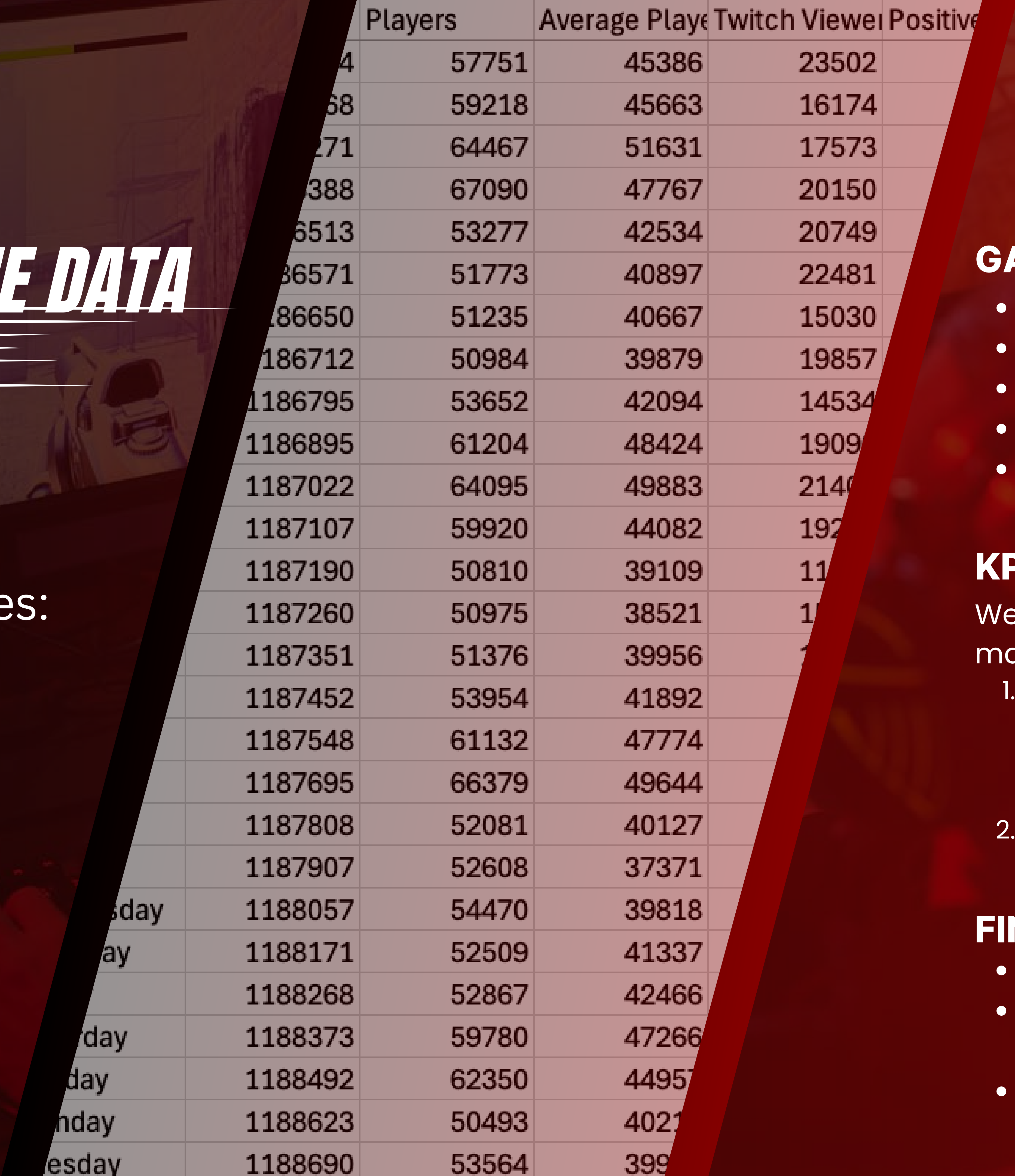
(1) Twitch API

(2) Steam API

Third-party Websites:

(1) SteamDB

(2) Sullygnome



GAMES WE FOCUSED ON

- Online Multiplayer Shooting Game
- Data Sufficiency (>5years)
- Available on Steam
- Final selections:
- (1) Rainbow Six Siege (2) Counter-Strike 2 (3) Rust

KPI

We chose Daily "Peak Player" as the main KPI for different reasons:

1. Similar to Daily Active Users (DAU), a KPI commonly used in the gaming industry but not usually disclosed to the public.
2. No missing values (comparing to Average Player)

FINAL DATATSETS

- 1 dataset for each game
- 5+ years of time series data (daily)
- 33+ columns

MODELING

APPROACHES WE TOOK

1. Linear Regression
2. Granger Causality Test
3. Causal Discovery Using Model Invariance (CDMI)
4. Latent Peter and Clark Momentary Conditional Independence(LPCMCI)

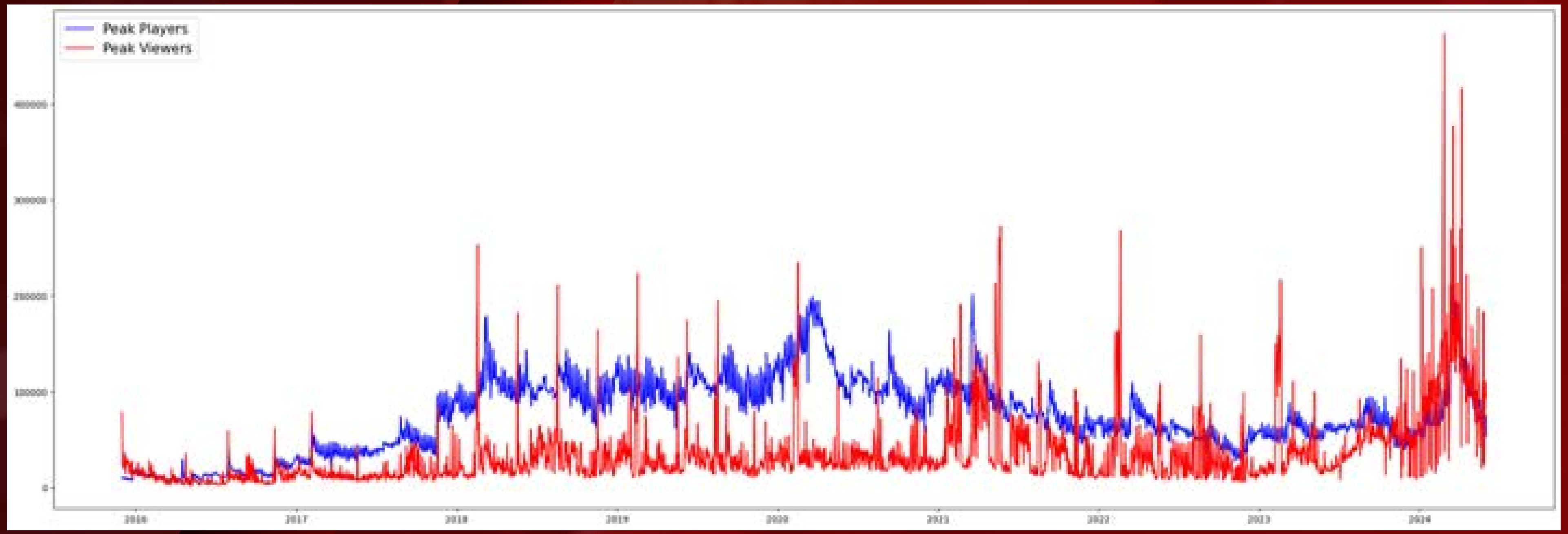
Simpliest

Most Complex

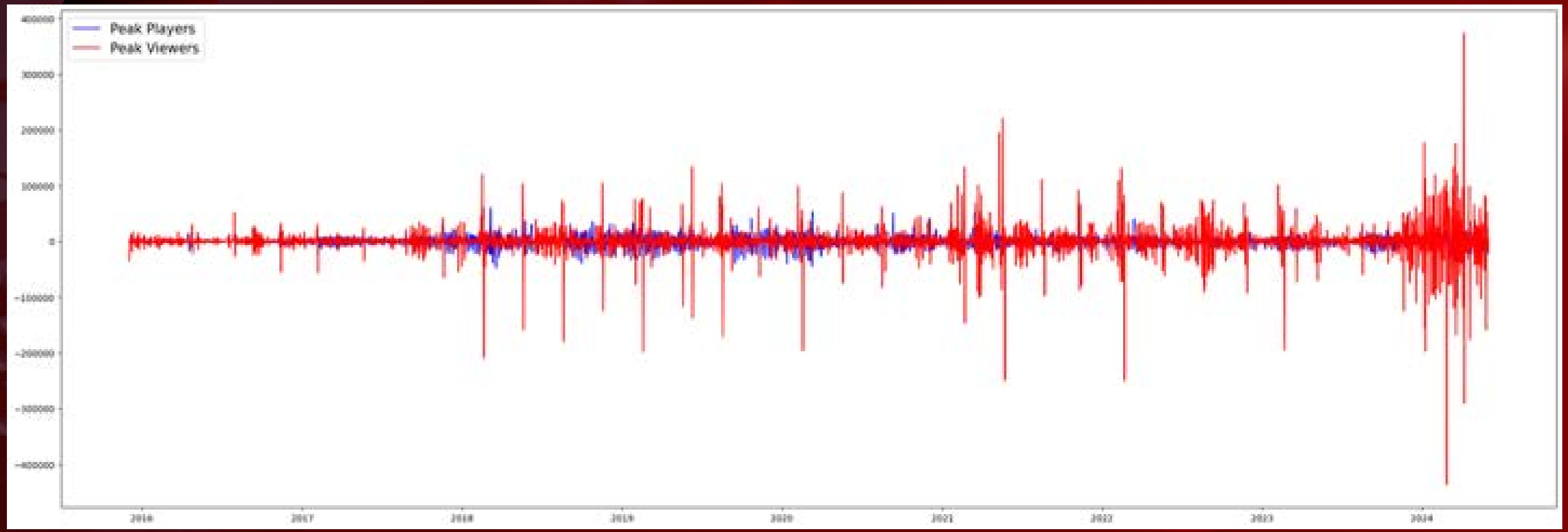
MODELING

DATA PREPROCESSING

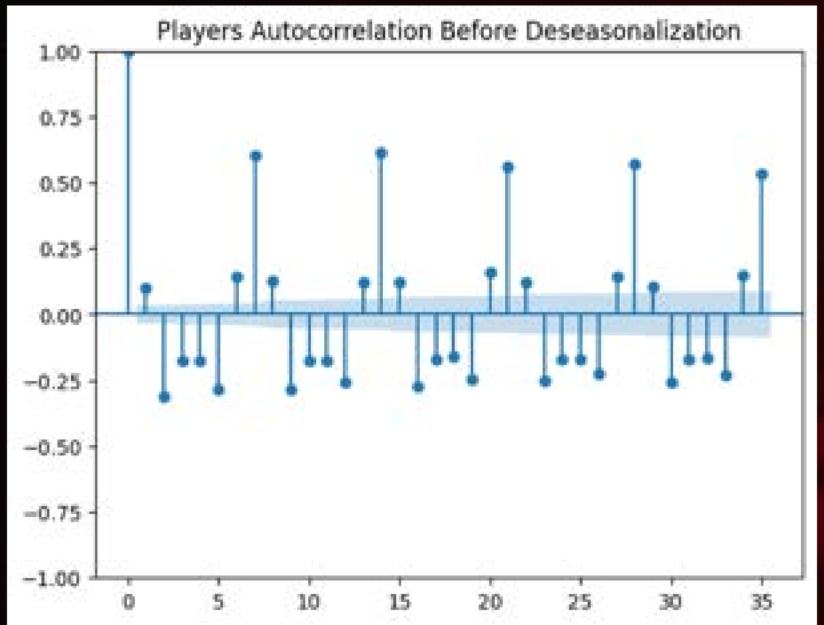
- Achieve stationarity for time series analysis
  a. First Difference
  b. Deseasonalization
- Lag data for modeling input

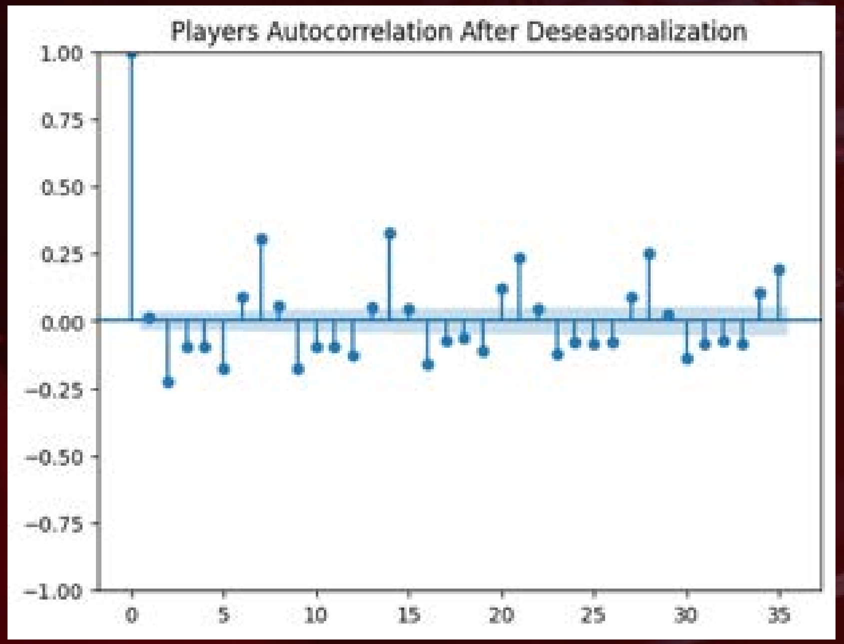


“Players” and “Peak viewers” Before First Difference



“Players” and “Peak viewers” After First Difference





MODELING

LINEAR REGRESSION

- Linear approximation of the relationship between time series
- Helps us understand how viewership is quantitatively associated with players

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     deseasonalized_players   R-squared:                       0.018
Model:                                OLS   Adj. R-squared:                  0.012
Method:                     Least Squares   F-statistic:                     3.222
Date:                    Mon, 08 Jul 2024   Prob (F-statistic):           8.47e-06
Time:                            19:41:29   Log-Likelihood:                -31655.
No. Observations:                    3091   AIC:                         6.335e+04
Df Residuals:                        3073   BIC:                         6.345e+04
Df Model:                              17
Covariance Type:                nonrobust
================================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                      -100.7951    117.396     -0.859      0.391    -330.978     129.388
Peak viewers                  0.0083      0.005      1.819      0.069      -0.001       0.017
Rating                       49.6415   1643.005      0.030      0.976   -3171.857    3271.140
Final price                 -13.0917     38.622     -0.339      0.735     -88.818      62.635
Monday                      -49.1228    308.377     -0.159      0.873    -653.769     555.524
Tuesday                     154.4082    304.382      0.507      0.612    -442.405     751.222
Wednesday                   147.4945    301.713      0.489      0.625    -444.085     739.074
Thursday                    -37.8509    305.163     -0.124      0.901    -636.195     560.493
Friday                      -22.0609    304.271     -0.073      0.942    -618.656     574.534
Saturday                    -69.2453    302.710     -0.229      0.819    -662.780     524.290
Sunday                     -224.4179    306.175     -0.733      0.464    -824.746     375.910
Free Weekend / Free Week(bool) 2758.2477 720.578    3.828      0.000    1345.384    4171.112
Tournament (INTL)           997.6599    773.009      1.291      0.197    -518.007    2513.327
is_historical_low_shift_5    59.1233    379.969      0.156      0.876    -685.896     804.143
Peak viewers_shift_1          0.0097      0.005      2.143      0.032       0.001       0.019
Peak viewers_shift_6          0.0086      0.004      2.014      0.044       0.000       0.017
Peak viewers_shift_13         0.0104      0.004      2.407      0.016       0.002       0.019
Final price_shift_3        -100.8643     38.713     -2.605      0.009    -176.771     -24.958
Final price_shift_4        -104.1269     38.655     -2.694      0.007    -179.920     -28.334
==============================================================================
Omnibus:                     1220.617   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            26490.487
Skew:                           1.350   Prob(JB):                         0.00
Kurtosis:                      17.085   Cond. No.                     4.66e+18
==============================================================================
```

MODELING
GRANGER CASUALITY TEST

- Determine the predictability of one variable to another
- Tell the significant lags (in forecasting) between time series
- **NOT TRUE CAUSALITY**

Granger Causality Result	
number of lags 1	p = 0.045
number of lags 2	p = 0.0024
number of lags 3	p = 0.0001
number of lags 4	p = 0.0002

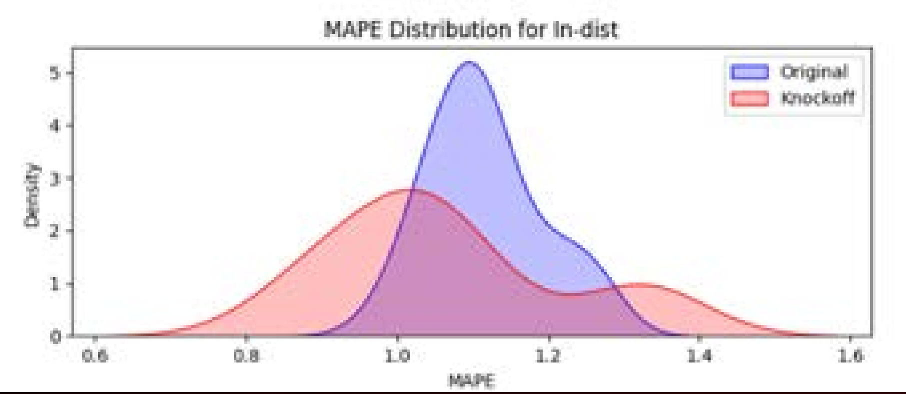
Null Hypothesis: “Peak viewers” does not granger-cause “ Players”
Alternative Hypothesis: “Peak viewers” granger-causes “Players”

MODELING

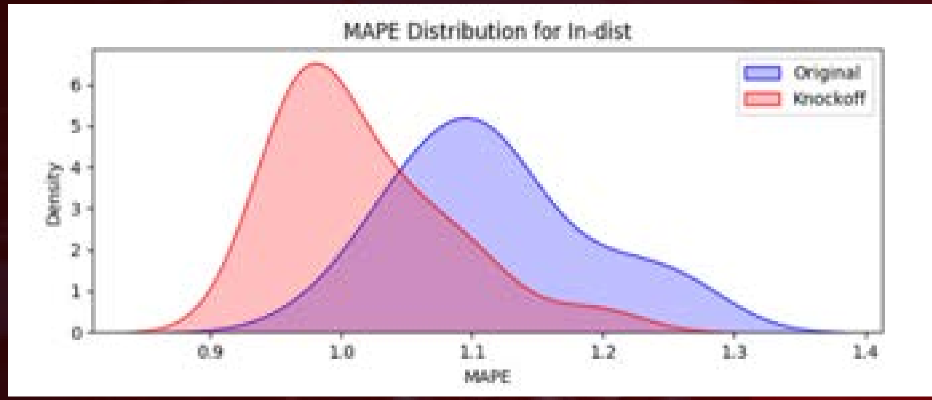
CAUSAL DISCOVERY USING MODEL INVARIANCE

- Tests for causality from observational time series
- Based on Model Invariance before and after intervention to identify causal relationships under certain assumptions

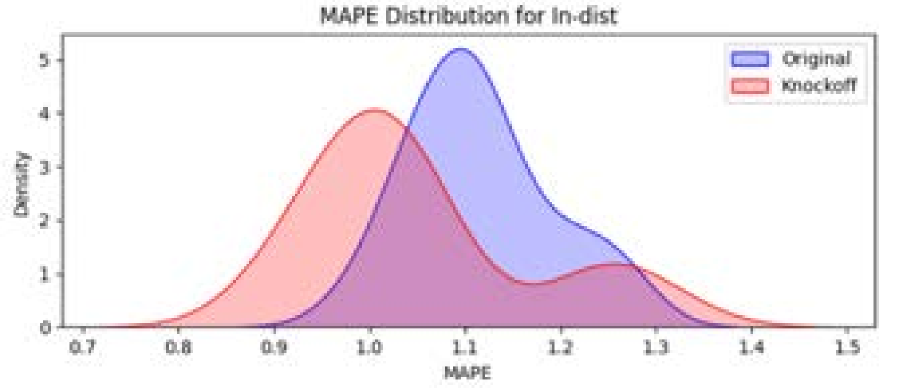
Causal Variables



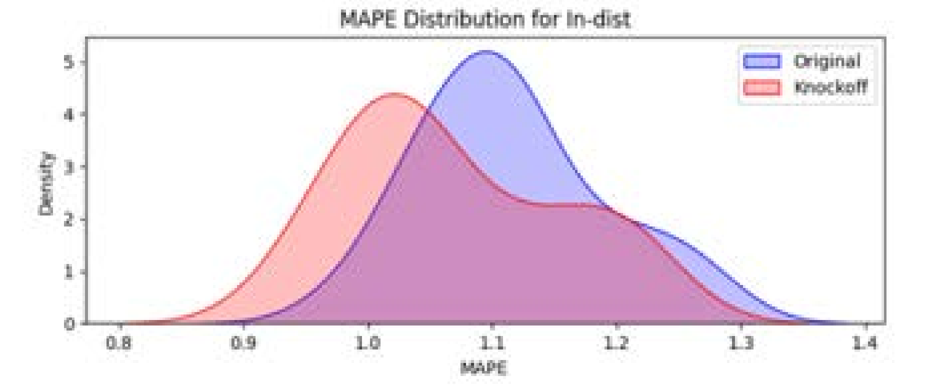
Peak viewers_shift_5



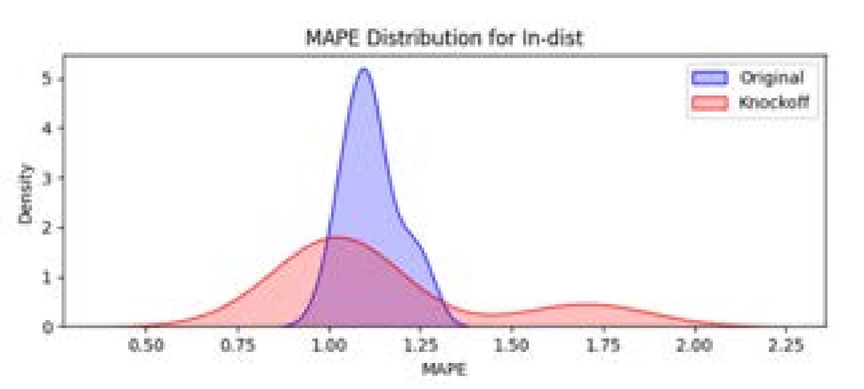
Peak viewers_shift_6



Peak viewers_shift_11



Peak viewers_shift_7



Peak viewers_shift_10

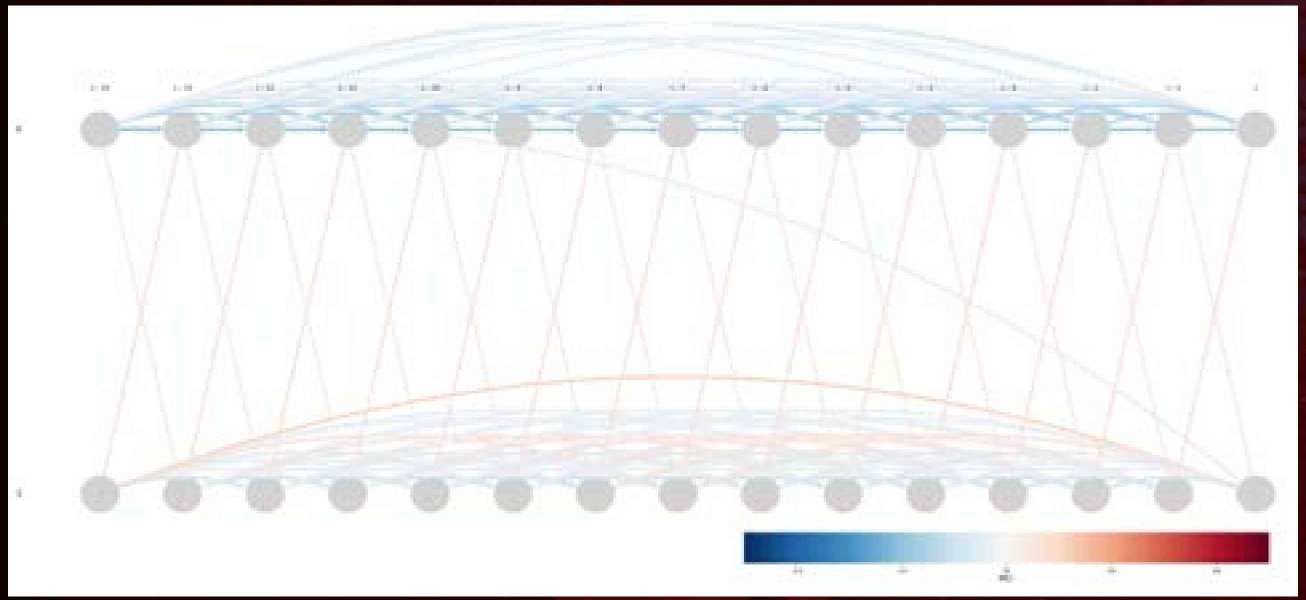
Results of the other two games

MODELING

LPCMCI

- Based on conditional independence tests
- 'Latent' for unobserved variables are believed to exist in the system
- Ability to conduct causal effect estimation

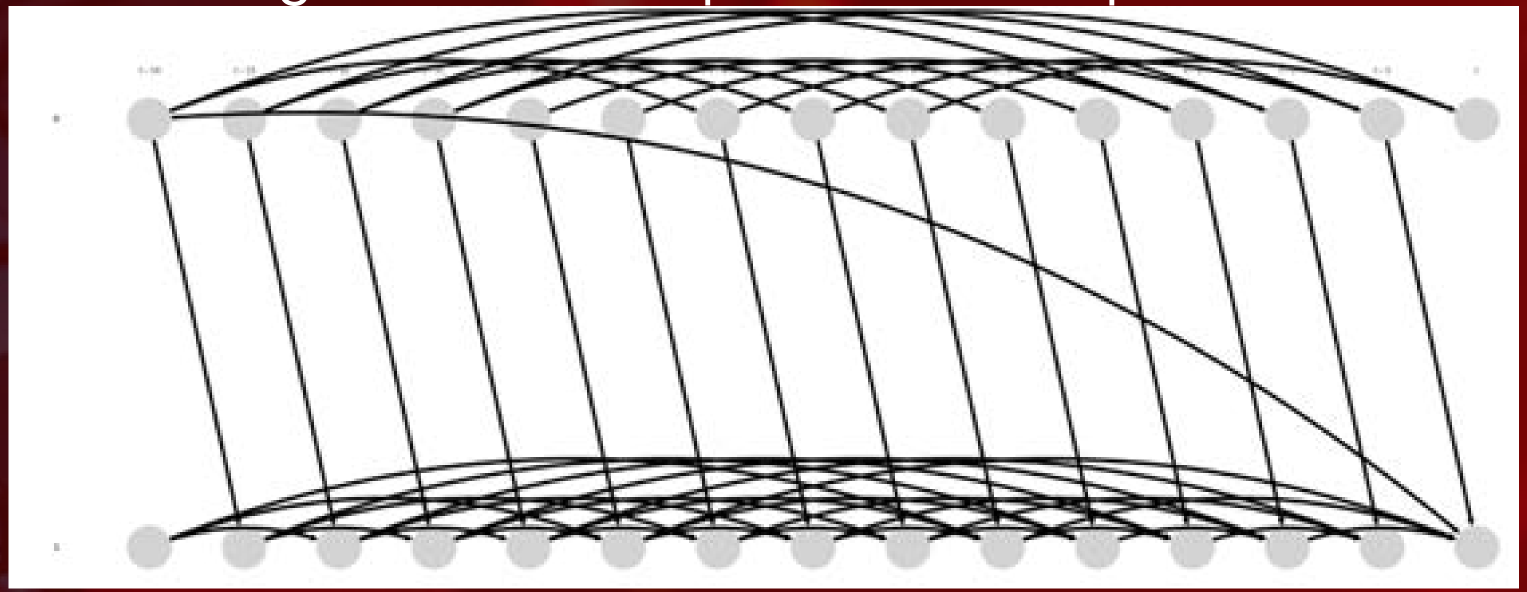
0 - Peak Viewer Diff   1 - Peak Player Diff



Variable 0 at time **t-1** -> Variable 1 at time t with p-value: 0.04696
Variable 0 at time **t-14** -> Variable 1 at time t with p-value: 0.00173

Causal Effect Estimation w/Simplified Casual Graph

Because our original causal graph is too complex and the algorithm could not solve for it, we simplified the DAG by pruning links with higher p-values, trying to represent the original relationships as much as possible



Estimated causal effect ≈ 0.00, which suggests a minimal effect.

However, we do find positive results for other two games (0.0235 and 0.0418, respectively)

[Results of the other two games]

MODELING
SUMMARY

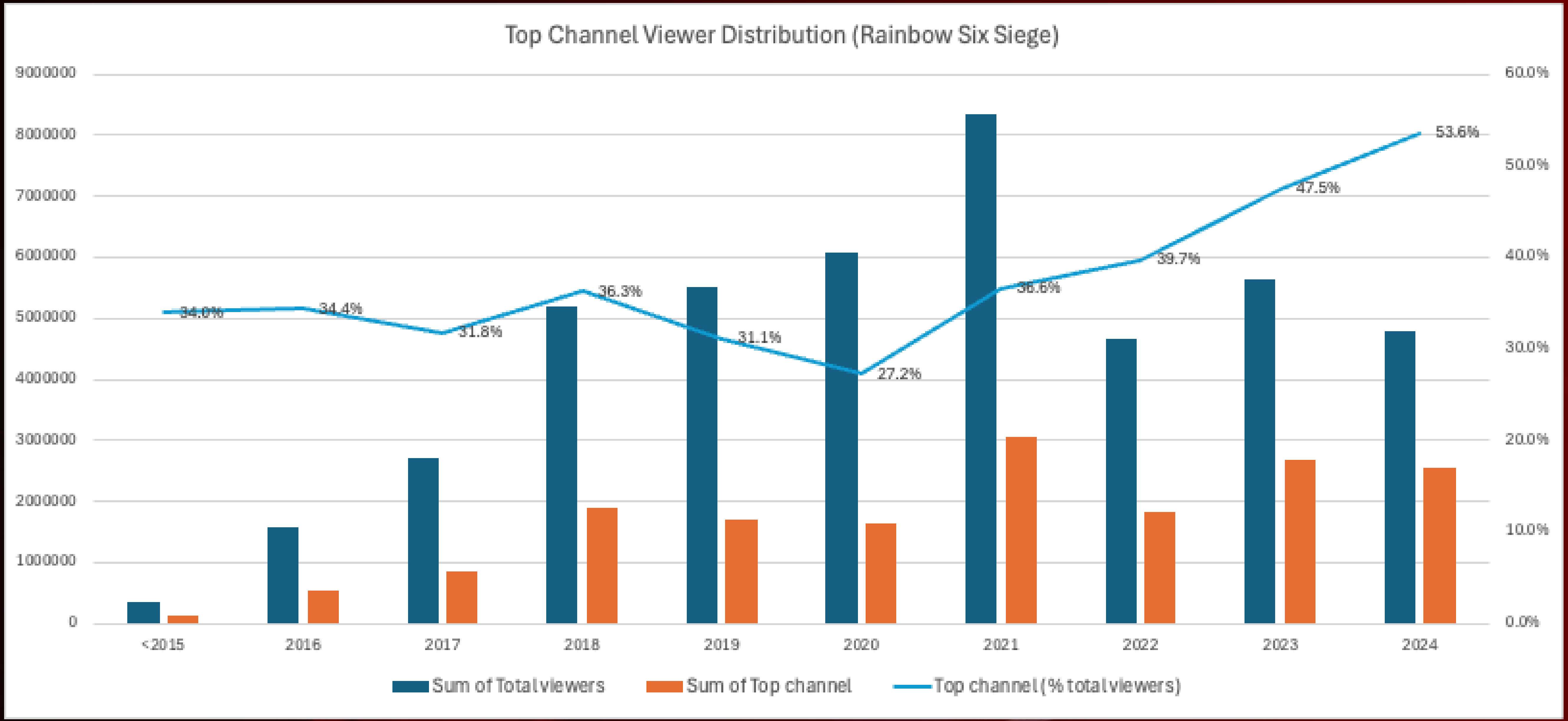
From the results of our models, we can have 4 main takeaways:

1. It is highly positive that a causal relationship exists between Twitch Viewership and Peak Player for the game Rainbow Six Siege.
2. The two variables have a lagged relationship: the impact from viewership to players usually take between 1-2 weeks to reflect.
3. It is likely a positive relationship where effect is between 0 - 0.04, depending on the game
4. However, the causal relationship and its causal effect varies between games in terms of lagged effect and effect size. CS2 shows a more immediate casual pattern (significant time lag being t-1, t-2) while Rainbow Six Siege gives a causal effect close to 0, which could be a result of various reasons (for example, over-pruning or Six Invitational 2024 being an anecdotal event).

BUSINESS QUESTIONS

1. Once we confirm the causal relationship, how could gaming companies increase viewership?
2. Follow-up analysis on the recent success in RS6 to get inspirations
    a. Do top streamers have more influence on a game than ever?
    b. Is holding tournaments a good way to promote a game?

Q1: DO TOP STREAMERS HAVE MORE INFLUENCE ON A GAME THAN EVER?



Results of the other two games

*note: data in 2015 & 2024 are insufficient

Q2: IS HOLDING TOURNAMENTS A GOOD WAY TO PROMOTE A GAME?

```
df_1[df_1['Tournament (INTL)'] == 1].describe()[['Players', 'Peak viewers']]
```

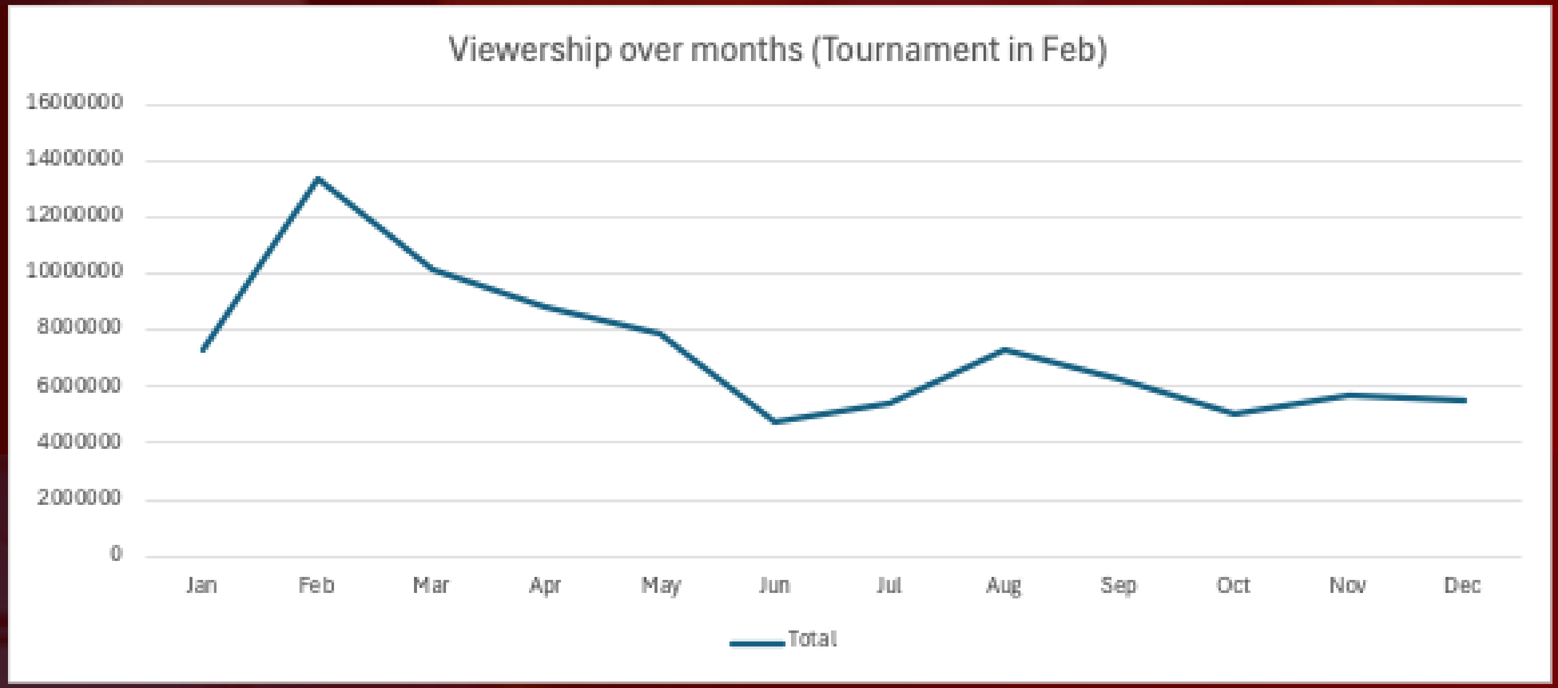
	Players	Peak viewers
count	83.000000	83.000000
mean	82264.253012	136521.012048
std	29418.982722	69968.870455
min	27697.000000	12456.000000
25%	60866.000000	95344.000000
50%	77464.000000	131222.000000
75%	97319.000000	163340.500000
max	160654.000000	376665.000000

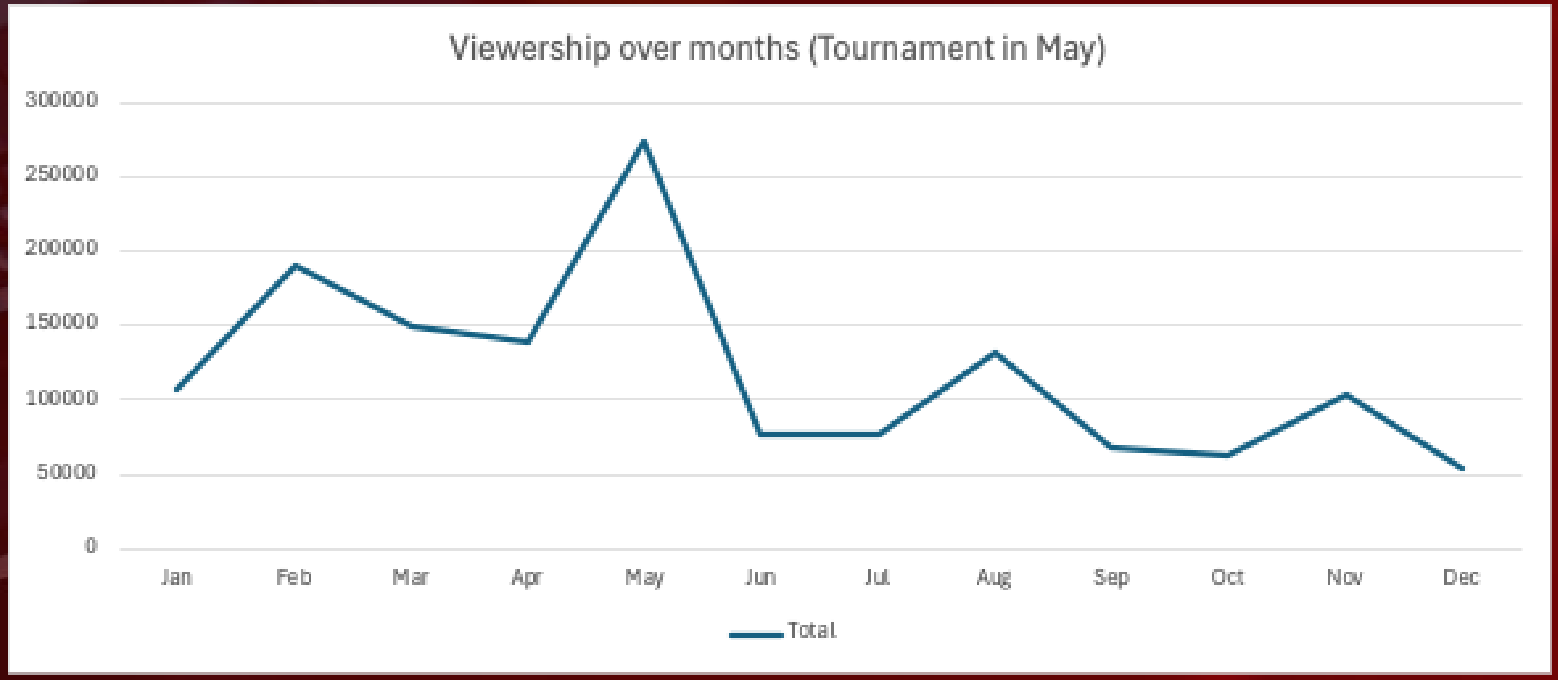
+9.78% in Players
+319% in Viewership

```
df_1[df_1['Tournament (INTL)'] == 0].describe()[['Players', 'Peak viewers']]
```

	Players	Peak viewers
count	3023.000000	3023.000000
mean	74931.974198	32620.073106
std	38801.926900	32792.009279
min	5949.000000	1699.000000
25%	47668.500000	14068.000000
50%	72877.000000	22800.000000
75%	102278.500000	39856.500000
max	201933.000000	473907.000000

Results of the other two games





Aboved graphs are based on Rainbow Six Siege Data

*note: data in 2015 & 2024 are insufficient

RECOMMENDATIONS(1)

1. Develop a game-unique marketing strategy

RECOMMENDATIONS(2)

Meanwhile,

2. Focus on game development
    a. The impact of most events is short-term. Having a good game (product) is essential.
    b. Companies should focus on:
        i. Improve user experience, such as develop new game mode, anti-cheat updates.
        ii. Be responsive to user's feedbacks.
3. Treat Twitch / Streaming (streamers' review/ chat) as a new channel to collect user feedbacks.

FUTURE DIRECTIONS

- ‘True’ Experiment for causal inference
- More (behavioral / demographic) data on viewer / player for deeper insights
- More complex and accurate models to quantify viewer/player relationship modeling
- In-depth game information (updates/ features)
- Further detailed study to understand between-game discrepancy of the viewership effect
    - Why Twitch has more causal influence in particular games?

THANK YOU

APPENDIX(1)

Granger Causality results for CS2 & RUST

CS2

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=5.3907  , p=0.0203  , df_denom=3175, df_num=1
ssr based chi2 test:   chi2=5.3958  , p=0.0202  , df=1
likelihood ratio test: chi2=5.3913  , p=0.0202  , df=1
parameter F test:         F=5.3907  , p=0.0203  , df_denom=3175, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=5.3351  , p=0.0049  , df_denom=3172, df_num=2
ssr based chi2 test:   chi2=10.6870 , p=0.0048  , df=2
likelihood ratio test: chi2=10.6690 , p=0.0048  , df=2
parameter F test:         F=5.3351  , p=0.0049  , df_denom=3172, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=5.9685  , p=0.0005  , df_denom=3169, df_num=3
ssr based chi2 test:   chi2=17.9450 , p=0.0005  , df=3
likelihood ratio test: chi2=17.8945 , p=0.0005  , df=3
parameter F test:         F=5.9685  , p=0.0005  , df_denom=3169, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=4.7178  , p=0.0009  , df_denom=3166, df_num=4
ssr based chi2 test:   chi2=18.9250 , p=0.0008  , df=4
likelihood ratio test: chi2=18.8688 , p=0.0008  , df=4
parameter F test:         F=4.7178  , p=0.0009  , df_denom=3166, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=3.9858  , p=0.0013  , df_denom=3163, df_num=5
ssr based chi2 test:   chi2=19.9983 , p=0.0013  , df=5
likelihood ratio test: chi2=19.9356 , p=0.0013  , df=5
parameter F test:         F=3.9858  , p=0.0013  , df_denom=3163, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=3.6203  , p=0.0014  , df_denom=3160, df_num=6
ssr based chi2 test:   chi2=21.8111 , p=0.0013  , df=6
likelihood ratio test: chi2=21.7365 , p=0.0014  , df=6
parameter F test:         F=3.6203  , p=0.0014  , df_denom=3160, df_num=6

Granger Causality
number of lags (no zero) 7
ssr based F test:         F=4.0739  , p=0.0002  , df_denom=3157, df_num=7
ssr based chi2 test:   chi2=28.6527 , p=0.0002  , df=7
likelihood ratio test: chi2=28.5241 , p=0.0002  , df=7
parameter F test:         F=4.0739  , p=0.0002  , df_denom=3157, df_num=7
```

"Peak viewers" granger causes "deseasonalized_players" from lag = 1

Rust

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.9723  , p=0.3242  , df_denom=3176, df_num=1
ssr based chi2 test:   chi2=0.9732  , p=0.3239  , df=1
likelihood ratio test: chi2=0.9730  , p=0.3239  , df=1
parameter F test:         F=0.9723  , p=0.3242  , df_denom=3176, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=5.2402  , p=0.0053  , df_denom=3173, df_num=2
ssr based chi2 test:   chi2=10.4970 , p=0.0053  , df=2
likelihood ratio test: chi2=10.4797 , p=0.0053  , df=2
parameter F test:         F=5.2402  , p=0.0053  , df_denom=3173, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=6.9560  , p=0.0001  , df_denom=3170, df_num=3
ssr based chi2 test:   chi2=20.9140 , p=0.0001  , df=3
likelihood ratio test: chi2=20.8455 , p=0.0001  , df=3
parameter F test:         F=6.9560  , p=0.0001  , df_denom=3170, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=4.4409  , p=0.0014  , df_denom=3167, df_num=4
ssr based chi2 test:   chi2=17.8141 , p=0.0013  , df=4
likelihood ratio test: chi2=17.7643 , p=0.0014  , df=4
parameter F test:         F=4.4409  , p=0.0014  , df_denom=3167, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=5.9951  , p=0.0000  , df_denom=3164, df_num=5
ssr based chi2 test:   chi2=30.0797 , p=0.0000  , df=5
likelihood ratio test: chi2=29.9381 , p=0.0000  , df=5
parameter F test:         F=5.9951  , p=0.0000  , df_denom=3164, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=8.8590  , p=0.0000  , df_denom=3161, df_num=6
ssr based chi2 test:   chi2=53.3728 , p=0.0000  , df=6
likelihood ratio test: chi2=52.9290 , p=0.0000  , df=6
parameter F test:         F=8.8590  , p=0.0000  , df_denom=3161, df_num=6

Granger Causality
number of lags (no zero) 7
ssr based F test:         F=7.4846  , p=0.0000  , df_denom=3158, df_num=7
ssr based chi2 test:   chi2=52.6413 , p=0.0000  , df=7
likelihood ratio test: chi2=52.2094 , p=0.0000  , df=7
parameter F test:         F=7.4846  , p=0.0000  , df_denom=3158, df_num=7
```

"Peak viewers" granger causes "deseasonalized_players" from lag = 2

APPENDIX(2)

Linear Regression results for CS2 & RUST

CS2

OLS Regression Results

Dep. Variable:	deseasonalized_players	R-squared:	0.009
Model:	OLS	Adj. R-squared:	0.005
Method:	Least Squares	F-statistic:	1.963
Date:	Mon, 08 Jul 2024	Prob (F-statistic):	0.0144
Time:	20:10:19	Log-Likelihood:	-37921.
No. Observations:	3180	AIC:	7.587e+04
Df Residuals:	3164	BIC:	7.597e+04
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	241.4805	963.981	0.251	0.802	-1648.611	2131.572
Peak viewers	0.0133	0.005	2.415	0.016	0.002	0.024
Rating	7.938e+04	4.06e+04	1.956	0.051	-194.726	1.59e+05
Final price	676.8137	968.618	0.699	0.485	-1222.369	2575.996
Tournament (INTL)	1863.8389	3080.301	0.605	0.545	-4175.751	7903.429
Events	1.715e+04	1.24e+04	1.380	0.168	-7211.545	4.15e+04
Friday	-406.3806	1603.068	-0.254	0.800	-3549.538	2736.776
Monday	225.6946	1714.035	0.132	0.895	-3135.037	3586.427
Saturday	-439.8242	1614.763	-0.272	0.785	-3605.914	2726.265
Sunday	-1097.3885	1627.341	-0.674	0.500	-4288.138	2093.361
Thursday	-585.8990	1607.373	-0.365	0.716	-3737.498	2565.700
Tuesday	1609.4030	1708.365	0.942	0.346	-1740.213	4959.019
Wednesday	935.8752	1711.212	0.547	0.584	-2419.323	4291.073
Peak viewers_shift_1	0.0172	0.006	3.058	0.002	0.006	0.028
Peak viewers_shift_2	0.0116	0.005	2.138	0.033	0.001	0.022
Final price_shift_4	-2527.6810	962.627	-2.626	0.009	-4415.118	-640.244
is_historical_low_shift_2	38.6516	1356.995	0.028	0.977	-2622.028	2699.331

Omnibus:	659.521	Durbin-Watson:	2.195
Prob(Omnibus):	0.000	Jarque-Bera (JB):	20365.405
Skew:	0.224	Prob(JB):	0.00
Kurtosis:	15.390	Cond. No.	1.66e+21

Rust

OLS Regression Results

Dep. Variable:	deseasonalized_players	R-squared:	0.025
Model:	OLS	Adj. R-squared:	0.020
Method:	Least Squares	F-statistic:	4.800
Date:	Mon, 08 Jul 2024	Prob (F-statistic):	2.82e-10
Time:	20:37:55	Log-Likelihood:	-33362.
No. Observations:	3181	AIC:	6.676e+04
Df Residuals:	3163	BIC:	6.687e+04
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-14.0932	139.995	-0.101	0.920	-288.583	260.396
Peak viewers	0.0227	0.004	6.262	0.000	0.016	0.030
Rating	1.172e+04	9205.101	1.273	0.203	-6331.677	2.98e+04
Final price	-44.9266	60.881	-0.738	0.461	-164.296	74.443
Tournament (INTL)	-1000.0289	2079.159	-0.481	0.631	-5076.666	3076.608
Events	3565.9543	3565.288	1.000	0.317	-3424.556	1.06e+04
Friday	-86.8187	381.649	-0.227	0.820	-835.123	661.486
Monday	70.5528	382.671	0.184	0.854	-679.756	820.862
Saturday	-50.5195	378.851	-0.133	0.894	-793.339	692.300
Sunday	102.8997	379.920	0.271	0.787	-642.014	847.814
Thursday	-179.6083	381.088	-0.471	0.637	-926.813	567.597
Tuesday	197.6223	381.133	0.519	0.604	-549.671	944.915
Wednesday	-68.2215	380.658	-0.179	0.858	-814.583	678.140
Peak viewers_shift_4	0.0103	0.004	2.854	0.004	0.003	0.017
Peak viewers_shift_6	0.0129	0.004	3.573	0.000	0.006	0.020
Peak viewers_shift_11	-0.0124	0.004	-3.438	0.001	-0.020	-0.005
Peak viewers_shift_13	0.0093	0.004	2.581	0.010	0.002	0.016
Final price_shift_4	-151.6197	60.887	-2.490	0.013	-271.001	-32.238
is_historical_low	318.0461	663.362	0.479	0.632	-982.618	1618.710

Omnibus:	2202.794	Durbin-Watson:	2.261
Prob(Omnibus):	0.000	Jarque-Bera (JB):	61925.167
Skew:	2.906	Prob(JB):	0.00
Kurtosis:	23.819	Cond. No.	4.76e+18

APPENDIX(3)

CDMI results for CS2 & RUST

No significant lag was found for CS2

CS2

	In-dist	Out-dist	Mean	Uniform
Peak viewers	0	0	0	0
Final price	0	0	0	0
is_historical_low	0	0	0	0
Peak viewers_shift_1	0	0	0	0
Peak viewers_shift_2	0	0	0	1
Peak viewers_shift_3	0	0	0	0
Peak viewers_shift_4	0	0	0	1
Peak viewers_shift_5	0	0	0	0
Peak viewers_shift_6	0	0	0	0
Peak viewers_shift_7	0	0	0	0
Peak viewers_shift_8	0	0	0	1
Peak viewers_shift_9	0	0	0	1
Peak viewers_shift_10	0	0	0	1
Peak viewers_shift_11	0	0	0	0
Peak viewers_shift_12	0	0	0	0
Peak viewers_shift_13	0	0	0	0
Peak viewers_shift_14	0	0	0	0
Rating_shift_1	0	0	0	0
Rating_shift_7	0	0	0	0
Final price_shift_1	0	0	0	0
Final price_shift_2	0	0	0	0
Final price_shift_3	0	0	0	0
Final price_shift_4	0	0	0	0
Final price_shift_5	0	0	0	0
Final price_shift_6	0	0	0	0
Final price_shift_7	0	0	0	0
is_historical_low_shift_2	0	0	0	0
is_historical_low_shift_4	0	0	0	0
is_historical_low_shift_6	0	0	0	0

Peak viewers from 5,6, days and 14 days ago are significant

Rust

	In-dist	Out-dist	Mean	Uniform
Peak viewers	0	0	0	1
Final price	0	0	0	0
is_historical_low	0	0	0	0
Peak viewers_shift_1	0	0	0	0
Peak viewers_shift_2	0	0	0	1
Peak viewers_shift_3	0	0	0	0
Peak viewers_shift_4	0	0	0	0
Peak viewers_shift_5	1	0	0	1
Peak viewers_shift_6	1	0	0	1
Peak viewers_shift_7	0	0	0	1
Peak viewers_shift_8	0	0	0	0
Peak viewers_shift_9	0	0	0	1
Peak viewers_shift_10	0	0	0	0
Peak viewers_shift_11	0	0	0	1
Peak viewers_shift_12	0	0	0	0
Peak viewers_shift_13	0	0	0	1
Peak viewers_shift_14	1	0	0	1
Rating_shift_1	0	0	0	0
Rating_shift_7	0	0	0	0
Final price_shift_1	0	0	0	0
Final price_shift_2	0	0	0	0
Final price_shift_3	0	0	0	0
Final price_shift_4	0	0	0	0
Final price_shift_5	0	0	0	0
Final price_shift_6	0	0	0	0
Final price_shift_7	0	0	0	0
is_historical_low_shift_1	0	0	0	0
is_historical_low_shift_2	0	0	0	0
is_historical_low_shift_3	0	0	0	0
is_historical_low_shift_4	0	0	0	0
is_historical_low_shift_5	0	0	0	0
is_historical_low_shift_6	0	0	0	0
is_historical_low_shift_7	0	0	0	0

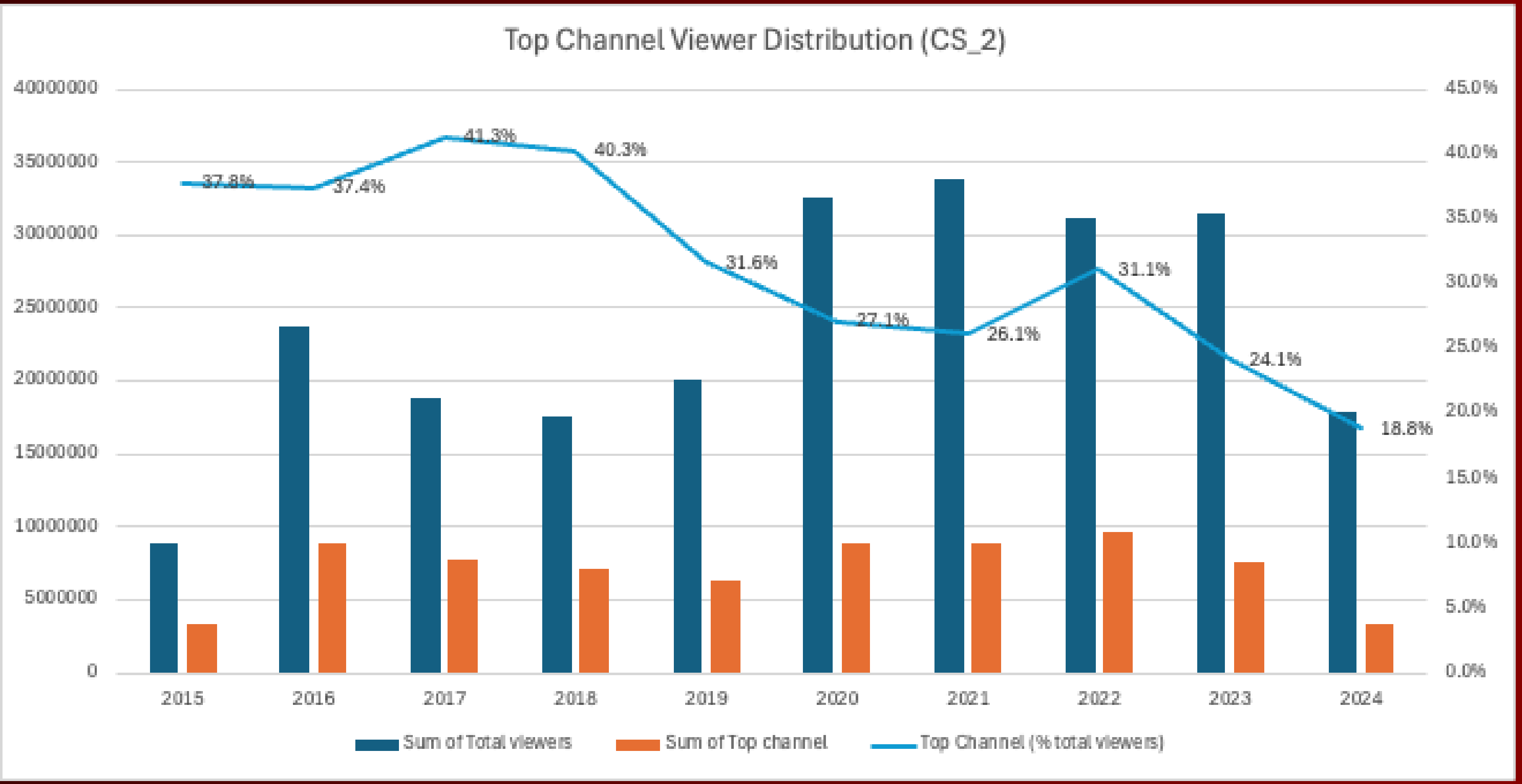
APPENDIX(4)

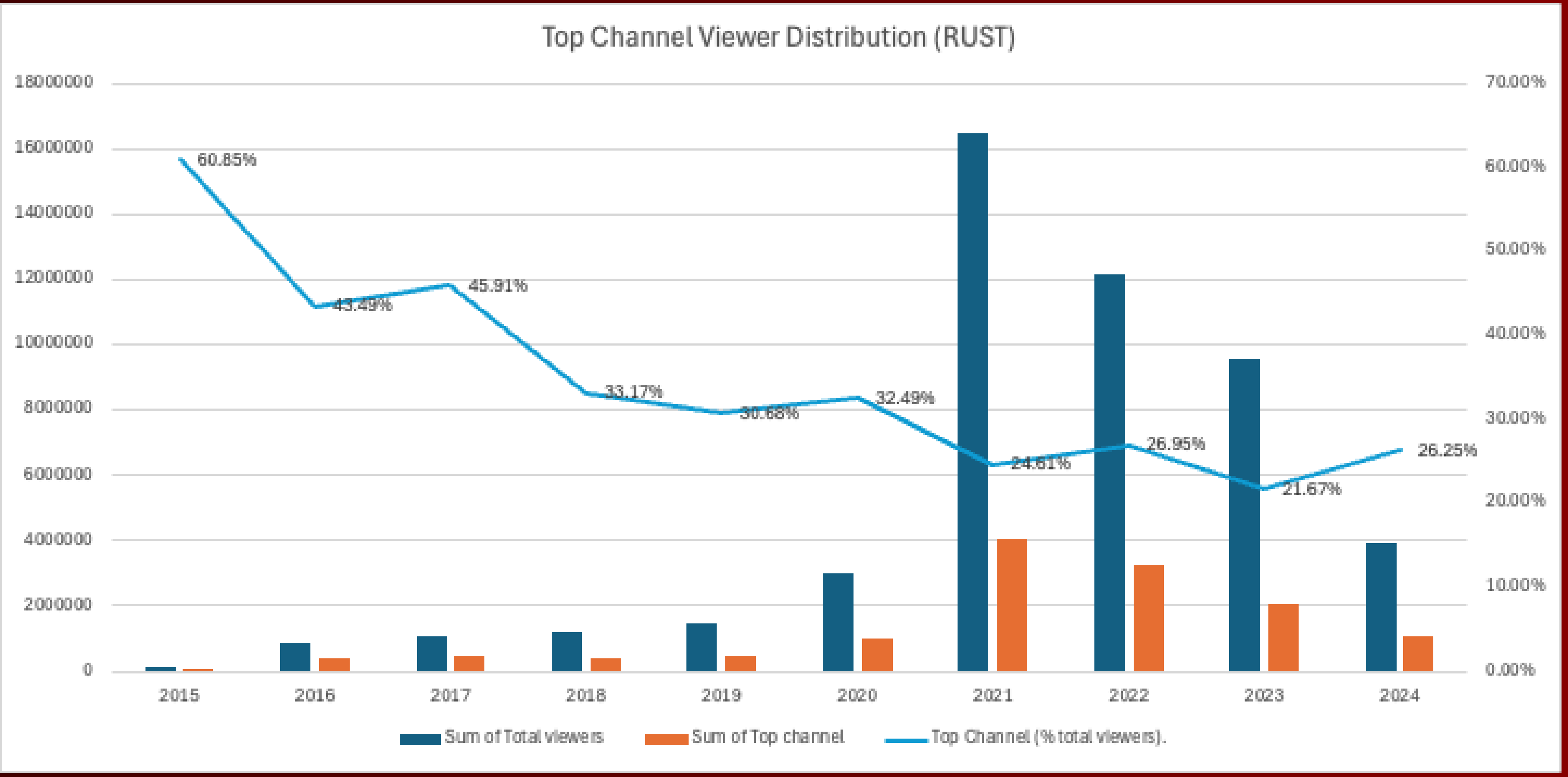
LPCMCI results for CS2 & RUST

	CS2	Rust
Significant Links	• Variable 0 at time t-1 -> Variable 1 at time t **(p-value: 0.00162)** • Variable 0 at time t-2 -> Variable 1 at time t **(p-value: 0.02314)**	• Variable 1 at time t-0 -> Variable 0 at time t **(p-value: 0.00000)** • Variable 1 at time t-4 -> Variable 0 at time t **(p-value: 0.00105)**
Estimated Casual Effect	0.02	0.04

APPENDIX(5)

Top channel viewer distribution plots (CS2 / RUST)



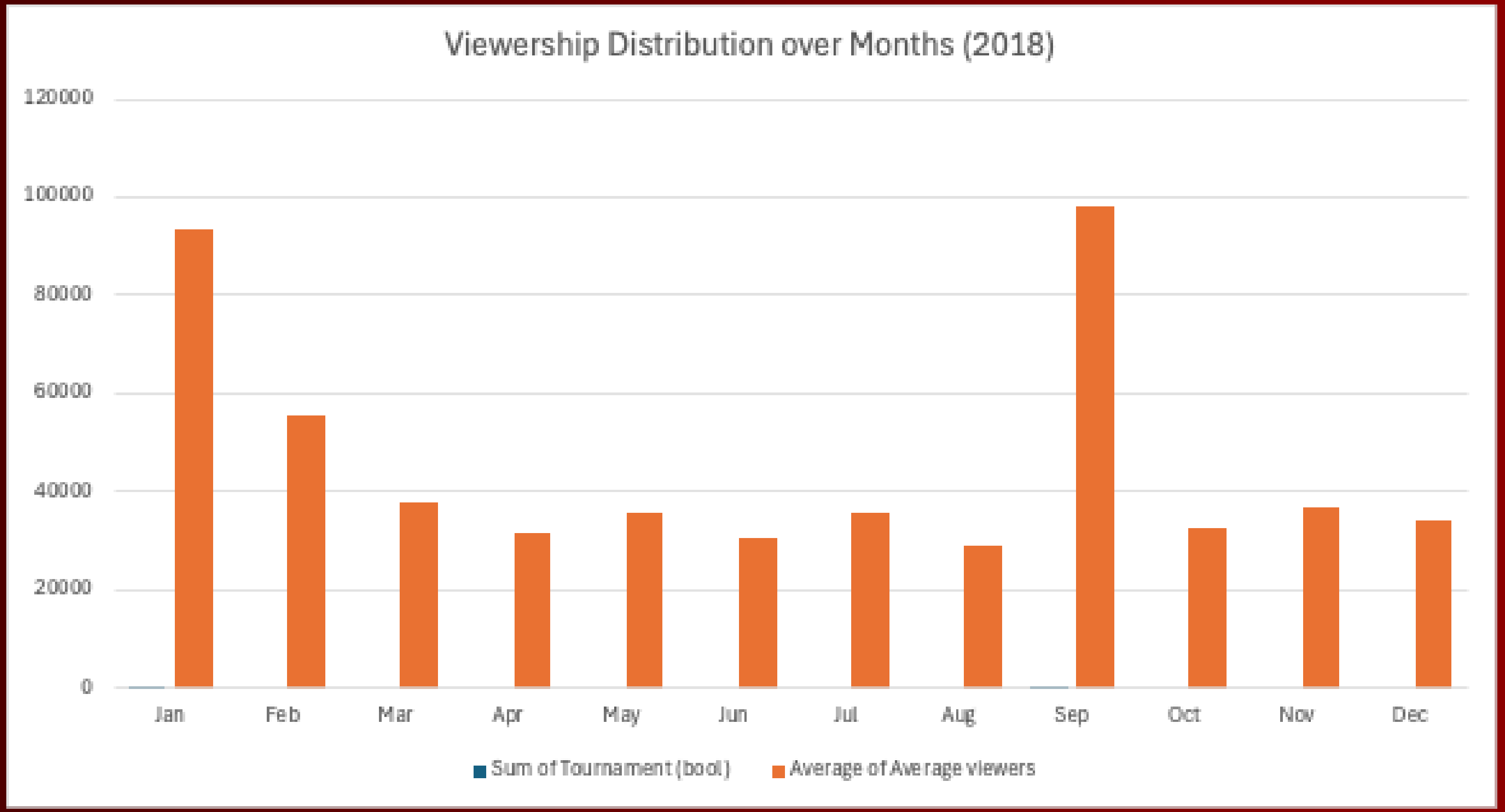


APPENDIX(6)

Viewership Distribution (During Tournament / Not During Tournament) (CS2/ RUST)

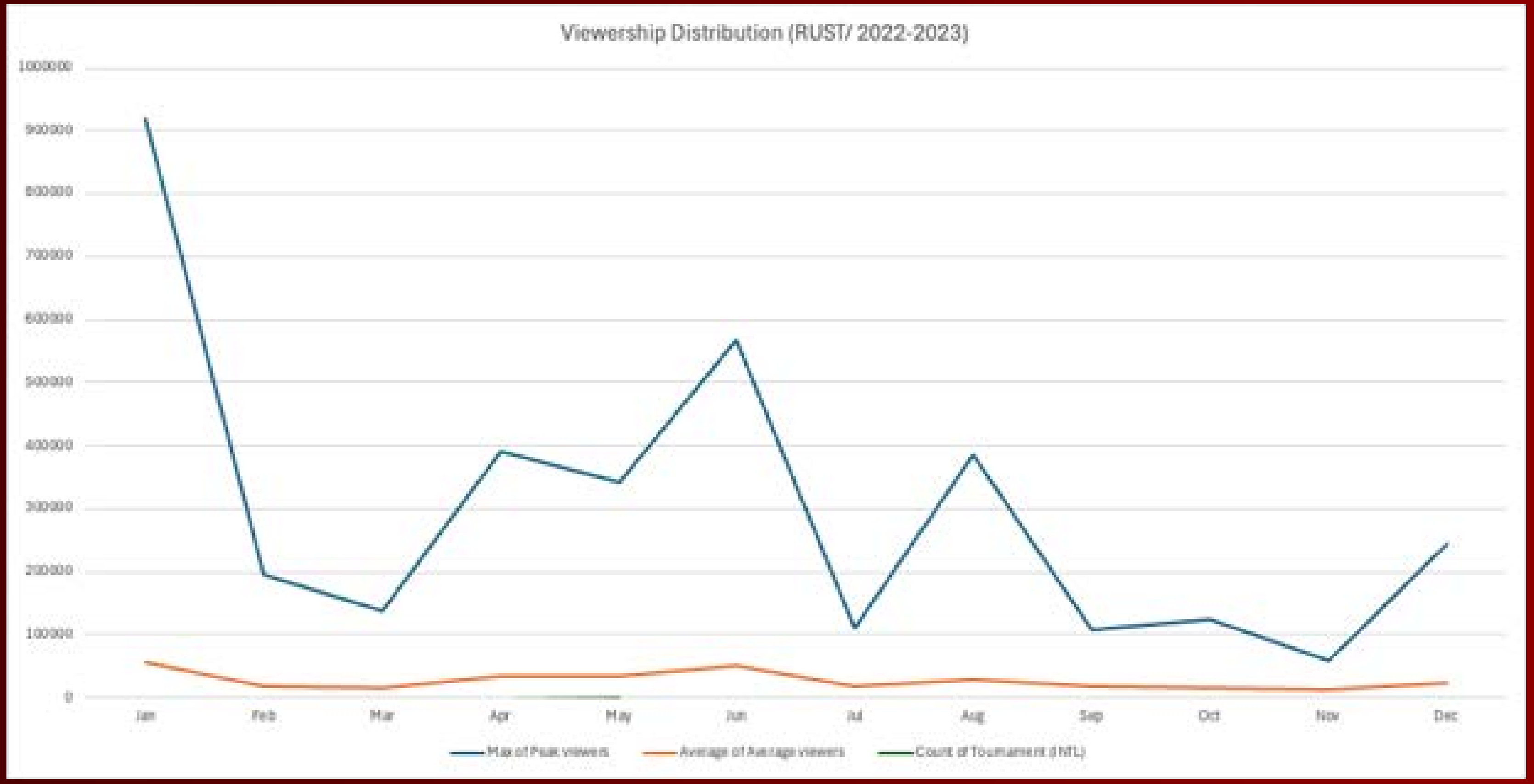
Years (DateT	2018	
Row Labels	Sum of Tourn	Average of Average viewers
Jan	14	93552.6452
Feb	0	55783.0714
Mar	0	37739.1613
Apr	0	31840.7
May	0	35522.9677
Jun	0	30413.1667
Jul	0	35970.6129
Aug	0	29163.3548
Sep	17	98006.1
Oct	0	32532.2903
Nov	0	36883.5333
Dec	0	34365.2903

CS2 2018



Row Labels	Max of Peak viewers	Average of Average viewers	Count of Tournament (INTL)
Jan	917741	56196.17742	
Feb	195251	19729.76786	
Mar	136869	15963.3871	
Apr	391822	35973.03333	3
May	342239	34029.01613	5
Jun	566990	50186.11667	
Jul	109641	19282.33871	
Aug	384738	29264.83871	5
Sep	108823	18156.3	
Oct	124621	16364.20968	
Nov	60204	12825.11667	
Dec	243825	25079.30645	5
Grand Total	917741	27803.30959	18

Rust 2022-2023

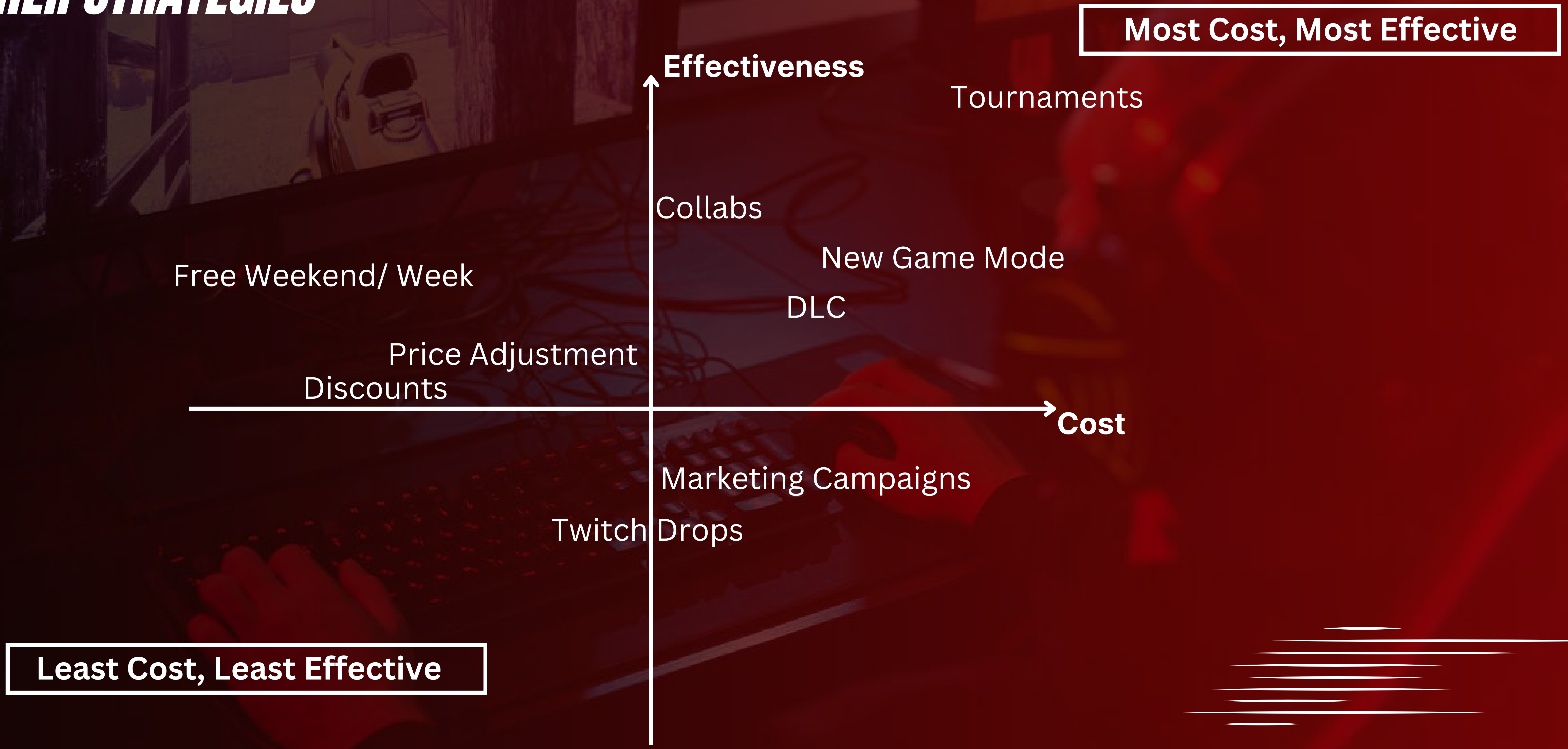


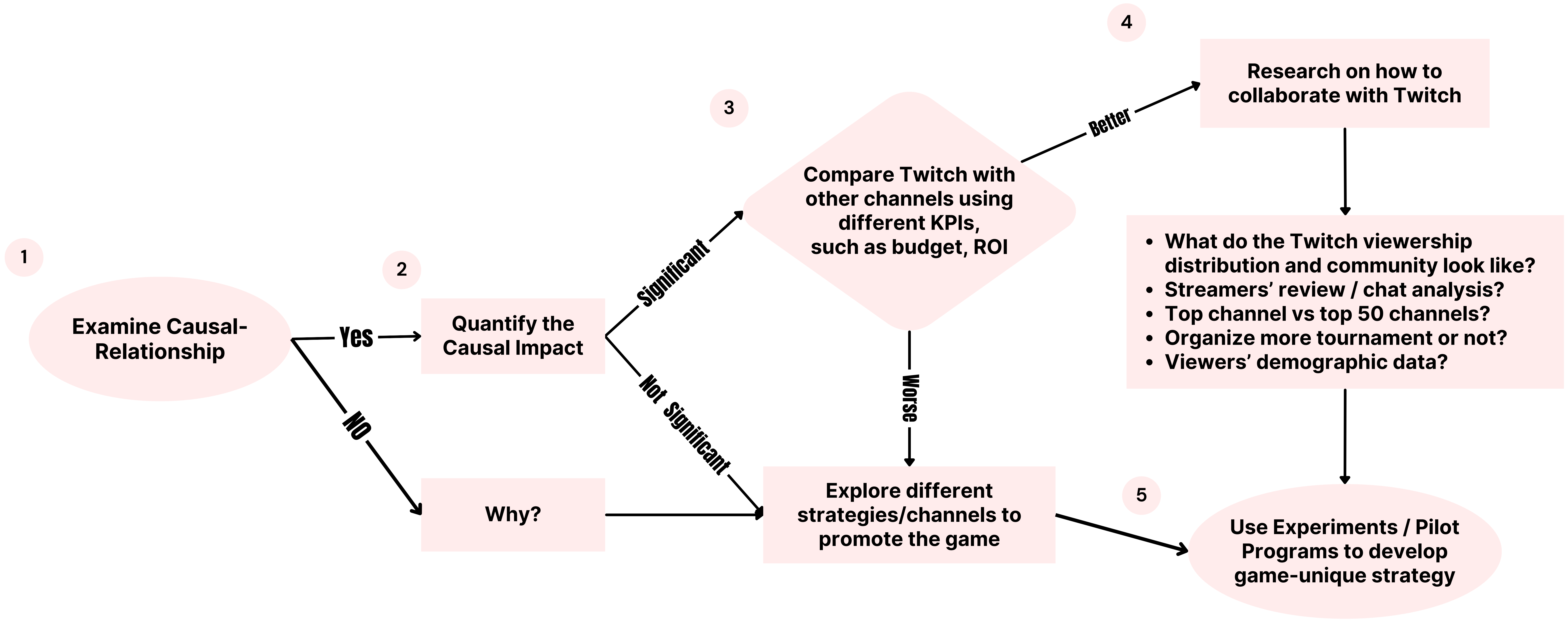
APPENDIX(7)

Twitch Drop Example: RUST 2020 twitch drops event

APPENDIX(8)

OTHER STRATEGIES




1
Examine Causal-Relationship
Yes
NO
2
Quantify the Causal Impact
Why?
Significant
Not Significant
3
Compare Twitch with other channels using different KPIs, such as budget, ROI
Better
Worse
4
Research on how to collaborate with Twitch
• What do the Twitch viewership distribution and community look like?
• Streamers' review / chat analysis?
• Top channel vs top 50 channels?
• Organize more tournament or not?
• Viewers' demographic data?
Explore different strategies/channels to promote the game
5
Use Experiments / Pilot Programs to develop game-unique strategy

OTHER STRATEGIES