July 2024

Productive Creators:

A New Studio Indicator

The Role of Indicators

What is a good indicator?

- Strong causal driver of business outcomes.
- Movable— connected to creator behaviours that can be nurtured.
- Predictable.
- Easy to build.
- Easy to communicate.

Studio Indicators

Indicator	Source Data	Size ¹	Definition	Concern	
Total Creators	Time Spent	9.4M	Total users who downloaded Studio.	Too Broad	
Active (L28)	Time Spent	3.7M	No. of users with time spent > 0.	Not quality adjusted.	
Time Spent (L28)	Time Spent	392K Hours	Time spent by anyone with an active studio session.	Not quality adjusted.	
New User Retention (L7)	Time Spent	60%	% active in current period, over those active in current & past.	Not quality adjusted.	
Funnel (Playtime): Inactive, Active, Core, Top	Time Spent + Playtime	5.7M, 3.6M, 50K, 2.3K	Number of active creators with 0, 0-100, 100-100K, 100K+ amount of playtime in hours.	Is actually an outcomeNot an intrinsic behaviourDoes not rule out luck	
Productive Creators (L28)	Time Spent + Collaboration + Publishing +Tenure	0.42M	(Long Tenure OR Recently Engaged) AND (Collaborating OR Publishing)	Complex, involves multiple serie and thresholds.	

Productive Creators: Definition

Only <10% of active creators also productive.

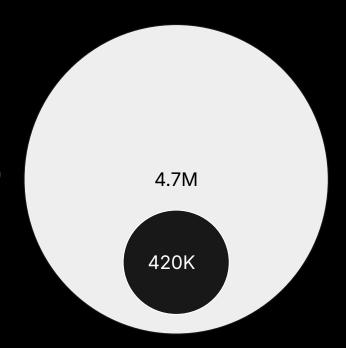
Productivity:

(1000H Tenure OR Active L28>4)

AND

(Collaboration L28 >=1 OR Team Publishing>3)

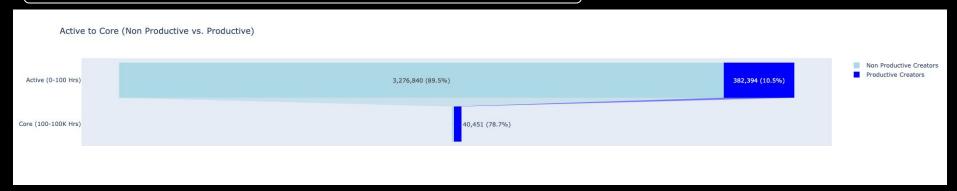
"Quantity of Time x Quality of Time"

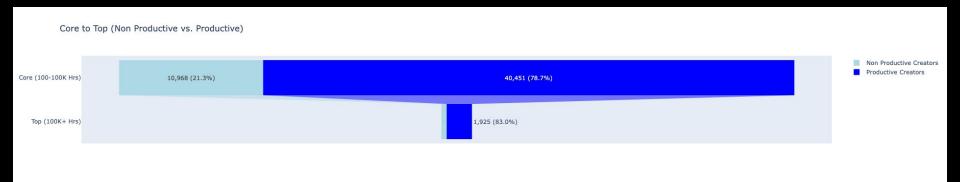


Productive in Active (L28) in 2024-07-01

Funnel

About ~80% of current top and core creators are productive.





Studio Eng → Productivity → Playtime

Platform Level Correlations

Y: Agg. Playtime WoW Growth X: Agg. Indicator WoW Growth Period: 2022-10 to 2024-07

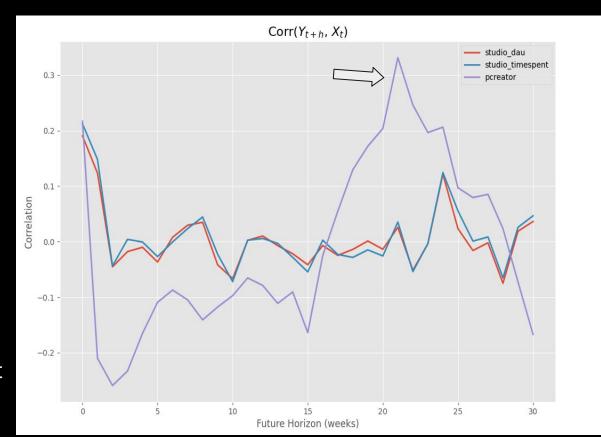
Productive Creators correlated to *future* playtime.

Problems:

- $Y(t-1), X(t-1) \rightarrow Y(t+h)$
- $Y(t-1), X(t-1) \rightarrow X(t)$
- How far back?

Solution:

Control for as many lags without overfitting.



Platform Level VAR

Vector AutoRegression:

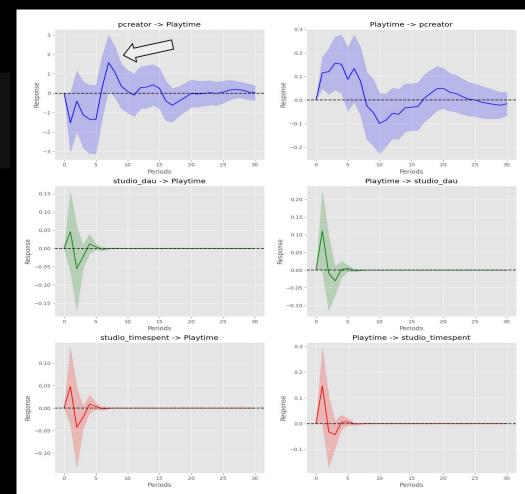
$$Y_t = \alpha^Y + \sum_r \beta_r^Y Y_{t-r} + \sum_r \tau_r^Y X_{t-r} + \epsilon_t^Y$$

$$X_t = \alpha^X + \sum_r \beta_r^X X_{t-r} + \sum_r \tau_r^Y Y_{t-r} + \epsilon_t^X$$

A 1 pp jump in productivity growth leads to a 1.5 pp jump in playtime growth in 8 weeks.

Indicator	Lag Order Chosen		
DAU	2		
Time Spent	1		
Productive	9		

Impulse Responses



Tests of Predictability

- Granger Causality Test: Can series X predict future values of series Y?
 - Null Hypothesis: All Taus are 0.

$$Y_t = \alpha^Y + \sum_r \beta_r^Y Y_{t-r} + \sum_r \tau_r^Y X_{t-r} + \epsilon_t^Y$$

$$X_t = \alpha^X + \sum_r \beta_r^X X_{t-r} + \sum_r \tau_r^Y Y_{t-r} + \epsilon_t^X$$

Indicator	Indicator → Playtime (P-Value)	Playtime → Indicator (P-Value)		
DAU	0.282	0.1350		
Time Spent	0.177	0.1304		
Productive	0.044	0.001		

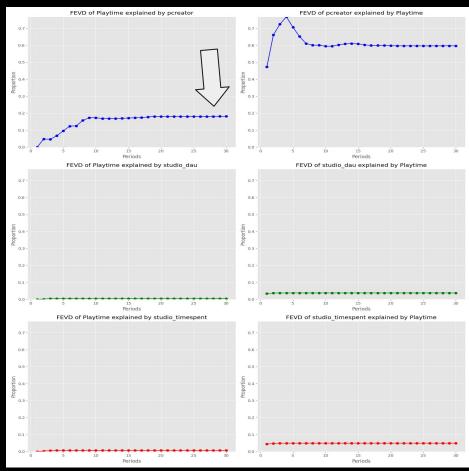
Only playtime and productivity predict each other.

Forecast Error Variance Decomposition

How much one series is explained by shocks to the other series?

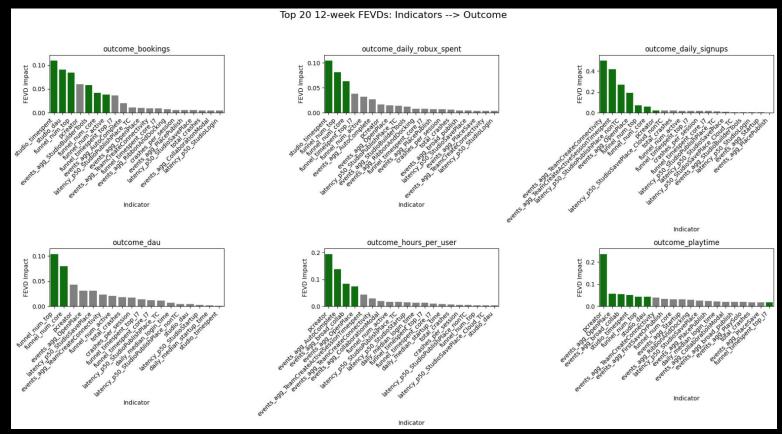
Productivity growth explains 20% of future playtime growth.

Playtime growth explains 60% of productivity growth.



RUBLOX Full set of results: here.

Extended Variance Decomposition

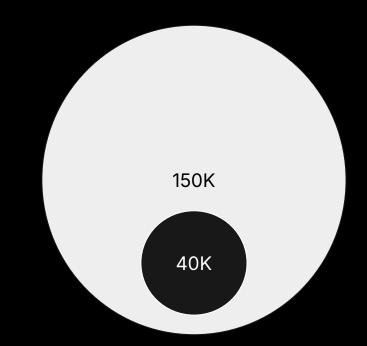


What if a creator was productive for a long time?

How much does it matter compared to mere activity?

Consistently Productive: Being a Productive Creator on the first date of every month, for 9 months.

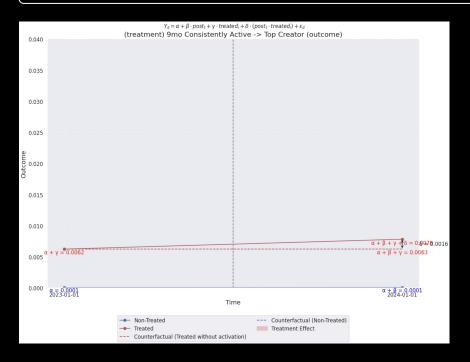
Consistently Active: Being a Active L28 at least once on first date of every month, for 9 months.

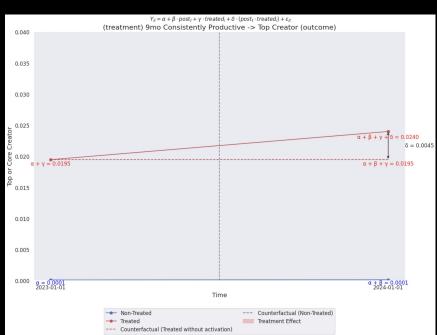


Consistently Productive vs Active between 2023-02 to 2023-10 (9 months).

Outcome: Prob(Top Creator in Future)

The impact of being "productive" on Prob(Top in Future) is ~280% more than simply being active.

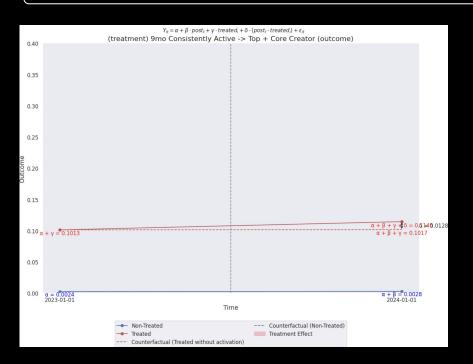


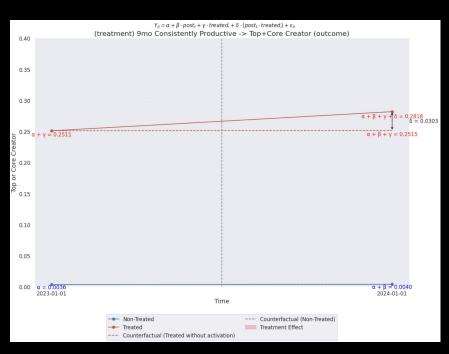


Consistent productivity/activity captured at end of each month from 2023-02 to 2023-10. For outcomes, Pre Period: 2023-01 and Post Period: 2024-01.

Outcome: Prob(Top or Core Creator in Future)

The impact of being "productive" on Prob(Top or Core in Future) is ~240% more than simply being active.

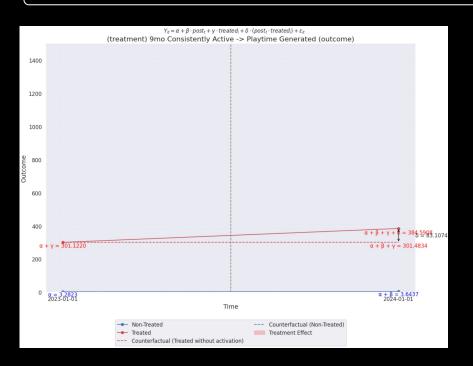


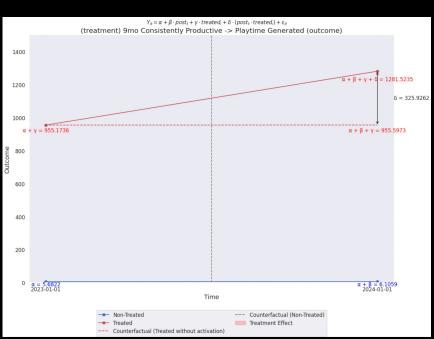


Consistent productivity/activity captured at end of each month from 2023-02 to 2023-10. For outcomes, Pre Period: 2023-01 and Post Period: 2024-01.

Active/Productive → **Playtime Generated in Future**

The impact of being "productive" on Playtime Generated is ~400% more than simply being active.





Consistent productivity/activity captured at end of each month from 2023-02 to 2023-10. For outcomes, Pre Period: 2023-01 and Post Period: 2024-01.

Lift

1.5 pp Lift to Playtime Growth (Weekly) 35% Lift to Playtime Generated (Annual)

1% pp inc in Productive Creators

Creator is Consistently Productive

Studio Eng → Productivity → Playtime

Onboarding Tutorial → Productivity

Pos stat sig impact of new studio tutorial on productivity of new creators.



Estimand	Model	Equations	Estimate (b)	Std. Error	t-value	p-value
ATE for Enrollment	Bivariate OLS	Y = a + b*Z + e	0.0007	0.0003	2.5536	0.0107
ATE for Enrollment	Multivariate OLS	Y = a + b*Z + c*D + e	0.0007	0.0003	2.4406	0.0147
ATE for Enrollment	DML	Y = b*Z + g(X) + e	0.0007	0.0003	2.386	0.017
ATE for Enrollment	DML (Interactive)	Y = g(Z,X) + e	0.0007	0.0003	2.5536	0.0107
LATE for Compliance	Bivariate IV	Y = a + b*T + e T = c + d*Z + u	0.0025	0.001	2.5545	0.0106
LATE for Compliance	Multivariate IV	Y = a + b*T + c*X + e T = e + f*Z + g*X + u	0.0024	0.001	2.477	0.0132
LATE for Compliance	DML IV	Y = b*T + g(X) + e T = m(Z,X) + u	0.0023	0.001	2.3701	0.0178
LATE for Compliance	DML IV (Interactive)	Y = g(T,X) + e $T = m(Z,X) + u$	0.0033	0.001	3.2118	0.0013

Y:Productive/Not, T:Compliance, Z:Enrollment, X: Covariates. N=1.4 million, First stage: AUC of T on Z is 0.8, on T+X is 0.85. Enrollment rate 50%, compliance rate 14%. Launch date: 08-2023 for 25 days. Eligibility is joining 1 month prior to experiment.

CATE

Stat sig CATE:

- In 15 year olds
- Early enrollers
- With 2-4 universes.
- 0-50m Time Spent

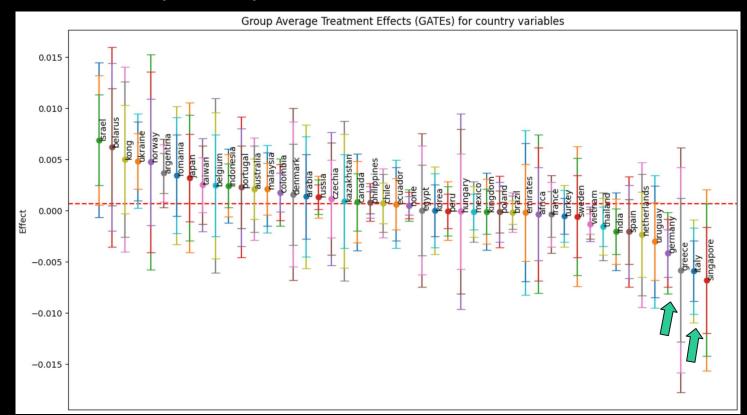
CATEs for attr roblox tenure years CATEs for attr_age_year CATEs for attr dac content gameasset 0.0035 0.001 -0.0020.0005 attr_roblox_tenure_years attr_dac_content_gameasset CATEs for attr universe count CATEs for attr_studio_timespent_I28 CATEs for attr_days_since_xp_start 0.002 0.02 0.000 0.01 -0.001 -0.002 attr universe count

Method: DML-IRM

GATE

ROBLOX

Tutorial failed to work in Italy, Germany.



Code Assist (GPT) → Productivity

No stat sig impact of code assist (GPT) on productivity of scripters.



Estimand	Model	Equations	Estimate (b)	Std. Error	t-value	p-value
ATE for Enrollment	Bivariate OLS	Y = a + b*Z + e	0.0058	0.0048	1.1902	0.234
ATE for Enrollment	Multivariate OLS	Y = a + b*Z +c*D + e	0.0047	0.0045	1.0403	0.2982
ATE for Enrollment	DML	Y = b*Z + g(X) + e	0.0056	0.0042	1.3322	0.1828
ATE for Enrollment	DML (Interactive)	Y = g(Z,X) + e	0.0063	0.0043	1.4663	0.1426
LATE for Compliance	Bivariate IV	Y = a + b*T + e T = c + d*Z + u	1.1459	1.1216	1.0217	0.3069
LATE for Compliance	Multivariate IV	Y = a + b*T + c*X + e T = e + f*Z + g*X + u	1.004	1.1216	0.8952	0.3707
LATE for Compliance	DML IV	Y = b*T + g(X) + e T = m(Z,X) + u	1.4453	1.4521	0.9953	0.3196
LATE for Compliance	DML IV (Interactive)	Y = g(T,X) + e $T = m(Z,X) + u$	1.3256	1.2582	1.0536	0.2921

Y: Productive/Not, T: Compliance, Z: Enrollment, X: Covariates. N=85k; Feb 2024 A/B Test: Control: 20%, GPT: 40%, CodeLlama: 40%. Weak instrument problem.

Code Assist (CodeLlama) → Productivity

No stat sig impact of code assist (CodeLlama) on productivity of scripters.



Estimand	Model	Equations	Estimate (b)	Std. Error	t-value	p-value
ATE for Enrollment	Bivariate OLS	Y = a + b*Z + e	0.0005	0.0048	0.104	0.9172
ATE for Enrollment	Multivariate OLS	Y = a + b*Z + c*D + e	0.0000	0.0045	-0.0087	0.993
ATE for Enrollment	DML	Y = b*Z + g(X) + e	-0.0003	0.0042	-0.0771	0.9386
ATE for Enrollment	DML (Interactive)	Y = g(Z,X) + e	-0.0004	0.0043	-0.0924	0.9264
LATE for Compliance	Bivariate IV	Y = a + b*T + e T = c + d*Z + u	0.1019	0.976	0.1044	0.9168
LATE for Compliance	Multivariate IV	Y = a + b*T + c*X + e T = e + f*Z + g*X + u	-0.0085	0.9732	-0.0087	0.993
LATE for Compliance	DML IV	Y = b*T + g(X) + e T = m(Z,X) + u	-0.0605	0.9155	-0.066	0.9473
LATE for Compliance	DML IV (Interactive)	Y = g(T,X) + e $T = m(Z,X) + u$	-0.0667	0.9183	-0.0727	0.9421

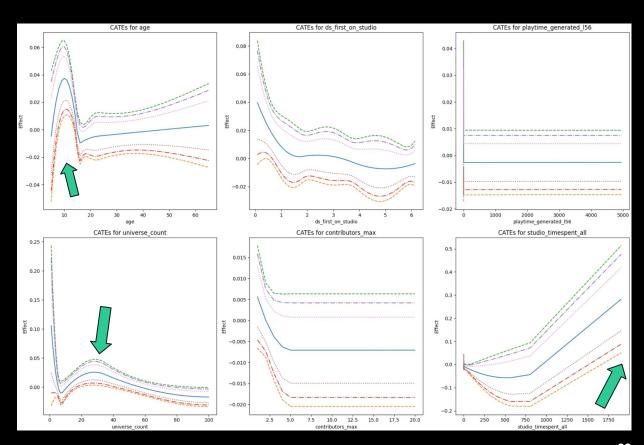
Y: Productive/Not, T: Compliance, Z: Enrollment, X: Covariates. N=85k; Feb 2024 A/B Test: Control: 20%, GPT: 40%, CodeLlama: 40%. Weak instrument problem.

CodeLlama: CATE

Stat sig CATE:

- 10 year olds
- 0-50 minutes spent on studio
- 20-60 universes.

Method: DML-IRM

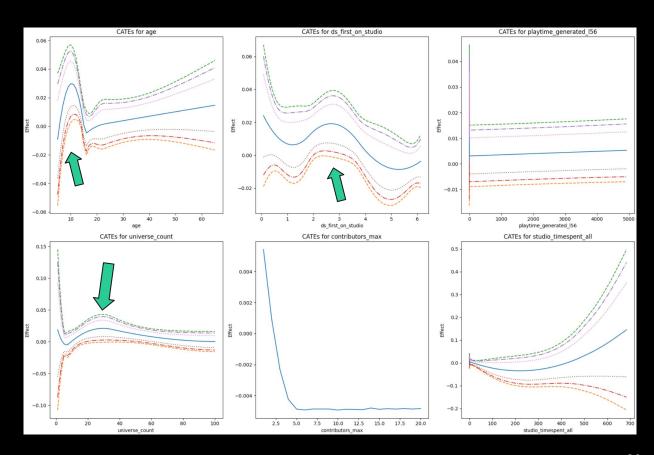


GPT: CATE

Pos stat sig:

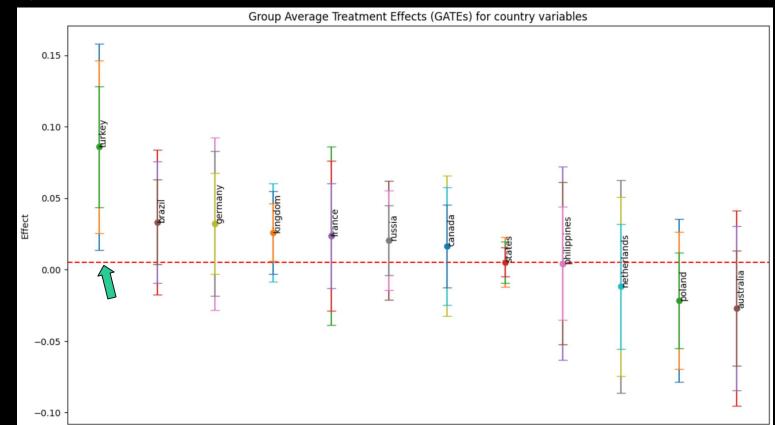
- 10 year olds
- 2-3 year tenure
- 25-50 universes

Method: DML-IRM

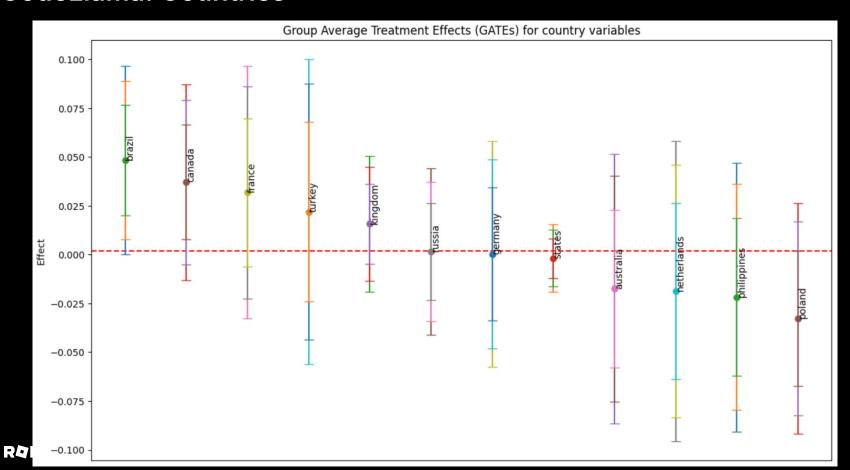


GPT: Countries

Pos stat sig impact in Turkey.

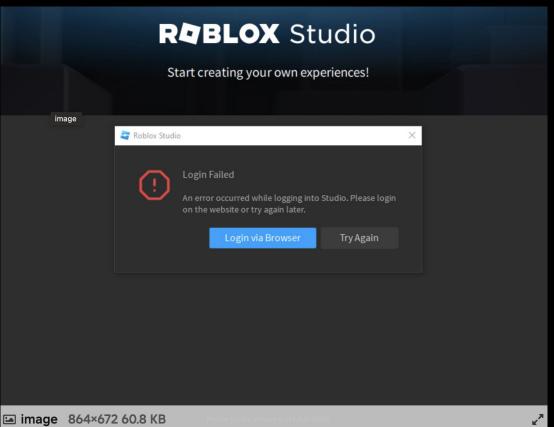


CodeLlama: Countries



Mac Bug Fixing

In April large number of Mac users began to face serious issues at login.



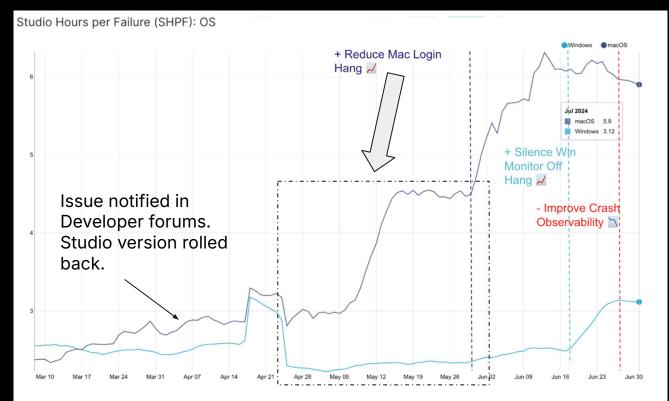
Mac Bug Fixing: Studio Hours Per Failure

Focused bug fixing in mid-May led to approx 30% inc in the SHPF for Mac users.

Context: Engineers confirmed that no major update went out to Windows in May, and that this fix would majorly benefit Mac users, esp. who had not logged in for a long time.

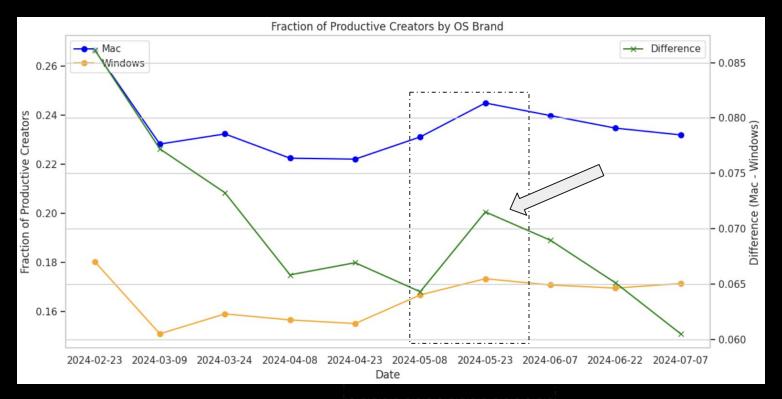
Dev forum link.

Git commit link.



Natural Experiment: Mac Bug Fixing

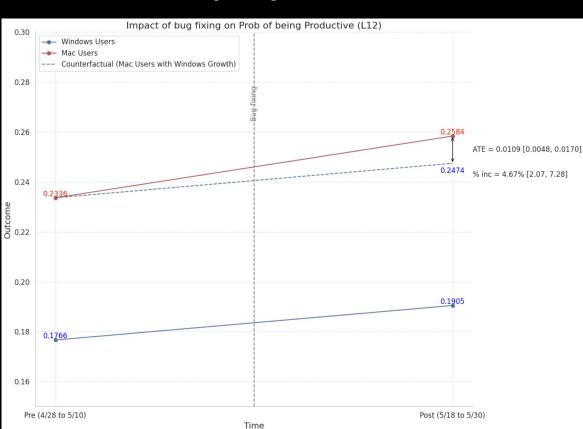
Declining Mac/window differences in productivity:



Mac Bug Fixing: Instrumented Diff-in-Diff

A 5% stat sig increase in productivity in mac users, due to bug-fixing.

Thus a 10% increase in SHPF is associated with a 2% increase in Productivity in Mac users.



Suggested Enhancements

- Improvements:
 - Productivity not predictive of Bookings!
 - Thresholds could change over time or by genre.
- Linking productivity to creator milestones/movement through funnel.
- Measuring creator industriousness code quality, efficiency, consistency, etc.
- Break up by actions (script, build, design, test, maintain, etc.)

Side Projects

- Observational studies of Gen Al Rollouts:
 - Material Gen, Texture Gen, Chat Assistant
- New techniques / designs:
 - Double ML + Diff in Diff
 - Genre Level Panel VAR
- Offline Evaluation for Reinforcement Learning Based Price Optimization
 - Bandits with Kalman Filter + Upper confidence bound