BELIEFS THAT ENTERTAIN

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SCIENCE/ECONOMICS OF LEISURE

Communal motivation for all the papers in this session:

Leisure is much understudied by economists, despite the fact that 1/5th of waking hours are spent consuming entertainment.

- Aguiar et al, 2012.

OUR RESEARCH QUESTION

- How does the player experience in video games lead to continued play?
- In a competitive game, players care whether they win or lose. This seems pretty obvious.
- Economic theory suggests that they may also care about their interim beliefs during the game.

WHY VIDEO GAMES?

- Big high-quality data.
- About 9% of all leisure time is spent "playing games and computer use".
  - American Time Use Survey, 2018
- The U.S. video game industry earned revenues of $180 billion in 2020 which is greater than the global movie and North American sports industries combined.
  - https://www.marketwatch.com/story/videogames-are-a-bigger-industry-than-sports-and-movies-combined-thanks-to-the-pandemic-11608654990

WHAT DO WE DO?

- We use a data set of 2.8 million matches of *League of Legends*.
  - One of the most popular PC games since release in 2009.
  - In 2021, 115 million monthly active players (players who play at least once per month), with a peak of 50 million concurrent players on a typical day.

- *League of Legends* is a 10-player, 2-team competitive computer game. Matches last about 30 minutes.

WHAT DO WE DO?

- Using 84 million minutes, we compute minute-to-minute predictions of which team wins.

- We then use these *belief-paths* to explain 28 million players' subsequent game engagements.

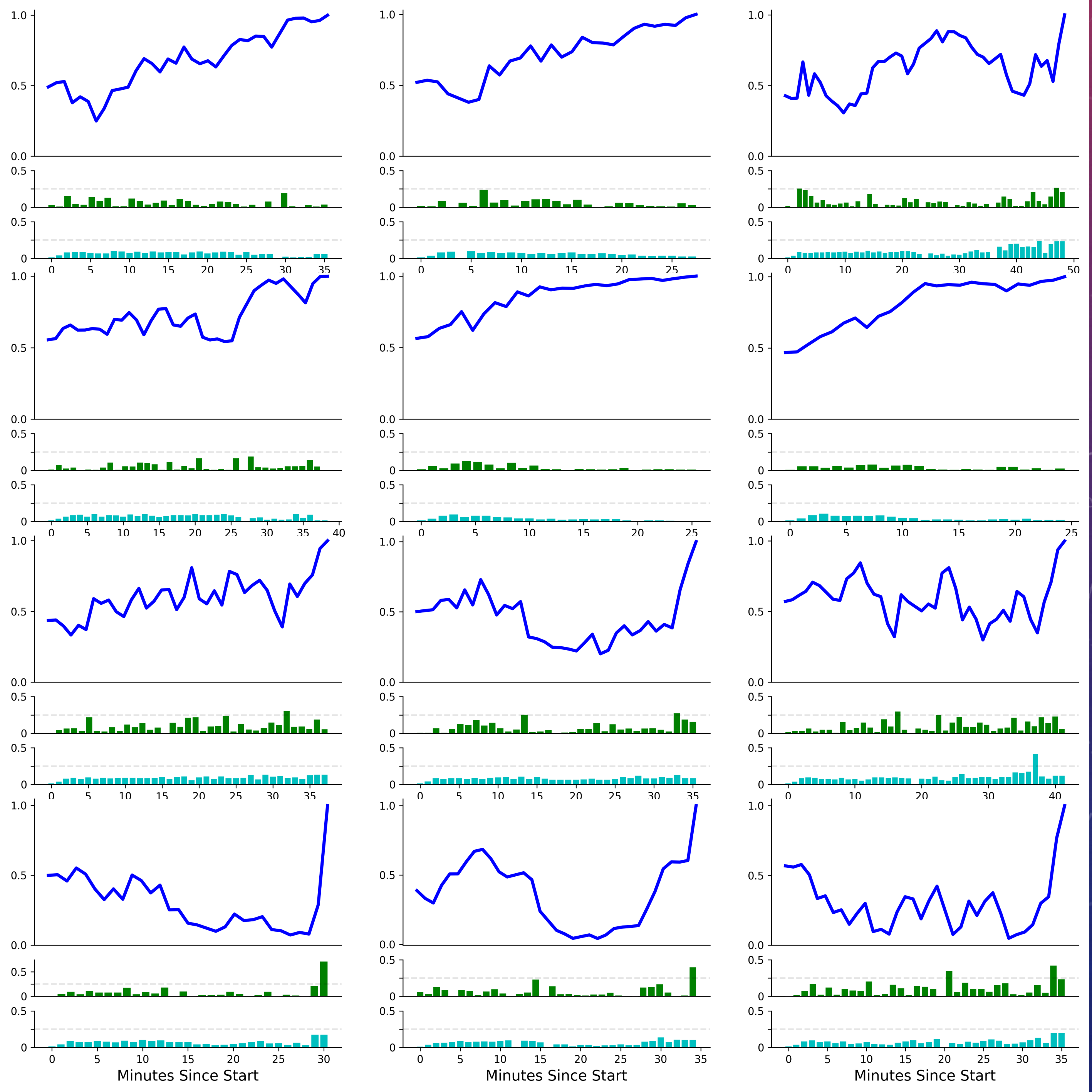
MATCH ANALYSIS

ESTIMATING THE PROBABILITY OF WINNING

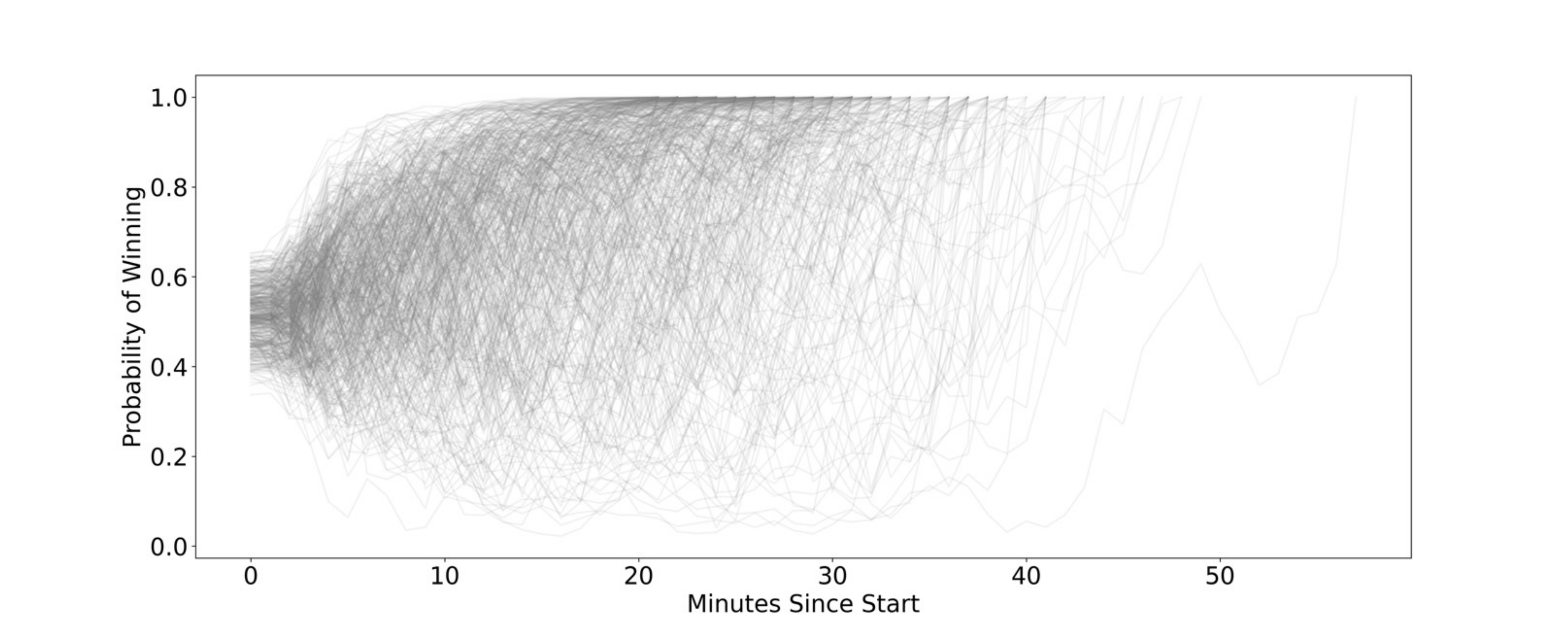
- We estimate p_t using gradient boosted trees (LightGBM), minimizing MSE.
- At each minute, we feed in 133 game-state variables.
- Predicted value is $\widehat{p_t}$.
- Surprise is defined as $|\ \widehat{p_t} - \widehat{p_{t-1}}\ |$
- Suspense is defined as $\mathrm{E}[|\ \widehat{p_{t+1}} - \widehat{p_t}\ |]$. This needs to be estimated. We run a second predictive model using gradient boosted trees (LightGBM), minimizing MSE, to estimate surprise as a function of game-state.
- Our predicted surprise is our measure of suspense.

SAMPLE MATCH PATHS

- $\widehat{p}_t$: blue line
- Surprise_t: green bars
- Suspense_t: blue bars



$\widehat{p_t}$ FOR 1,000 MATCHES (WINNERS ONLY)



EMPIRICAL STRATEGY

- Empirical strategy: regress “continued play in the next 60 minutes” on attributes of the belief path, $\{\widehat{p_t}\}_{t=0}^{T}$.
- Critically, players are randomly assigned to matches!

EMPIRICAL STRATEGY

Theory: ***Anticipatory utility*** predicts that players want to have high expectations of victory.

- Loewenstein (1987), Caplin and Leahy (2001)

Main variables of interest: **Avg** $\widehat{\boldsymbol{p}}_{\boldsymbol{t}}$

EMPIRICAL STRATEGY

Theory: ***Reference-dependent utility*** predicts that players want to have low expectations of victory to keep the reference point low.

- Kahneman and Tversky (1979), Koszegi and Rabin (2006)

Loss aversion: effect should be bigger for losers

Main variables of interest: **Avg** $\widehat{p_t}$

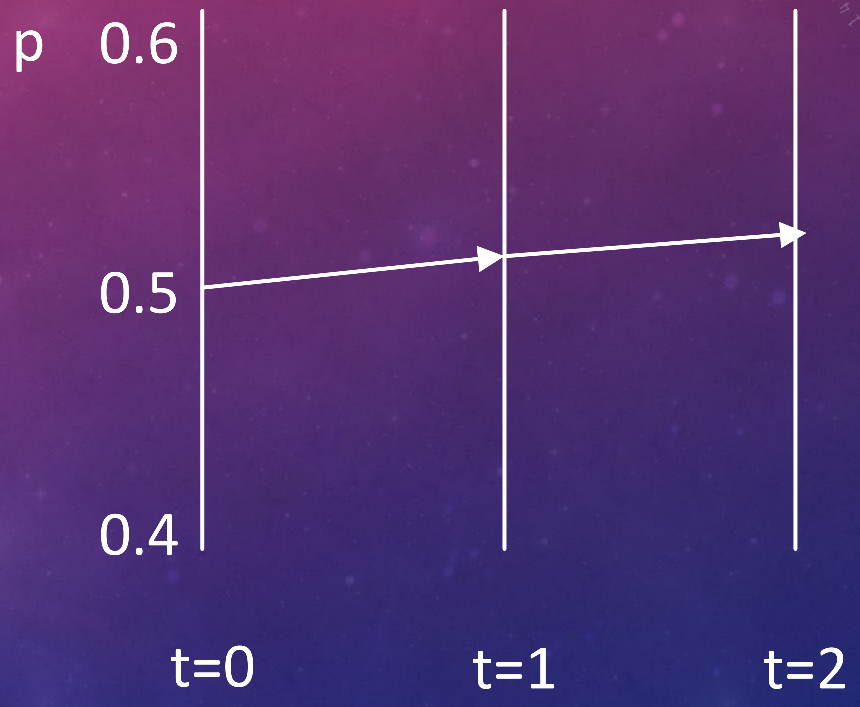
EMPIRICAL STRATEGY

Theory: People may have preferences for ***suspense and surprise***

- Ely, Frankel, and Kamenica (2015)

Main variables of interest:
Avg Surprise, Avg Suspense

Low surprise at t=2



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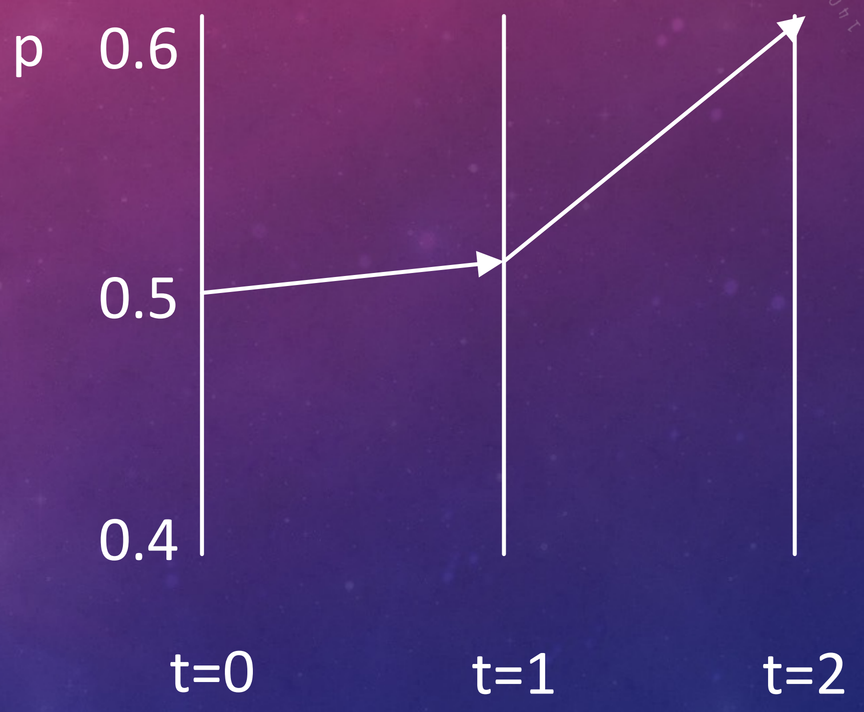
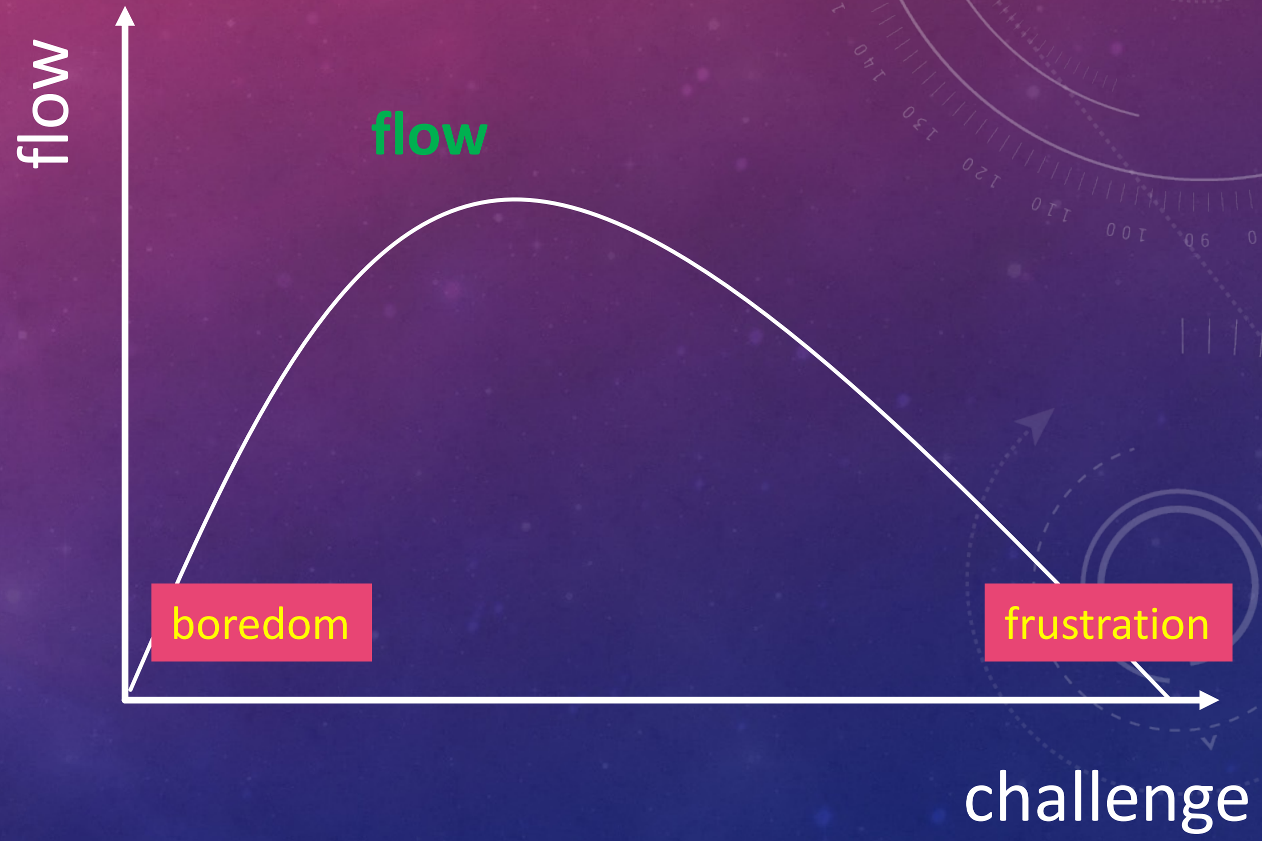


EMPIRICAL STRATEGY

Main variable of interest: $\widehat{p_0}$

A state of *flow* is characterized by intense concentration on the present moment, a merging of action and awareness, a loss of self-awareness, a distortion of the sense of time, and intrinsic reward.

- Nakamura and Csikszentmihalyi (2009)



MAIN REGRESSION

- Outcome = Continued Play
- Lower average $\hat{p}_t$ leads to more engagement.
    - Consistent with reference-dependence but not anticipatory utility.
    - Loss aversion: effect is bigger for losers than for winners.

	Losers			Winners		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{p}$ Average†	-7.693***	-9.272***	-9.563***	-5.131***	-4.891***	-5.256***
	(0.134)	(0.209)	(0.206)	(0.136)	(0.211)	(0.208)
Surprise Average†		-13.71***	-14.18***		0.433	0.0903
		(1.785)	(1.726)		(1.802)	(1.743)
Suspense Average†		30.45***	30.56***		2.082	1.049
		(2.243)	(2.174)		(2.264)	(2.195)
$\hat{p}$_0			10.23*			28.39***
			(3.034)			(3.208)
$\hat{p}$_0^2			-5.768			-24.70***
			(3.089)			(3.124)
Peak $\hat{p}$_0			.887			.575
Mean of DV	58.753	58.753	58.753	59.678	59.678	59.678
SD of DV	49.2	49.2	49.2	49.1	49.1	49.1
R2	.0132	.0132	.0132	.0124	.0124	.0124
Clusters	2756558	2756555	2752074	2756356	2756355	2751870
N	1.38e+07	1.38e+07	1.38e+07	1.38e+07	1.38e+07	1.38e+07

$^{*}\ p < 1e-2$, $^{**}\ p < 1e-4$, $^{***}\ p < 1e-6$

MAIN REGRESSION

- Surprise and suspense only matters for losers.
- Every unit of surprise is a unit of suspense in expectation.
- On net, surprise-suspense has a positive effect overall.

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	(1)	(2)	(3)	(4)	(5)	(6)
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MAIN REGRESSION

- Finally, $\widehat{p_0}$ has not much effect on losers but significant effects on winners.
- Winners have single-peaked $\widehat{p_0}$ that peaks at $\widehat{p_0} = 0.575$.
- Implies that winners enjoy games that were slightly less challenging than even.

	Losers			Winners		
	(1)	(2)	(3)	(4)	(5)	(6)
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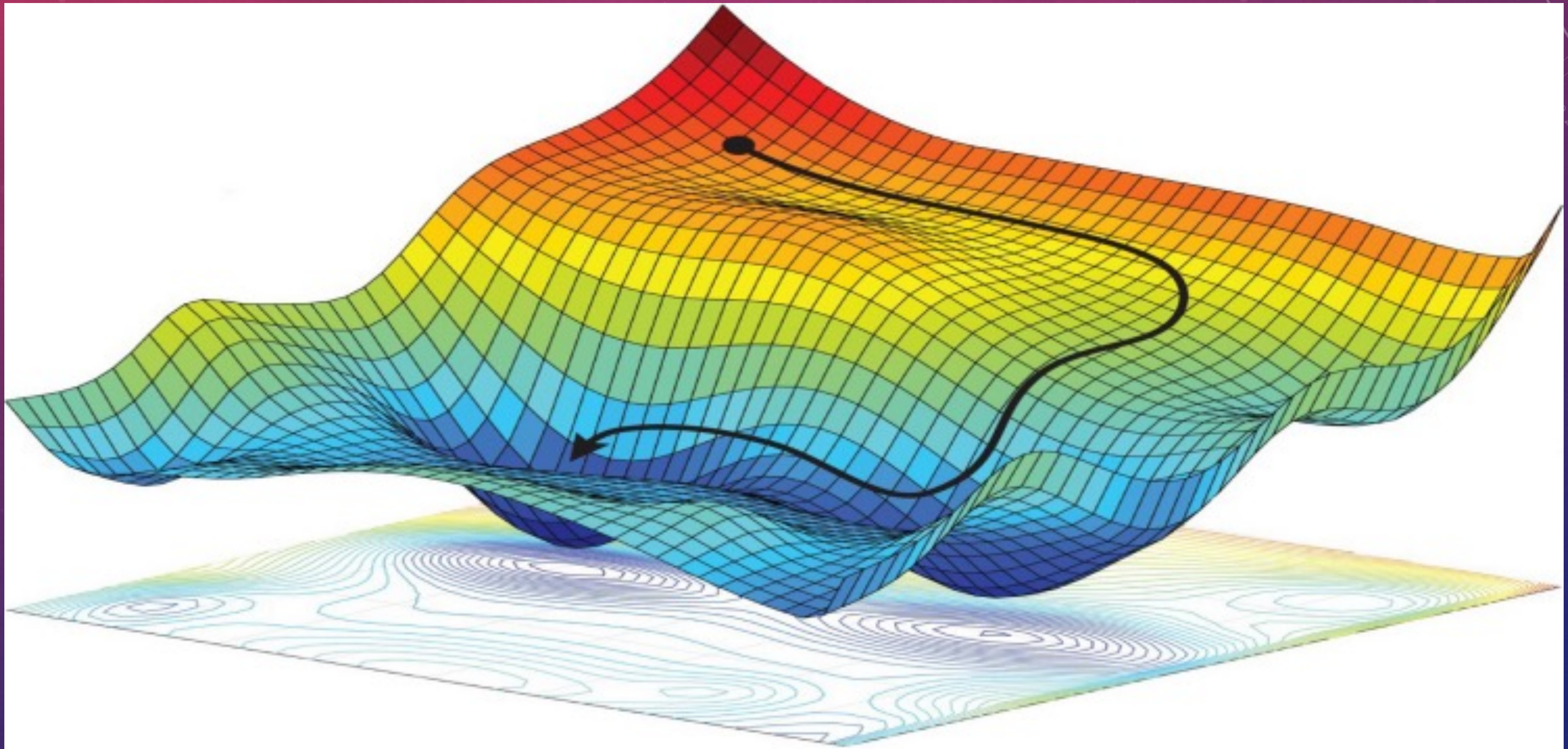
GAME OPTIMIZATION



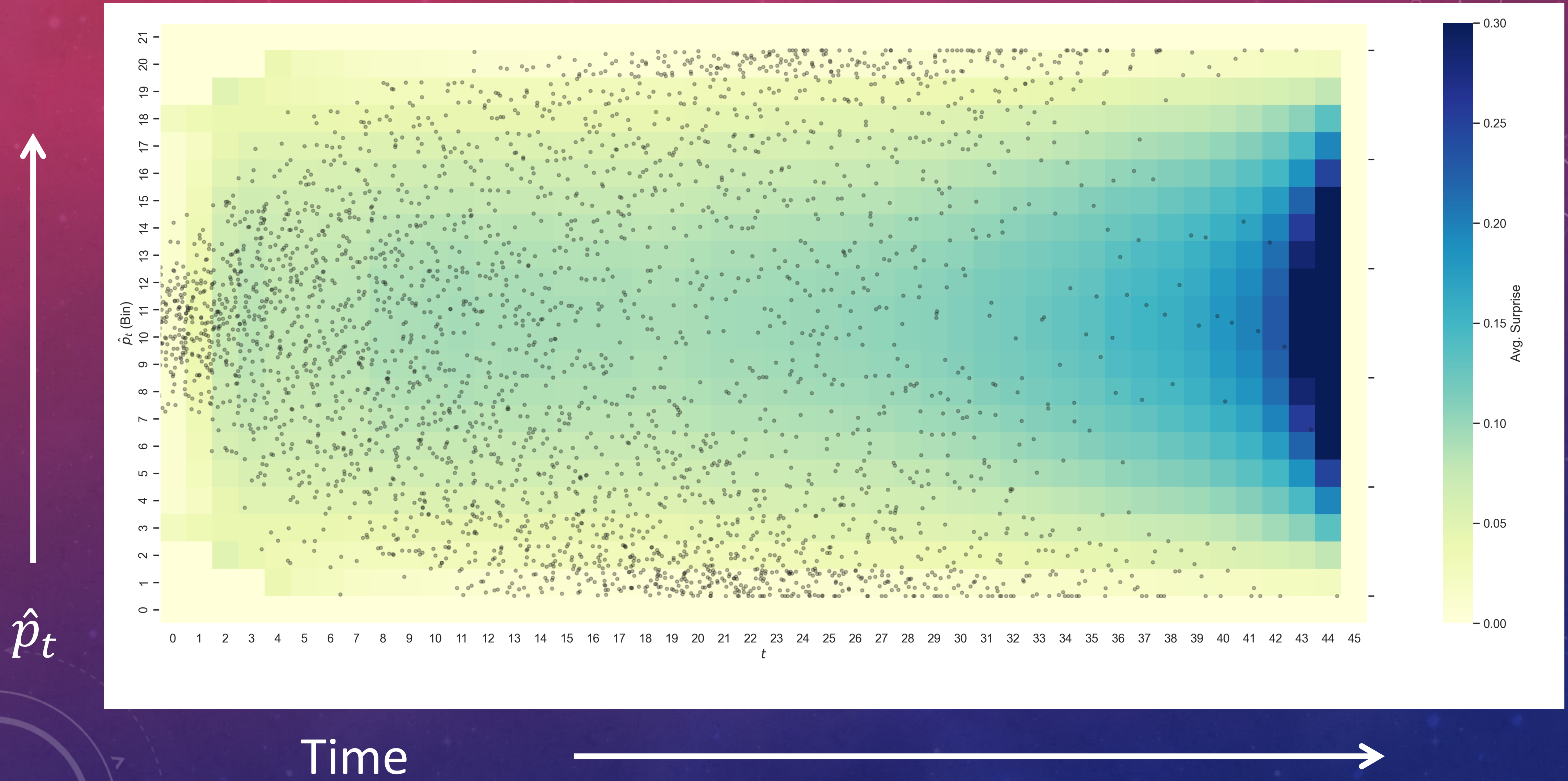
GAME OPTIMIZATION

- This leads to the deeper question, what is the optimal version of the game *League of Legends?*
- The game, which we will refer to as G, is a data-generating process that creates belief-paths of p_t and $susp_t$. What is the optimal G?
- We discretize the probability of victory (we use 20 interior bins).
- We can think of the transition probability of going from probability-bin *i* to probability-bin *j* at minute *t*, as being described by a matrix M_t.
- Define G as an initial distribution for p_0 and a sequence of matrices M_t :

$$G = \{F(p_0), \{M_t\}_{t=0}^{T=44}\}$$

G_0, UNALTERED LEAGUE OF LEGENDS

More blue = more average surprise in that cell

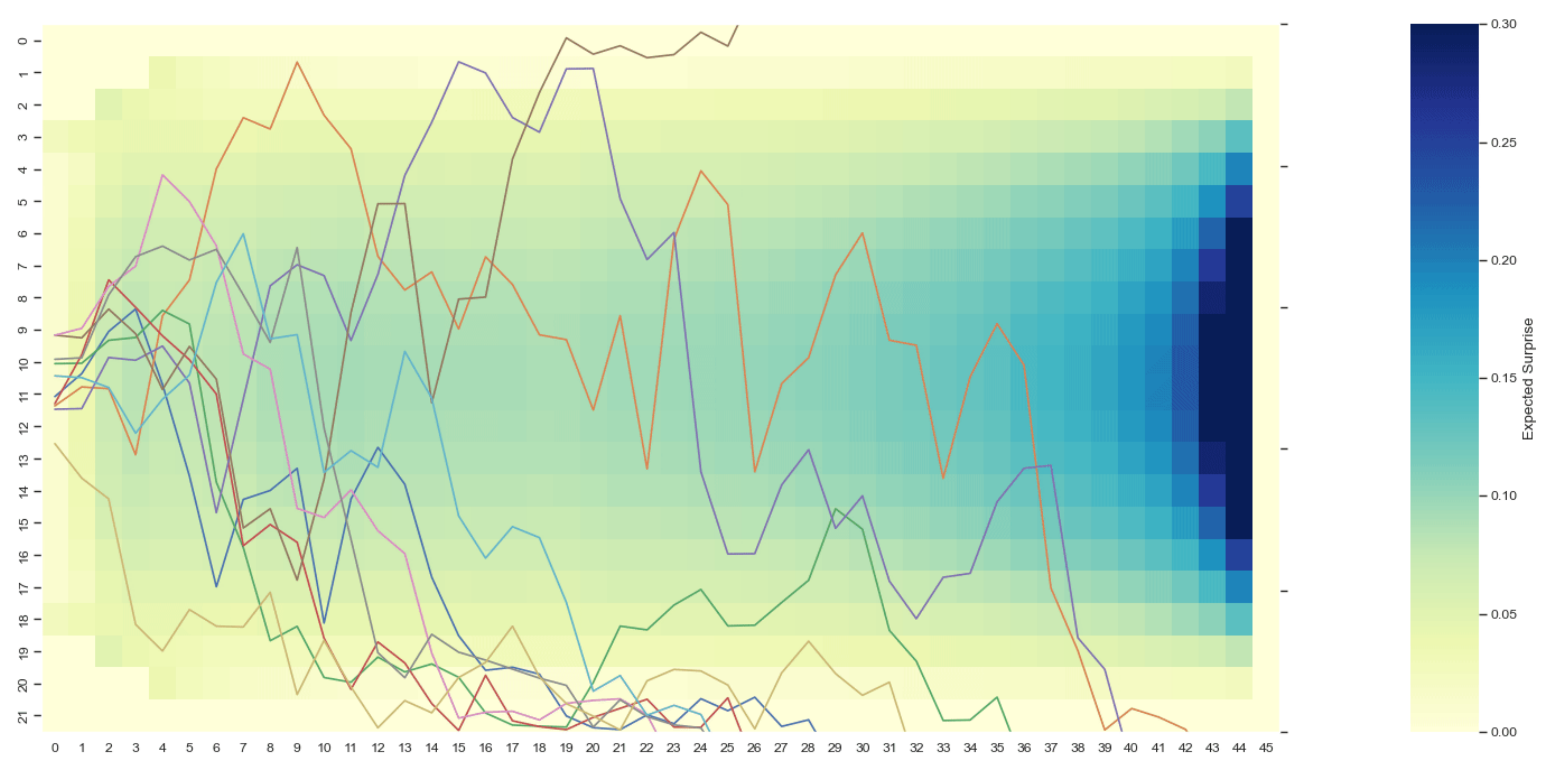


GAME OPTIMIZATION

- We want to optimize the information structure of the game for continued play.
- We use an evolutionary algorithm to find locally optimal mutants of *League of Legends.*
- Why evolution instead of convex optimization?
  - Our objective function is machine-learned continue play from the full vector of the *belief- and suspense-paths.* Convex?!
  - *G* is high-dimensional (about 1000 choice variables).
- We use *high-dimensional evolutionary algorithm* to optimize the information structure.

EVOLVING TO THE OPTIMAL GAME

More blue = more average surprise in that cell

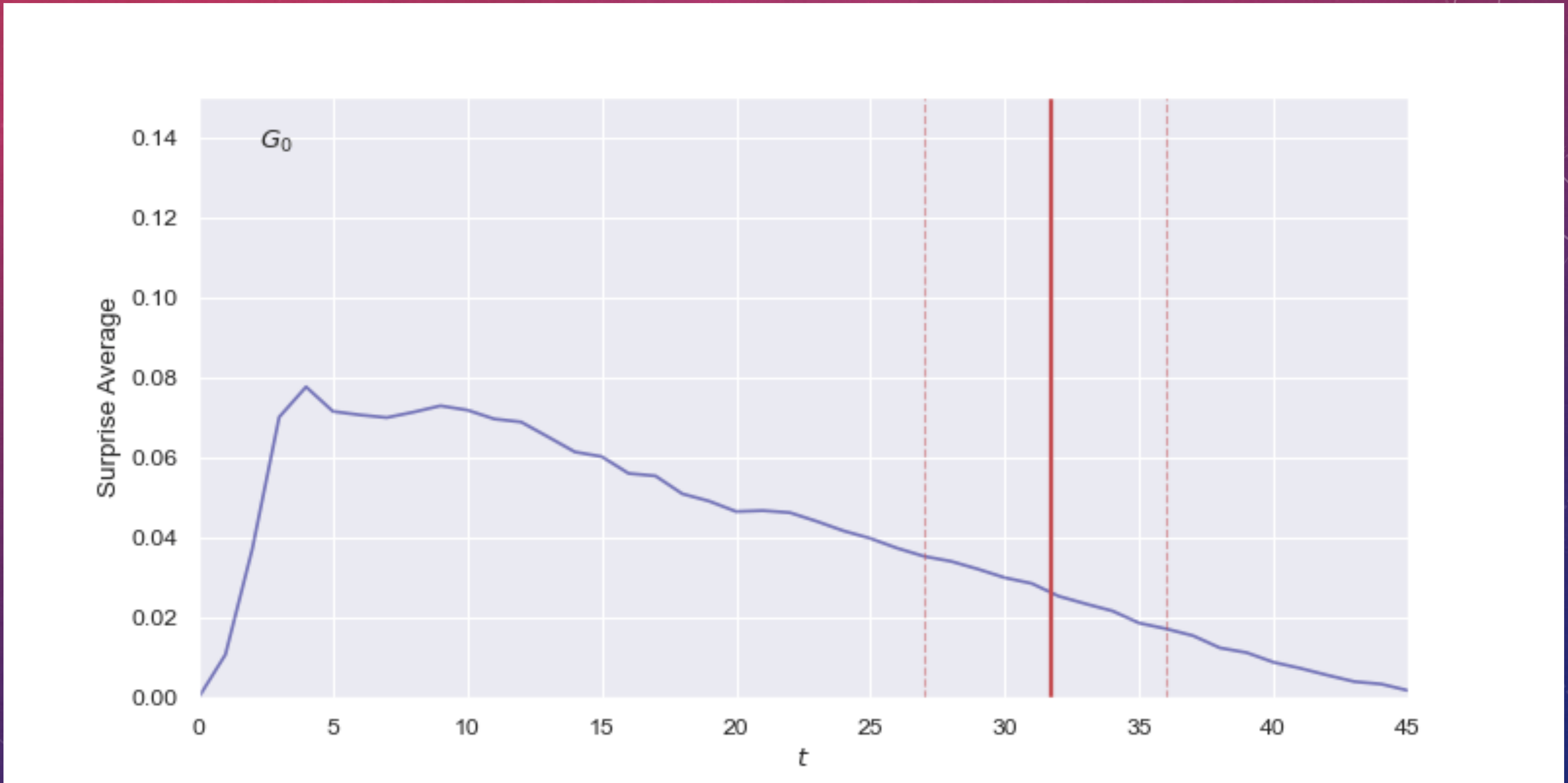


$\hat{p}_t$

Time

EVOLUTION OF AVERAGE SURPRISE

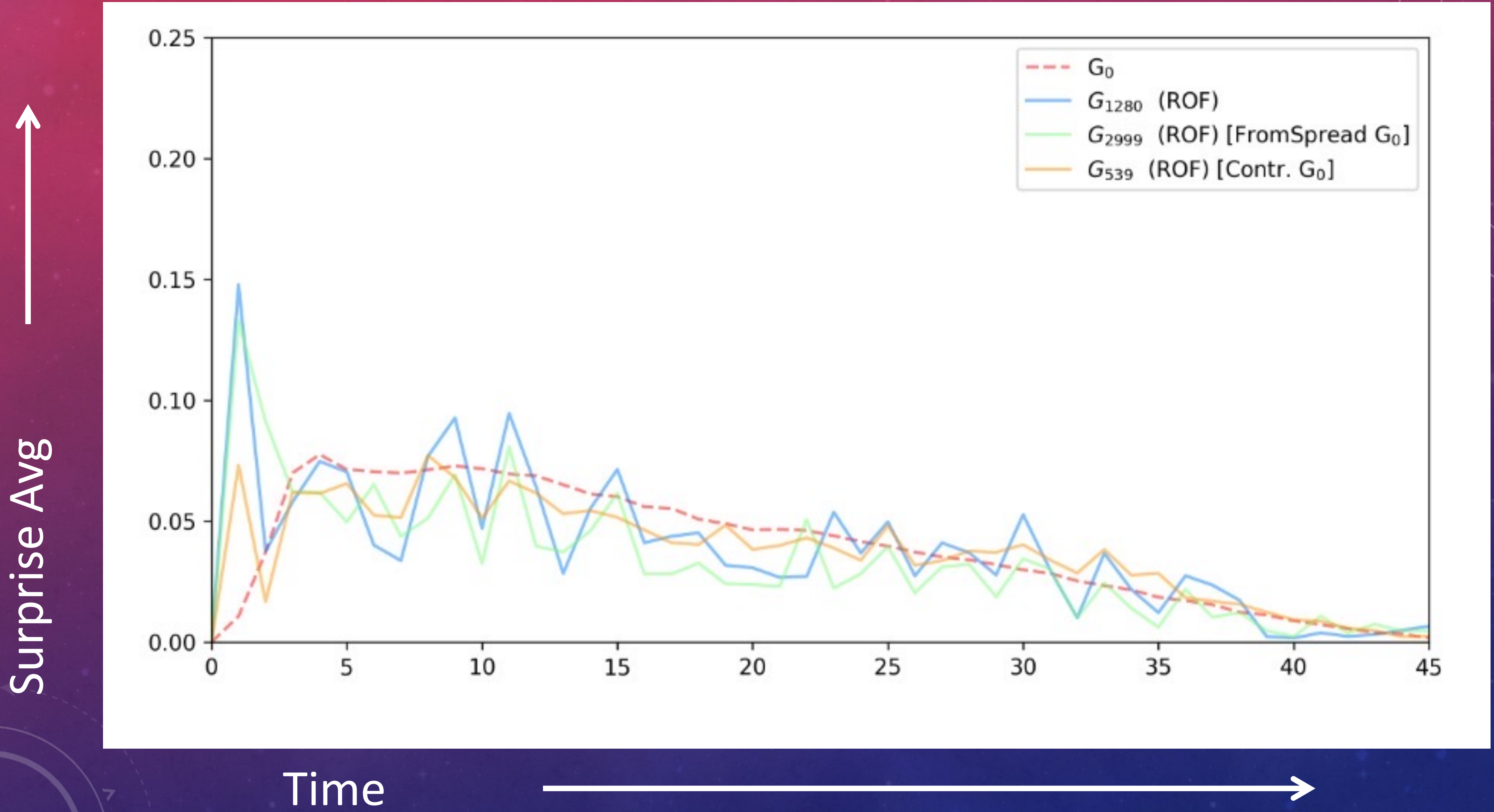
Unconditional average surprise over time



Surprise Avg

Time

GAME OPTIMIZATION



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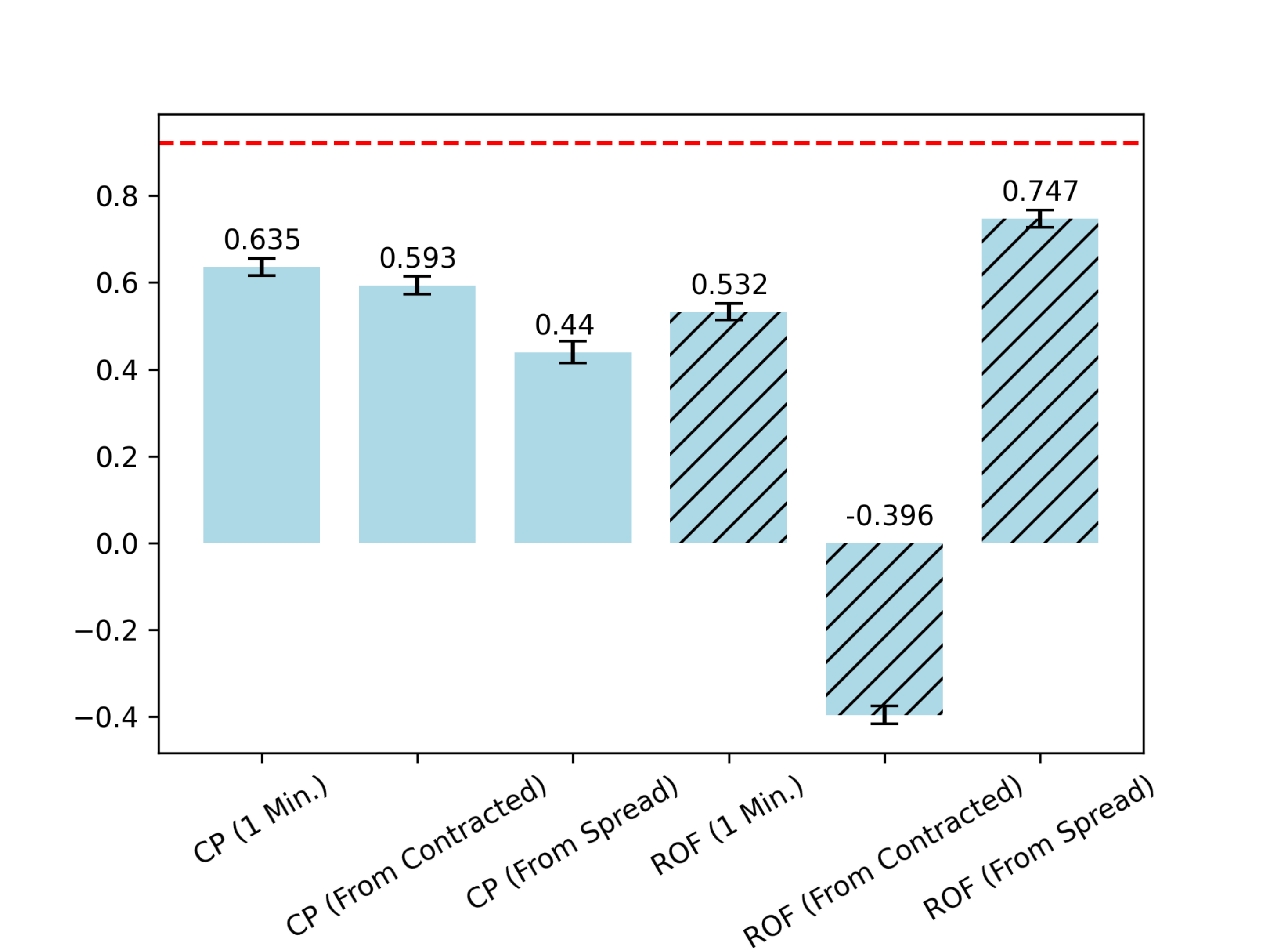

- Dotted red line indicates the win effect.
- Our optimized game increases engagement. We can't make everyone a winner but we can make it as if everyone received an additional 81% of a win.

CONCLUSION

- Beliefs entertain!
- Lagging behind increases engagement. The effect is bigger for losers than winners (loss aversion).
- Surprise bad, suspense good.
- Evolutionary game-optimization reveals *League of Legends* is close to optimal, but should reveal more information in the first 1-2 minutes.
- The small tweaks have sizable effects. They can increase continued play equal to 81% of the win-effect.

PAPER COMING SOON

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