The Popularity Effects of Soccer Leagues Remaining Active During COVID Lockdowns

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Introduction

In the spring of 2020, global sports activity came to an abrupt halt due to the COVID-19 pandemic. For the first time in modern history, almost every major sports league ceased operations to mitigate the spread of the virus. However, in the midst of this shutdown, the Belarusian Premier League (BPL), the most prominent soccer league in the eponymous Belarus, made the nearly unique decision to remain fully operational, allowing matches to continue and even allowing spectators to attend. In a flash, this turned the BPL from a fairly obscure league into some of the only live soccer entertainment available in the entire world, granting it a massive boost in international attention.

In this paper, I will investigate whether this temporary exogenous shock to viewership resulted in a permanent increase in the league's popularity. Specifically, I test a "consumption commitment" or "habit formation" hypothesis: that the accumulation of "informational capital," such as knowledge of teams, players, and competitive narratives, during the lockdown created switching costs that led to fan retention even after major leagues such as the English Premier League (EPL) and La Liga resumed.

The first section of this paper provides an overview of existing literature regarding both the BPL's pandemic performance and the economic theory of habit formation. The theoretical model ~~section~~ adopts Chetty and Szeidl's (2005) framework to sports consumption, predicting that the high cost of acquiring new knowledge acts as a barrier to exit, potentially locking in new fans. Following the theoretical model, I present a dynamic difference-in-differences empirical model using Google Trends data to measure the relative popularity of the BPL against the control leagues (Kazakhstani Premier League and Azerbaijani Premier League) over time. The results of this analysis suggest that, while the BPL experienced a statistically significant explosion in popularity during the lockdown, this effect was transient, with viewership returning to the pre-pandemic baselines shortly after global sports resumed.

Literature Review

The Belarusian Premier League's unique decision to continue playing during global lockdowns was examined by Reade, Schreyer, and Tovar (2020). Given that the BPL even continued allowing spectators into the stands, they examined the impact of the COVID-19 pandemic on stadium attendance at BPL games, finding that attendance, unsurprisingly, declined significantly during the initial phase of the pandemic. This suggests that any attentional gains from remaining in operation would have come from online or broadcast media, rather than local and in-person consumption.

More broadly, the hypothesis that the BPL has enjoyed a long-term increase in popularity from this temporary burst of attention can be construed as the result of consumption stickiness in the form of habit formation. Chetty and Szeidl (2005) demonstrate that this phenomenon is more than just psychological, developing a model with micro-foundations for habit in the form of "consumption commitments." These commitments take the form of restrictions that impose extra costs on consumers who wish to deviate from a particular pattern of consumption, making past consumption patterns more likely to persist. In this context, the time and effort that a viewer invests in learning the new league's teams and players can create switching costs if the viewer later abandons the league and the informational capital they have built up.

This study ~~aims to make~~ a novel contribution to the existing literature in multiple ways. To start, while existing research into the impact of the COVID-19 pandemic on European football leagues focuses on stadium attendance as an outcome variable, this study s~~pecifically~~ looks into the impact on online attention. This is important because fans continued to consume digital content during the near-complete shutdown, changing the relationship that fans have with sports leagues (Wymer, Thompson, Martin 2020). Online attention is thus a much more direct and relevant measure of popularity in the pandemic and post-pandemic social environment. Furthermore, this study follows Goodman-Bacon and Marcus (2020), who recommend the use of a dynamic “event study” specification to identify the causal effects of pandemic-related policy choices. Finally, this study follows Malagon-Selma, Debon, and Domenech (2023) in using Google Trends data as a proxy for popularity, as it provides granular, consistent data free from the reporting errors often found in traditional broadcast ratings.

Theoretical Model

To provide micro-foundations for the hypothesis of persistent Belarusian Premier League (BPL) popularity, I adapt the consumption commitment framework of Chetty and Szeidl (2005). I model the viewing decision as an optimization problem ~~where~~ consumers face transaction costs to adjusting their stock of “information capital” (league-specific knowledge of teams, players, narratives, etc.).

The Environment and Utility

Consider a representative sports consumer with an infinite time horizon; risk neutrality is assumed for tractability. The consumer derives utility from two distinct goods:

- General Soccer (a_t): A composite good representing the consumption of established major leagues such as the English Premier League or La Liga. I classify this as the "adjustable" good because I assume the consumer possesses a "saturated" stock of knowledge regarding these leagues (a sunk cost incurred in the past). Put simply, they are already familiar with the teams, players, and narratives. Consequently, consumption is modeled as a direct flow: the consumer can instantaneously increase or decrease a_t and derive utility immediately without paying any new cognitive "learning" costs.
- BPL Informational Capital (x_t): The "commitment good" in the model This represents the consumer's active level of engagement with the Belarusian Premier League. While discrete acts of viewership (watching a match) provide the immediate entertainment, in this continuous-time framework, I model engagement as the variable x_t. This encapsulates both the accumulated knowledge (team narratives, player names) and the ongoing investment of attention required to maintain that knowledge against depreciation (δ). Thus, x_t serves as a proxy for the effective flow of entertainment the consumer derives from the league, which is high when they are deeply engaged and near-zero when they are not. Due to adjustment costs (learning new information) it cannot be adjusted instantaneously; instead, it evolves according to the "(S,s) rule" described below, creating stickiness in viewership habits.

The consumer maximizes expected lifetime utility given by:

$$U = E_0 \int_0^{\infty} e^{-\rho t} \left[\mu_a a_t + \mu_x x_t \right] dt$$

where ρ is the discount rate and μ_a and μ_x are preference parameters representing the marginal utility of general football and BPL capital, respectively. E_0 denotes the expectation operator conditional on information available at time t = 0, reflecting that the consumer must make current engagement decisions based on expected future utility despite uncertainty regarding future shocks. I assume a linear utility function for tractability, which allows me to focus purely on the costs of switching rather than risk aversion.

Constraints and Adjustment Costs

While the level of General Football can be adjusted instantaneously and costlessly (the consumer can simply stop watching), the stock of BPL capital is subject to frictions:

- Depreciation: Without active maintenance, informational capital decays over time (e.g. player names are forgotten). This occurs at a rate δ such that $dx_t = -\delta x_t dt$.
- Transaction Costs: Actively changing the level of engagement x_t, either by investing time to learn about the league or actively re-allocating mental energy elsewhere, incurs a fixed cognitive cost k:

$$Cost = k \times |\Delta x_t|$$

  This k represents "switching costs," acting as a barrier that discourages fans from constantly changing their viewing habits. Increasing engagement (+ Δx_t) requires effort in order to learn information about the BPL's players, teams, etc. Decreasing engagement (-Δx_t), involves the mental effort required to break an established habit, or to abandon teams and players the consumer has grown emotionally attached to.

Optimal Policy: The (S,s) Rule

Because changing engagement levels costs mental effort (k), the consumer does not continuously tweak x_t to be perfect. Instead, optimal behavior follows an (S,s) "adjustment rule." This rule creates a "Zone of Inaction" defined by a lower bound (L) and an upper bound (U):

- The Inaction Zone: As long as the ratio of BPL Capital to General Football stays within the band $L < \frac{x_t}{a_t} < U$ the consumer does nothing. Specifically, L and U represent the critical threshold ratios of BPL to General Soccer consumption at which the utility gain from re-optimizing one's viewership habits exceeds the fixed cognitive switching cost k.
- Even if their current engagement level is not optimal, the gain from fixing it is smaller than the cognitive cost k. They simply maintain their current habits.
- Adjustment: The consumer pays the cost to change x_t only if a substantial enough shock forces the ratio outside of these bounds.

The COVID-19 Shock and Hysteresis

The pandemic is modeled as a natural experiment in two phases:

- Phase 1 (The Lockdown): At $t = 0$, the supply of General Football rapidly goes to 0 as leagues shut down ($a_t \rightarrow 0$). The relative value of the BPL, represented by the ratio $\frac{x_t}{a_t}$, consequently shoots up, breaking through the upper adjustment threshold U. The consumer is thus effectively forced to pay the learning cost k, rapidly accumulating a high stock of BPL engagement (denoted x_{high}) to replace the missing utility from entertainment.
- Phase 2 (The Reopening): At $t = 1$, major leagues resume (a_t returns to normal). Here the consumer might ~~ideally~~ want to change their consumption pattern by lowering their BPL engagement. However, they now hold the high stock x_{high}, and, as discarding this

capital (switching back) incurs a cognitive cost, they do not immediately drop x back to zero. Provided that the new state remains above the lower bound L, they remain in the "Inaction Zone."

Prediction

This model predicts "hysteresis" (persistence) in viewership; the temporary shock leads to a permanently higher level of popularity for the BPL. Because changing one's level of engagement incurs a cognitive adjustment cost, x_t does not continuously track the optimal, frictionless level. Instead, it evolves according to the (S,s) rule, where the consumer maintains their current stock of engagement within a "Zone of Inaction." Consequently, even after reopening causes the optimal relative value of BPL engagement to decline, the actual ratio does not breach the lower bound L for a consumer with sufficiently high switching costs k. These consumers thus continue to watch the BPL following the viewing patterns established during the Lockdown phase. Mathematically, this implies the difference in engagement between the treatment and control groups remains positive post-lockdown:

$$\beta_{k,post-lockdown} \approx E\left[x_t^{BPL}\right] - E\left[x_t^{Control}\right] > 0$$

Empirical Model and Data

To test the hypothesis, I utilize a dynamic difference-in-differences (or "event study") specification. Difference-in-differences is a method used to isolate the specific impact of an event, which in this case is the decision to keep the Belarusian Premier League open during the lockdown. Instead of just looking at whether the league's popularity went up (which could happen for many reasons), I compare its change over time to 'control' leagues (Kazakhstan and Azerbaijan) that were similar but shut down. By subtracting the trend seen in those control leagues from the trend seen in Belarus, I can filter out general factors that affected everyone, such as global seasonality or the pandemic itself, leaving only the true effect of remaining active.

The dataset consists of monthly Google Trends search interest indices for the period September 2018 to October 2025. The treatment group is the Belarusian Premier League (BPL), while the control group consists of the Kazakhstan Premier League (KPL) and Azerbaijani Premier League (APL). These leagues were chosen due to their similarity to the BPL in both pre-pandemic Google Trends levels and trends. The outcome variable of $Popularity_{it}$ in this model is the Google Trends search interest index for league i in month t. It is measured on a relative scale from 0 to 100, where 100 represents the peak search interest in one of the three topics (each league) over the specified timeframe.

Estimating Equation:

I estimate the model with the following equation:

$$Popularity_{it} = \alpha_i + \lambda_t + \sum_{k=-m}^{q} \beta_k \times (Treat_i \times 1\{t = k\}) + \epsilon_{it}$$

- α_i represents league fixed effects to control for time-invariant differences between leagues.
- λ_t represents Year-Month time fixed effects to control for seasonality and other temporal shocks.
- $Treat_i$ is a binary indicator equal to 1 if the league is the BPL and 0 otherwise.
- $1\{t = k\}$ is an indicator for the time period k months relative to the start of the lockdown in March 2020, which is represented by $k = 0$.
- β_k are the coefficients of interest, measuring the difference in popularity between the BPL and the control leagues in period k.

If the hypothesis is correct, the β_k should be statistically insignificant for pre-lockdown periods (negative k) in order to validate the parallel trends assumption, followed by a large positive jump in β_k in the immediate aftermath of the lockdowns ($k = 0, 1, 2$) and then dropping back down but remaining positive and statistically significant for $k > 2$ to validate the idea of permanently higher popularity.

Results

The regression analysis was performed on 261 observations in the form of 87 months' worth of monthly data points on each of the 3 leagues spanning from September 2018 to November 2025. The model includes league and time fixed effects, with standard errors clustered at the league level. The Within R^2 is very high at 0.9864, indicating that the model's treatment indicators capture almost all of the variation in popularity within each league over time.

Key Findings:

1. Pre-Trend Stability: For periods leading up to the lockdown ($k < 0$), the coefficients are not statistically significant. This provides evidence for the parallel trends assumption that prior to the pandemic the BPL popularity moved in tandem with that of the KPL and APL.

2. The Lockdown Shock: As expected, there is an immediate and massive spike in the BPL's popularity at the onset of the lockdown. The coefficients jump from being not significantly different from 0 to 62, 100.5, and 47.5 in periods 0, 1, and 2, respectively, all significant at the 99% confidence level. This is a huge increase considering the measurement is on a 100 point scale, confirming that the BPL experienced a spike in popularity during the lockdowns.
3. Post-Lockdown Decay: The coefficients start to drop after this initial spike, but crucially for the hypothesis they continue dropping much faster than predicted. By period $t = 7$, the coefficients have returned to not being statistically different from 0, contradicting the idea of a permanent post-lockdown popularity boost. While there are intermittent spikes in significance in later periods (e.g. $t = 12$, $t = 20$), they are not evidence of the permanent popularity increase predicted by the "consumption commitment" theoretical model, but rather much more likely to just correspond to league-specific events such as season openers or championships. Particularly after about period $t = 21$, the BPL's popularity level appears statistically indistinguishable from that of the KPL and APL outside of very rare and sporadic deviations.

The table describing these results can be found in the Appendix, alongside a graph of the differences over time with 95% confidence bars.

Conclusion

This paper utilized the unique natural experiment of the COVID-19 lockdowns to test theories of consumption commitments and habit formation in sports viewership. By analyzing the Belarusian Premier League (BPL), the only European soccer league to remain open during the initial wave of lockdowns, I tested whether a temporary exogenous boost in consumption would lead to a permanently higher level of popularity due to the accumulation of informational capital.

The results lead to a failure to reject the null hypothesis that the BPL's long-term popularity was unaffected by the temporary spike. Despite its massive surge in popularity during the initial months of the global lockdown, this advantage rapidly dissipated as major leagues began to resume operations. The coefficients for the post-lockdown period largely returned to near-zero levels, suggesting that the switching costs associated with abandoning the BPL informational capital were not high enough to keep consumers above the lower bound of the "Zone of Inaction" described by the theoretical model once the "General Football" good became available once again.

These findings suggest that the utility derived from top-tier leagues such as the English Premier League or La Liga significantly outweighs the cognitive costs of switching, regardless of the capital accumulated in smaller leagues like the BPL. Further research could investigate whether this lack of persistence holds for other forms of entertainment consumption or if the sports attention economy simply has a particular "winner-take-all" nature.

Sources

Chetty, R., & Szeidl, A. (2005, October). Consumption commitments: Neoclassical foundations for habit formation. NBER Working Paper.

Goodman-Bacon, A., & Marcus, J. (2020, May). Using difference-in-differences to identify causal effects of COVID-19 policies. DIW Berlin Discussion Paper No. 1870. http://dx.doi.org/10.2139/ssrn.3603970

Google Trends. (n.d.). *Comparison of search interest for Belarusian Premier League, Kazakhstan Premier League, and Azerbaijan Premier League from September 2018 to November 2025* [Data set]. Google. Retrieved November 20, 2025, from https://trends.google.com/trends/explore?date=2018-09-01%202025-11-20&geo=US&q=%2Fm%2F08rl81,%2Fm%2F07l328,%2Fm%2F03nrtvd&hl=en

Malago´n-Selma, P., Debo´n, A., & Domenech, J. (2023). Measuring the popularity of football players with Google Trends. PLoS ONE, 18(8): e0289213. https://doi.org/10.1371/journal.pone.0289213

Reade, J. J., Schreyer, D., & Singleton, C. (2020). Stadium attendance demand during the COVID-19 crisis: Early empirical evidence from Belarus. Applied Economics Letters.

Wymer, S., Thompson, A.-J., & Martin, A. (2020). Diminishing the distance during social distancing: An exploration of Australian sport organizations' usage of social live streaming services throughout Covid-19. In Sport and the Pandemic (1st ed., p. 9). Routledge.

Appendix

Table:

Dependent Var.: popularity, Standard Errors in Parentheses

Treat_i x relative_time = -18 0.5000 (0.7443)

Treat_i x relative_time = -17 0.5000 (0.7443)

Treat_i x relative_time = -16 0.5000 (0.7443)

Treat_i x relative_time = -15 0.5000 (0.7443)

Treat_i x relative_time = -14 0.5000 (0.7443)

Treat_i x relative_time = -13 2.500. (0.7443)
Treat_i x relative_time = -12 0.5000 (0.7443)

Treat_i x relative_time = -11 1.500 (0.7443)

Treat_i x relative_time = -10 0.5000 (0.7443)

Treat_i x relative_time = -9 0.5000 (0.7443)

Treat_i x relative_time = -8 2.500. (0.7443)

Treat_i x relative_time = -7 2.500. (0.7443)

Treat_i x relative_time = -6 2.500. (0.7443)

Treat_i x relative_time = -5 -0.5000 (0.7443)

Treat_i x relative_time = -4 1.500 (2.233)

Treat_i x relative_time = -3 0.5000 (0.7443)

Treat_i x relative_time = -2 0.5000 (0.7443)

Treat_i x relative_time = 0 62.00*** (1.489)

Treat_i x relative_time = 1 100.5*** (0.7443)

Treat_i x relative_time = 2 47.50*** (0.7443)

Treat_i x relative_time = 3 17.50** (0.7443)

Treat_i x relative_time = 4 11.00* (1.489)

Treat_i x relative_time = 5 8.500** (0.7443)

Treat_i x relative_time = 6 5.500* (0.7443)

Treat_i x relative_time = 7 5.000. (1.489)

Treat_i x relative_time = 8 5.000 (2.977)

Treat_i x relative_time = 9 3.500* (0.7443)

Treat_i x relative_time = 10 2.500. (0.7443)

Treat_i x relative_time = 11 1.500 (0.7443)
Treat_i x relative_time = 12 3.000*** (1e-6)

Treat_i x relative_time = 13 3.500* (0.7443)

Treat_i x relative_time = 14 4.500* (0.7443)

Treat_i x relative_time = 15 6.500 (2.233)

Treat_i x relative_time = 16 4.500* (0.7443)

Treat_i x relative_time = 17 5.500* (0.7443)

Treat_i x relative_time = 18 3.500 (2.233)

Treat_i x relative_time = 19 3.500 (2.233)

Treat_i x relative_time = 20 3.500* (0.7443)

Treat_i x relative_time = 21 2.500. (0.7443)

Treat_i x relative_time = 22 0.5000 (0.7443)

Treat_i x relative_time = 23 0.5000 (0.7443)

Treat_i x relative_time = 24 0.5000 (2.233)

Treat_i x relative_time = 25 1.500 (0.7443)

Treat_i x relative_time = 26 1.500 (0.7443)

Treat_i x relative_time = 27 2.500. (0.7443)

Treat_i x relative_time = 28 1.500 (2.233)

Treat_i x relative_time = 29 3.000*** (1e-6)

Treat_i x relative_time = 30 6.28e-12 (1.489)

Treat_i x relative_time = 31 3.500 (2.233)

Treat_i x relative_time = 32 1.500 (0.7443)

Treat_i x relative_time = 33 6.27e-12 (1e-6)

Treat_i x relative_time = 34 -1.000 (1.489)

Treat_i x relative_time = 35 -1.000 (1.489)

Treat_i x relative_time = 36 -1.000 (1.489)

Treat_i x relative_time = 37 2.000*** (1e-6)

Treat_i x relative_time = 38 0.5000 (0.7443)

Treat_i x relative_time = 39 2.500. (0.7443)

Treat_i x relative_time = 40 1.500 (2.233)

Treat_i x relative_time = 41 4.000*** (1e-6)

Treat_i x relative_time = 42 2.000 (1.489)

Treat_i x relative_time = 43 2.000 (1.489)

Treat_i x relative_time = 44 2.500. (0.7443)

Treat_i x relative_time = 45 -1.000 (1.489)

Treat_i x relative_time = 46 0.5000 (0.7443)

Treat_i x relative_time = 47 -0.5000 (2.233)

Treat_i x relative_time = 48 6.16e-12 (1.489)

Treat_i x relative_time = 49 1.500 (0.7443)

Treat_i x relative_time = 50 2.000 (1.489)

Treat_i x relative_time = 51 1.500 (2.233)

Treat_i x relative_time = 52 3.500* (0.7443)

Treat_i x relative_time = 53 2.500. (0.7443)

Treat_i x relative_time = 54 2.000 (1.489)

Treat_i x relative_time = 55 -0.5000 (0.7443)

Treat_i x relative_time = 56 1.500 (0.7443)

Treat_i x relative_time = 57 -2.000*** (1e-6)

Treat_i x relative_time = 58 0.5000 (0.7443)

Treat_i x relative_time = 59 -1.000 (1.489)

Treat_i x relative_time = 60 -1.500 (0.7443)

Treat_i x relative_time = 61 1.500 (0.7443)

Treat_i x relative_time = 62 1.000 (2.977)

Treat_i x relative_time = 63 2.000 (1.489)

Treat_i x relative_time = 64 -4.000 (4.466)

Treat_i x relative_time = 65 0.5000 (0.7443)

Treat_i x relative_time = 66 -0.5000 (2.233)

Treat_i x relative_time = 67 -1.500 (0.7443)

Treat_i x relative_time = 68 -2.500 (5.210)

Fixed-Effects: -----------------

league_fe Yes

time_fe Yes

_______________________________ __________________

S.E.: Clustered by: league_fe

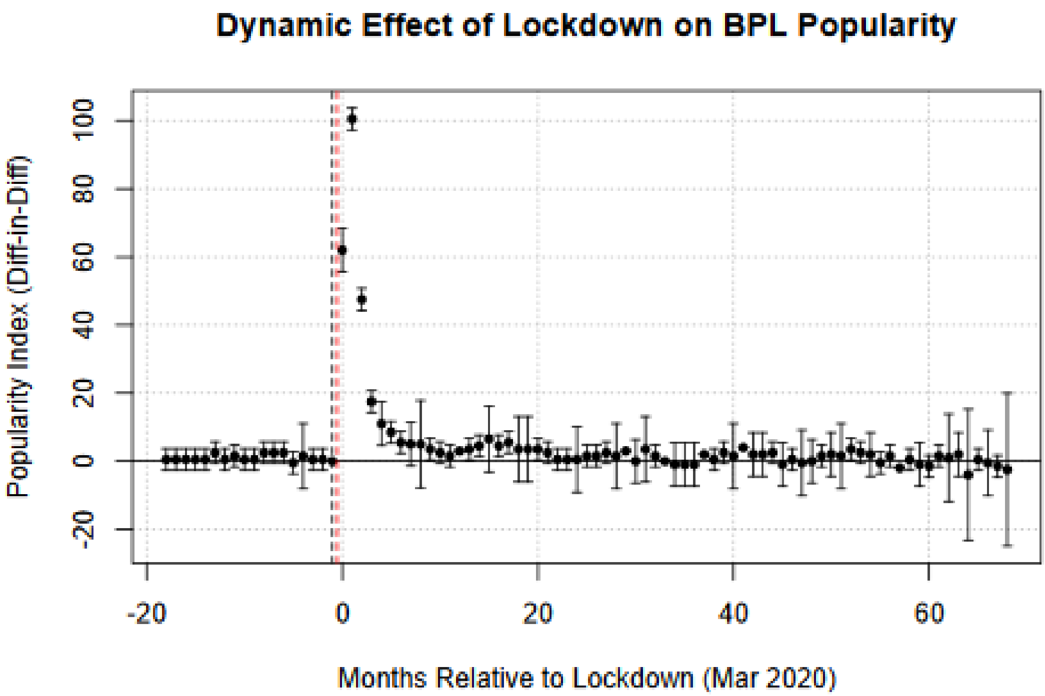
Observations 261

R2 0.99126

Within R2 0.98641

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Difference-in-Differences Plot:



Dynamic Effect of Lockdown on BPL Popularity
Popularity Index (Diff-in-Diff)
100
80
60
40
20
0
-20
-20
0
20
40
60
Months Relative to Lockdown (Mar 2020)