

What Makes Players Pay?

An Empirical Investigation of In-Game Lotteries

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Lotteries in Video Games: Loot Boxes

- ▶ An in-game (virtual) item that a user can purchase to receive a *randomized* reward
- ▶ Different from other randomness in video games
 - ▶ Purchasable
 - ▶ A stand-alone choice
- ▶ A prominent source of revenue for video games. In 2020:
 - ▶ Global revenue of \$15B (~10% of the gaming industry)
 - ▶ Used in ~58% of highest-grossing iPhone/Android mobile games

Loot Boxes Example: FIFA Ultimate Team Mode



Two Views on Loot Boxes

1. Enhance **gaming** experience

- ▶ Voluntary and useful in the game, complements the gameplay
- ▶ Another strategic dimension in the “game of skill”
- ▶ “Reflects the real-world excitement and strategy of building and managing a squad” (EA CEO re: Ultimate Team Mode)

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2. **Gambling** embedded into video games

- ▶ A *lottery* (for *real money*) to obtain a *prize*
- ▶ Consumers get direct utility from resolving uncertainty and collecting items
- ▶ Similar problem gambling as in other contexts
 - ▶ Addiction, impulsive consumption, other behavioral mechanisms → leads to over-spending
- ▶ A substantial share of consumers are minors

Regulation of Loot Boxes: No Consensus

- ▶ Banned due to being gambling (e.g. Belgium)
- ▶ Partially banned or regulated (e.g. Japan, China)
- ▶ Determined not gambling and allowed (e.g. Poland, New Zealand)
- ▶ Inquiries into loot boxes in major jurisdictions
 - ▶ US: A 2019 Workshop at the FTC
 - ▶ UK: A 2020 Government Call for Evidence
 - ▶ EU: A 2023 European Parliament's Resolution

More

A Stand-Alone Product or Part of the Game of Skill?

- ▶ In March 2022, the Dutch Council of State overruled the district court, making EA's Ultimate Team mode legal Ruling
- ▶ *"...obtaining and opening the [randomized] packs is not an isolated game. **They are part of a game of skill [...] used for game participation [...]** Because the packs are not a stand-alone game, they are not a game of chance and do not require a license"*

This Paper

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 - ▶ In-game functional value/complementarity with the game?
 - ▶ A direct utility from opening a loot box (a stand-alone product; includes habits & other behavioral mechanisms)?

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 - ▶ Video games have “whales” 🐳 – a small share of players responsible for most expenditures
 - ▶ Do 🐳 open loot boxes for other reasons than regular players?
 - ▶ Externalities for product design?

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 - ▶ Do 🐳 open loot boxes for other reasons than regular players?
 - ▶ Externalities for product design?
3. What are the implications of:
 - ▶ A full loot box ban
 - ▶ A ban on paid loot boxes
 - ▶ Spending limits

This Paper

1. A simple model to separate out complementary and direct values of loot boxes
2. Data from a Japanese mobile puzzle game
 - ▶ Describe consumers' behavior
 - ▶ Model-free evidence of the source of loot box value
3. Estimate an empirical model of gameplay with loot boxes
 - ▶ Forward-looking players that accumulate inventory
 - ▶ A two-step estimator using the terminal action property
4. Characterize consumer tastes, evaluate product design and policy counterfactuals
 - ▶ Measure the relative importance of complementarity
 - ▶ Evaluate alternative game and loot box designs
 - ▶ Measure the effects of potential regulatory actions

A Toy Model

- ▶ A consumer considers playing a video game with loot boxes. She makes two decisions:
 - ▶ Do I play the game, $Y_G \in \{0, 1\}$?
 - ▶ Do I open a loot box, $Y_L \in \{0, 1\}$?

- ▶ Playing the game, $Y_G = 1$, gives

$$U_G(Y_G = 1, Y_L) = \alpha + I(\text{win}|Y_L), \quad (1)$$

- ▶ Opening a loot box, $Y_L = 1$, gives

$$U_L(Y_L = 1) = \rho p, \quad (2)$$

and weakly increases the probability of winning at the game,
 $Pr(\text{win}|1) \geq Pr(\text{win}|0) \geq 0$

Two Sources of Loot Box Tastes

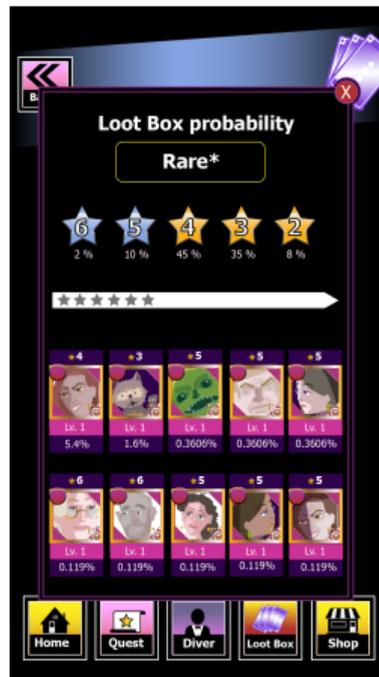
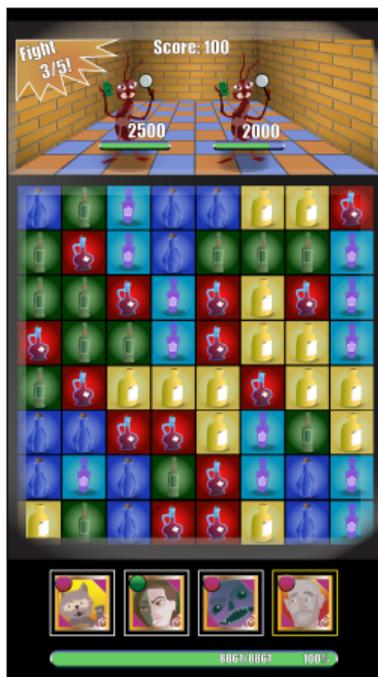
- ▶ Two reasons to open a loot box:
 1. Higher expected win utility, $[Pr(\text{win}|1) - Pr(\text{win}|0)]$
 - ▶ Open loot boxes more when the functional value is higher
 2. Persistent taste for opening loot boxes,
 - ▶ Want to open loot boxes regardless of functional value

- ▶ can capture various mechanisms
 - ▶ Direct utility from uncertainty
 - ▶ Habit formation: positive state dependence as part of
 - ▶ Variable-ratio schedule of reinforcement: higher β if higher variance of the draws

Empirical Context: A Japanese Mobile Video Game

- ▶ A free-to-play puzzle mobile game, run April 2015-July 2019
 - ▶ The mechanics is “match-three puzzle” (e.g. Candy Crush)
- ▶ Core features:
 - ▶ A sequence of 173+ stages of increasing difficulty
 - ▶ A player accumulates an inventory of items that help to complete stages (“divers”), vertically differentiated (“rarity”)
 - ▶ Chooses up to four divers before each stage play
 - ▶ Divers are accumulated either through play/points or through opening loot boxes
 - ▶ Loot boxes can be opened between stage plays using in-game currency, acquired through play or pay (~ 3.5\$)
 - ▶ A player can open 11 loot boxes at once (for the price of 10)

Examples of Game Visuals



Game Data

- ▶ Access to complete data logs
 - ▶ ~ 2.5M players
 - ▶ User play and loot box opening decisions, play and loot box outcomes, inventories, currency stocks, etc

Summary Statistics

Table 1: Summary statistics across users.

	Min	Mean	Median	Max	SD	Total
# of actions	1	106.31	10	119,007	540.61	267,521,534
- Played main stage games	0	38.44	4	28,586	115.67	96,719,354
- Played event games	0	48.16	0	83,805	378.10	121,186,908
- Opened rare lootboxes	0	7.88	3	6,204	30.54	19,829,420
- Opened normal lootboxes	0	11.84	2	24,426	58.93	29,785,852
Max main stage achieved	0	18.54	4	173	32.27	-
Win share: main stage games	0	0.94	1	1	0.14	-
Win share: event games	0	0.74	0.84	1	0.29	-
Opened 11 rare lootboxes at once	0	1.02	0	3,256	8.45	2,559,307
In-game currency received	0	78	18	178,698	457.52	196,267,039
- through gameplay	0	72.80	18	128,831	359.30	183,187,916
- through a purchase	0	5.20	0	49,867	119.89	13,079,123
In-game currency spent	0	66.76	9	178,606	442.07	168,001,147
- got through gameplay	0	61.58	9	128,739	340.72	154,962,617
- got through a purchase	0	5.18	0	49,867	119.75	13,038,530
Sessions	1	21.21	1	9,102	103.80	53,368,821
Unique days played	1	11.42	1	1,548	45.14	28,744,507
Length of play (in calendar days)	0	38.19	0	1,553	137.29	-

Actions correspond to playing the game or opening lootboxes. A session is defined as a sequence of actions that are no more than 1 hours apart.

Inequality in the Expenditures

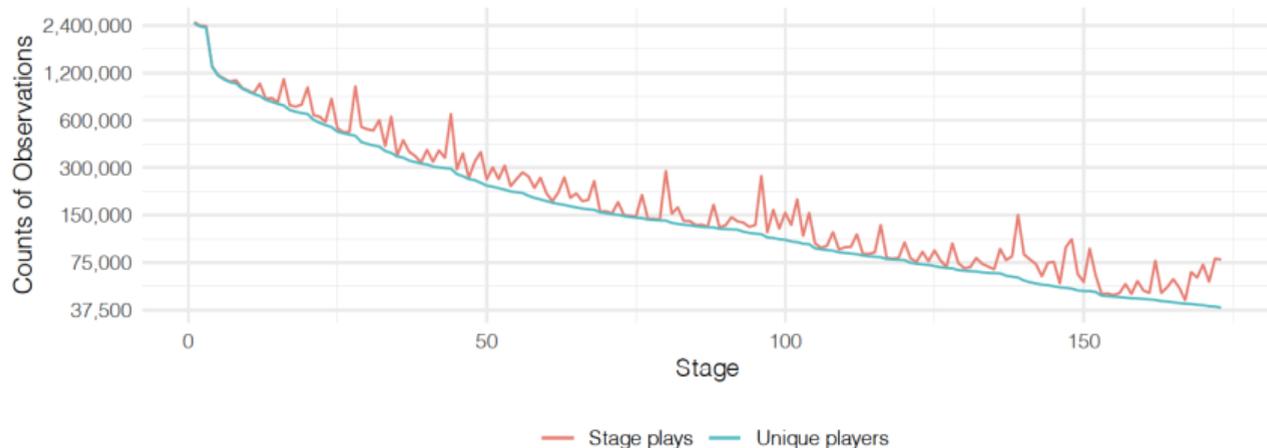
- ▶ Game purchases are highly concentrated:
 - ▶ 90% of money spent by 1.5% of players (🐦)
 - ▶ The highest: ~\$33K by one user, ~\$3K in one session
- ▶ “Organic” in-game currency expenditures are much less concentrated:
 - ▶ 90% of spending by 31.5% of players
 - ▶ Similar for gameplay
- ▶ 95.7% of money spent on loot boxes

Lorenz Curves

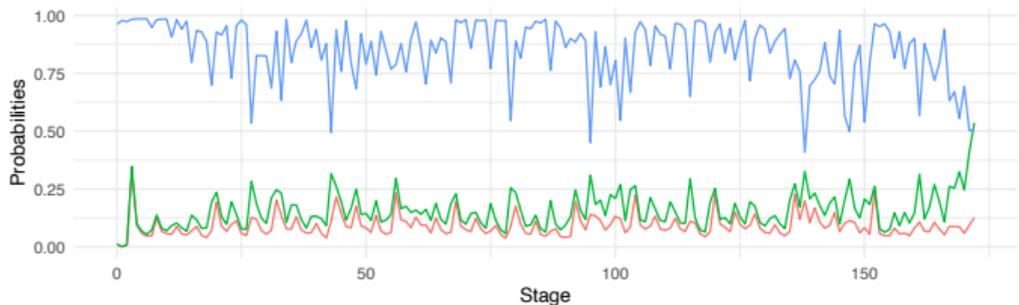
Descriptives: Game Progress by Stage

- ▶ 37K players reach stage 173
- ▶ Every four stages there is a harder “boss” stage

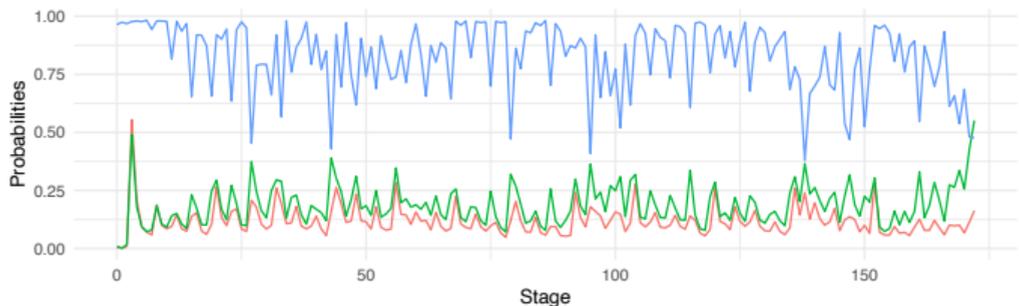
Figure 4: The Number of Plays and Unique Players Present at Each Stage



Descriptives: Players Reaching Stage 173 vs. All Players



— Probability to open at least one rare loot box — Probability to spend at least some dream drops — Stage win probability



— Probability to open at least one rare loot box — Probability to spend at least some dream drops — Stage win probability

Model-Free Evidence: Effects of Loot Box Outcomes

- ▶ Functional value of loot boxes \rightarrow “good” realizations should increase the utility from gameplay
- ▶ A stronger effect if larger impact on game performance
 - ▶ Added to the low- vs. high-quality inventories

Model-Free Evidence: Effects of Loot Box Outcomes

- ▶ Functional value of loot boxes → “good” realizations should increase the utility from gameplay
- ▶ A stronger effect if larger impact on game performance
 - ▶ Added to the low- vs. high-quality inventories
- ▶ Use loot box outcome as an instrument for inventory quality, controlling for the inventory in $t - 1$

$$I(a_{it} = \text{loot box} | a_{i,t-1} = \text{loot box}) = bR_{it} + \kappa_i + \kappa'_{s,R_{it-1}} + \xi_{it}$$

- ▶ where R_{it} is the total rarity of the top-4 divers in the inventory
- ▶ Include user i and stage s by rarity in $t - 1$ fixed effects
- ▶ Standard errors clustered two-way, on the user and stage levels

Effects of Inventory Quality on Loot Box Probability: Non-whales

Dependent variable: $I(a_{it} \in \{2, 3\} | a_{i,t-1} \in \{2, 3\})$

All

(1)

II. Non-whales:

\hat{R}_{it} (IV: $\text{rarity}_{L_{it-1}}$)	-0.1725*** (0.0513)
First stage ($R_{it} \sim \text{rarity}_{L_{it-1}}$)	0.1562*** (0.0383)
Average $I(a_{it} \in \{2, 3\} a_{i,t-1} \in \{2, 3\})$	0.6439
R ²	0.3236
Number of observations	14,563,179

Effects of Inventory Quality on Loot Box Probability: Non-whales

	<i>Dependent variable: $I(a_{it} \in \{2, 3\} a_{i,t-1} \in \{2, 3\})$</i>		
	All (1)	$R_{it-1} < 16$ (2)	$R_{it-1} \geq 16$ (3)
II. Non-whales:			
\hat{R}_{it} (IV: $\text{rarity}_{L_{it-1}}$)	-0.1725*** (0.0513)	-0.0880*** (0.0075)	-0.8094*** (0.2168)
First stage ($R_{it} \sim \text{rarity}_{L_{it-1}}$)	0.1562*** (0.0383)	0.4458*** (0.0380)	0.0320*** (0.0075)
Average $I(a_{it} \in \{2, 3\} a_{i,t-1} \in \{2, 3\})$	0.6439	0.5471	0.7141
R ²	0.3236	0.4155	0.2552
Number of observations	14,563,179	6,116,584	8,446,595

Effects of Inventory Quality on Loot Box Probability:

Dependent variable: $I(a_{it} \in \{2, 3\} | a_{i,t-1} \in \{2, 3\})$

All

(1)

III. Whales:

\hat{R}_{it} (IV: $\text{rarity}_{L_{it-1}}$)	-0.0080 (0.0363)
First stage ($R_{it} \sim \text{rarity}_{L_{it-1}}$)	0.0400** (0.0171)
Average $I(a_{it} \in \{2, 3\} a_{i,t-1} \in \{2, 3\})$	0.8025
R ²	0.1537
Number of observations	3,856,246

Play Utility

- ▶ Consider consumer i who reached stage s by time t
- ▶ Four choice options a_{it} : play stage s ($a_{it} = 1$), open 1/11 loot box(es) ($a_{it} = \{2, 3\}$), or leave the game forever ($a_{it} = 0$)
- ▶ State variables: stage s_{it} , diver rarity in inventory R_{it} , currency stock c_{it} , whether the current stage was lost q_{it} , state dependence d_{it} , loot box prices $\{p_{it}^1, p_{it}^{11}\}$
- ▶ The utility of playing is

$$u(a_{it} = 1) = \alpha_{G, s_{it}} - q_{it} \quad (3)$$

where

- ▶ $\alpha_{G, s_{it}} = \alpha_{G, s}$ is utility from playing stage s
- ▶ q_{it} captures the disutility of having lost the current stage and having to replay it

Win Probability

- ▶ The win probability is determined by

$$\Pr(\text{win}|s_{it}, q_{it}, D_{it}) = \zeta_{1,s,q} + \zeta_{2,s,q} * R_{it} + \zeta_{3,R_{it}} \quad (4)$$

where

- ▶ $\zeta_{1,s,q}$, $\zeta_{2,s,q}$ and $\zeta_{3,R_{it}}$ allow for stage-and-loss-specific effects of inventory rarity on the win probability
- ▶ R_{it} is the summed up rarity of top-4 divers in the inventory D_{it} of the player (from 8 to 24, 17 combinations)

One Loot Box Opening Utility

- ▶ If i opens a single loot box L_s , $a_{it} = 2$, with \Pr_s get diver $d \in D_{L_s}$
 - ▶ Updating the inventory $D_{i,t+1} = \{D_{it}, d\}$ and the implied R_{it+1}
- ▶ Pays p_{it}^1 , updating $c_{it+1} = c_{it} - p_{it}^1$
 - ▶ If $p_{it}^1 > c_{it}$, need to spend real money to acquire $p_{it}^1 - c_{it}$ of in-game currency
- ▶ Gets utility

$$u(a_{it} = 2) = \alpha_{L,1} - \mathbb{1}_{p_{it}^1 > c_{it}} \times (p_{it}^1 - c_{it}) + \eta d_{it} \quad (5)$$

where

- ▶ $\alpha_{L,1}$ is the direct utility of opening one loot box
- ▶ β is the (dis)utility of spending money on in-game currency
- ▶ η is state.dep. coef on $d_{it} = \mathbb{1}(a_{i,t-1} \in \{2, 3\})$

Eleven Loot Boxes Openings Utility

- ▶ Separate utility of consumer i opening eleven loot boxes, $a_{it} = 3$

$$u(a_{it} = 3) = \alpha_{L,11} \mathbb{1}_{p_{it}^{11} > c_{it}} \times p_{it}^{11} c_{it} + \eta d_{it} \quad (6)$$

where

- ▶ $\alpha_{L,11}$ is the direct utility of opening eleven loot box
- ▶ The utility of quitting the game forever, $a_{it} = 0$, is normalized to zero

Player's Objective

- ▶ A forward looking player chooses $a_{it} \forall t$ to maximize

$$\max_{\{a_{it} \forall t\}} E \sum_{t=1}^{\infty} \beta^{t-1} u_{it}(a_{it}, O_{it}; \cdot) + \varepsilon_{iat} \quad (7)$$

where

- ▶ $O_{it} = R_{it}, c_{it}, s_{it}, q_{it}, d_{it}, p_{it}^1, p_{it}^{11}$ are state variables Transitions
 - ▶ β are preference parameters
 - ▶ ε_{iat} are player, choice, time specific idiosyncratic shocks
- ▶ Writing out as a value functional using Bellman equation:

$$V(O_{it}, \varepsilon_{iat}) = \max_{a_{it} \in \{0,1,2,3\}} u(a_{it}) + \varepsilon_{iat} + E_{O', \varepsilon' | O_{it}, a_{it}} V(O', \varepsilon') \quad (8)$$

- ▶ Boils down to simple multinomial logit if we know

$$E_{O', \varepsilon' | O_{it}, a_{it}} V(O', \varepsilon')$$

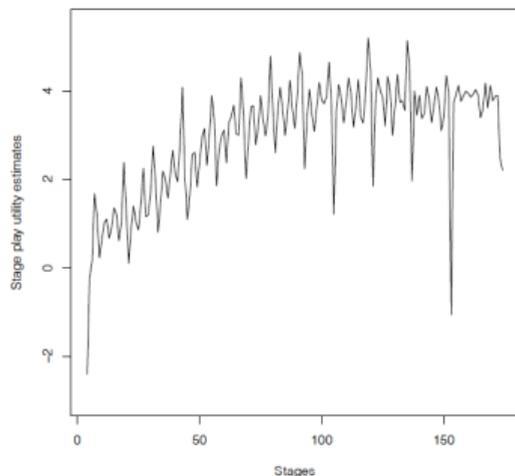
Estimation

- ▶ Use a two-step estimator [Hotz and Miller, 1993] leveraging terminal action property [Arcidiacono and Miller, 2011]
 1. Estimate the conditional choice probability ($CCP_0(O_{it}) = CCP(a_{it} = 0 | O_{it})$) of the terminal action, $a_{it} = 0$, and state transition probabilities, $G(\cdot)$
 2. Express $\int_{\epsilon_{it}} V(O_{it}, \epsilon_{it}) dF(\epsilon_{iat})$ as the function of $CCP_0(O_{it})$
 3. Compute expected $E_{O', \epsilon' | O_{it}, a_{it}} V(O', \epsilon')$ using $G(\cdot)$
 4. Use Berry [1994] inversion to estimate utility parameters

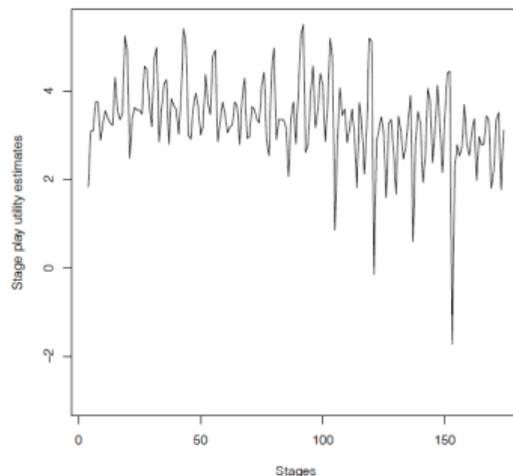
Details

Estimation Results: $\alpha_{G,s}$

Figure 9: Estimates of Preference for Stage Play, $\alpha_{G,s}$



(a) Non-whales



(b) Whales

- ▶ Increasing over the first 20 periods of the game
 - ▶ Aligned with the design: the first 10-15 stages are relatively simple to complete
- ▶ Even at later stages, systematically higher play utility from harder

Estimation Results: The Rest of

Table 5: Estimates of Preference for Loot Boxes and Winning in the Game

	Non-Whales		Whales	
	Estimate	S.e.	Estimate	S.e.
One loot box ($\alpha_{L,1}$)	-1.7180	(0.4514)	0.1125	(0.1844)
State dependence (η)	1.1262	(0.2751)	2.0187	(0.2671)
Eleven-pack loot box ($\alpha_{L,11} - \alpha_{L,1}$)	0.0312	(0.4311)	-0.4776	(0.1913)
Payment (γ)	-0.1954	(0.0098)	-0.1545	(0.0039)
Lose the game ($-\beta$)	-0.4293	(0.1136)	-1.4488	(0.0846)

Standard errors are computed using Bayesian bootstrap, with clustering (draws of observation weights) done at the stage level.

- ▶ For :
 - ▶ Stronger preference for loot boxes
 - ▶ Stronger state dependence
 - ▶ Lower preference for eleven-pack loot boxes
 - ▶ Less price responsive
 - ▶ Care about losing

Heterogeneity by Event Plays

Heterogeneity within whales and non-whales

Functional vs. Direct Loot Box Value

- **A:** Baseline future expected utility

$$\tilde{V}_{\text{baseline}}(O) = \ln \left(\underbrace{\left(\exp(u(a=1) + E_{R', \hat{O}', \epsilon' | O, a=1} V(O', \epsilon')) \right)}_{\text{Playing stage game}} \right) \quad (9)$$

$$+ \underbrace{\sum_{\bar{a} \in \{2,3\}} \left(\exp(u(a=\bar{a}) + E_{R', \hat{O}', \epsilon' | O, a=\bar{a}} V(O', \epsilon')) \right)}_{\text{Opening 1 or 11 loot boxes}} + \underbrace{\exp(u(a=0))}_{\text{Exit game}} \quad (10)$$

- Compare to utilities that shut down the two mechanisms, holding future actions fixed

Functional vs. Direct Loot Box Value

- ▶ **B:** No option to open loot boxes

$$\tilde{V}_{n,l.}(O) = \ln \left(\underbrace{\left(\exp(u(a_0 = 1) + E_{R', \hat{o}', \epsilon' | O, a_0=1} V(O', \epsilon')) \right)}_{\text{Playing stage game}} + \underbrace{\exp(u(a = 0))}_{\text{Exit game}} \right) \quad (11)$$

Functional vs. Direct Loot Box Value

- **B:** No option to open loot boxes

$$\tilde{V}_{n.l.}(O) = \ln \left(\underbrace{\left(\exp(u(a_0 = 1) + E_{R', \hat{\theta}', \epsilon' | O, a_0=1} V(O', \epsilon')) \right)}_{\text{Playing stage game}} + \underbrace{\exp(u(a = 0))}_{\text{Exit game}} \right) \quad (11)$$

- **C:** No rarity adjustments from opening loot boxes

$$\tilde{V}_{n.f.}(O) = \ln \left(\underbrace{\exp(\dots)}_{\text{Playing stage game}} + \underbrace{\sum_{\tilde{a} \in \{2,3\}} \exp(u(a = \tilde{a}) + E_{R', \hat{\theta}', \epsilon' | O, a=\tilde{a}} V(O', \epsilon'))}_{\text{Opening 1 or 11 loot boxes}} + \underbrace{\exp(\dots)}_{\text{Exit game}} \right) \quad (12)$$

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- ▶ **D:** Similarly, shut down the state dependence in opening loot boxes

Counterfactuals: Product Design

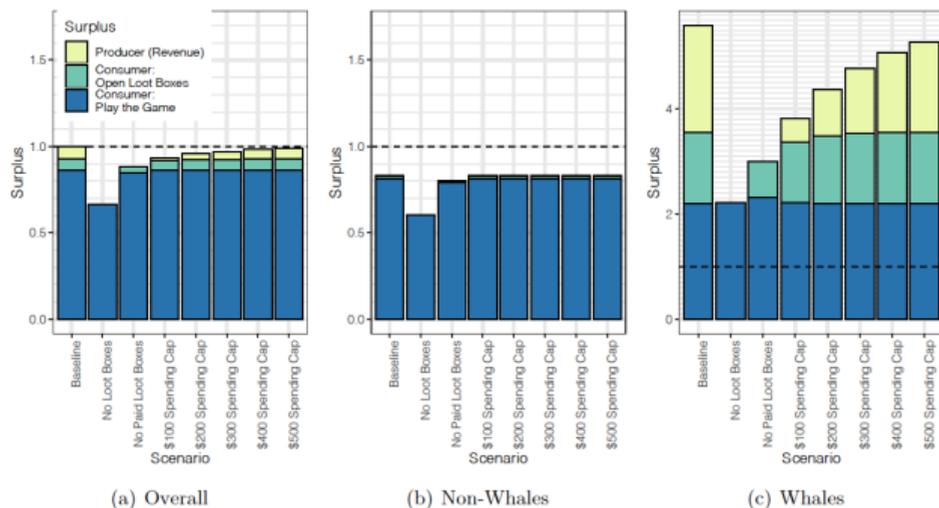
Table 9: Simulations under varying game stage win probabilities

	Revenue			# of Stage Games Played			Share of Consumers At Stage 20		
	Overall	Non-whales	Whales	Overall	Non-whales	Whales	Overall	Non-whales	Whales
Harder									
Win prob -50%	23.49	0.05	659.77	0.28	0.18	2.89	0.21	0.15	1.93
Win prob -40%	15.92	0.05	446.70	0.37	0.29	2.52	0.33	0.27	1.95
Win prob -30%	7.24	0.06	202.17	0.49	0.42	2.3	0.47	0.41	1.97
Win prob -20%	3.33	0.07	91.86	0.64	0.58	2.14	0.63	0.58	1.98
Win prob -10%	2.23	0.07	61.02	0.81	0.77	2.04	0.82	0.77	1.98
Current win prob	1.00	0.07	26.21	1.00	0.96	1.96	1.00	0.96	1.98
Win prob +10%	0.73	0.07	18.26	1.05	1.02	1.91	1.05	1.02	1.98
Win prob +20%	0.62	0.07	15.52	1.06	1.03	1.88	1.07	1.04	1.98
Win prob +30%	0.58	0.06	14.58	1.06	1.03	1.87	1.08	1.05	1.98
Win prob +40%	0.55	0.06	13.85	1.06	1.03	1.86	1.1	1.06	1.98
Win prob +50%	0.54	0.06	13.58	1.06	1.03	1.85	1.1	1.07	1.98
Easier									

- ▶ Evaluate outcomes under the counterfactual game difficulty
- ▶ A harder game design (lower win prob) increases revenue (from 🐳) but decreases engagement (from regular players)

Counterfactuals: Welfare Effects of Policies

Figure 10: Revenue and Consumer Surplus under Loot Box Bans and Spending Caps

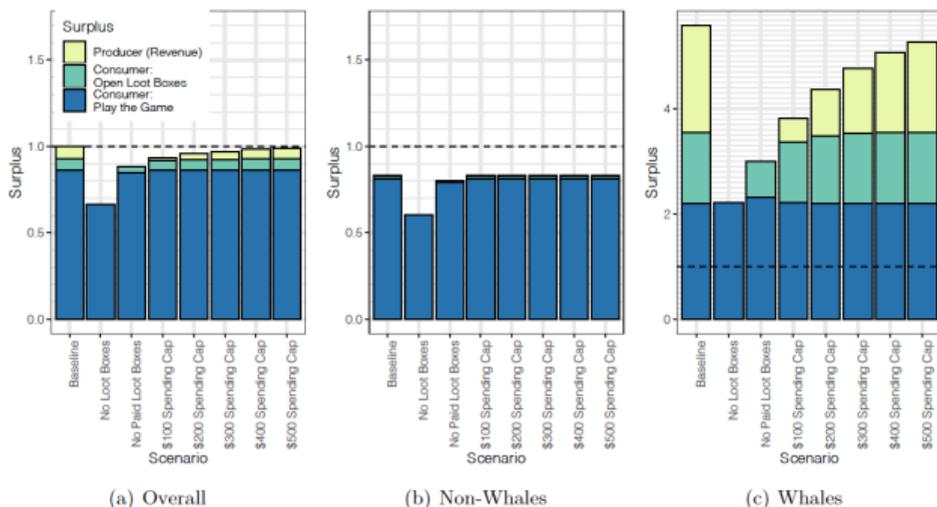


1. Baseline:

- ▶ Firm gets 7.4% of the total surplus
- ▶ Players: 6.3% of the total surplus from opening loot boxes, 86.3% from playing stages
 - ▶ For regular players: 1.8% from l.b. and 97.8% from playing
 - ▶ For 🐳: 24.3% from l.b. and 39.3% from playing

Counterfactuals: Welfare Effects of Policies

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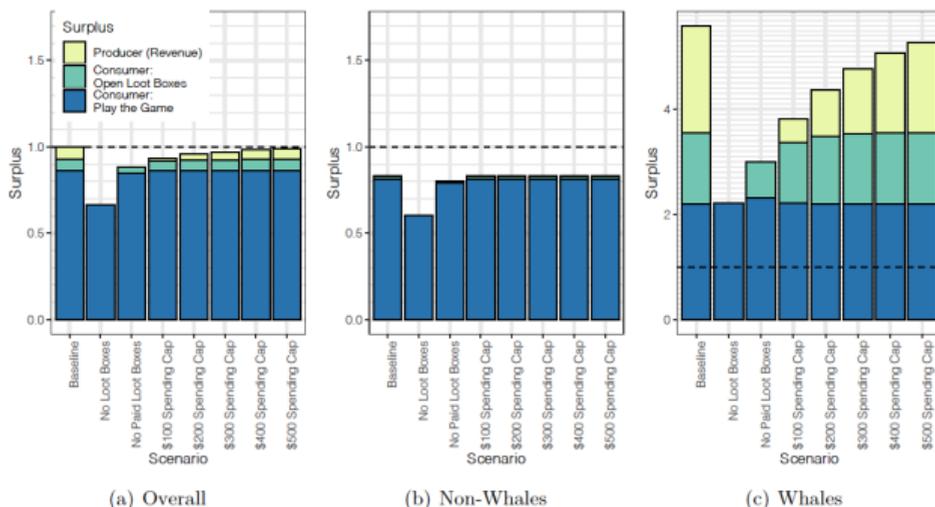


2. A blanket ban on loot boxes:

- ▶ Zero revenue and CS from loot boxes (by construction)
- ▶ Regular players get 25.4% less CS from playing stages
 - ▶ Due to the complementarity of loot boxes and the gameplay

Counterfactuals: Welfare Effects of Policies

Figure 10: Revenue and Consumer Surplus under Loot Box Bans and Spending Caps

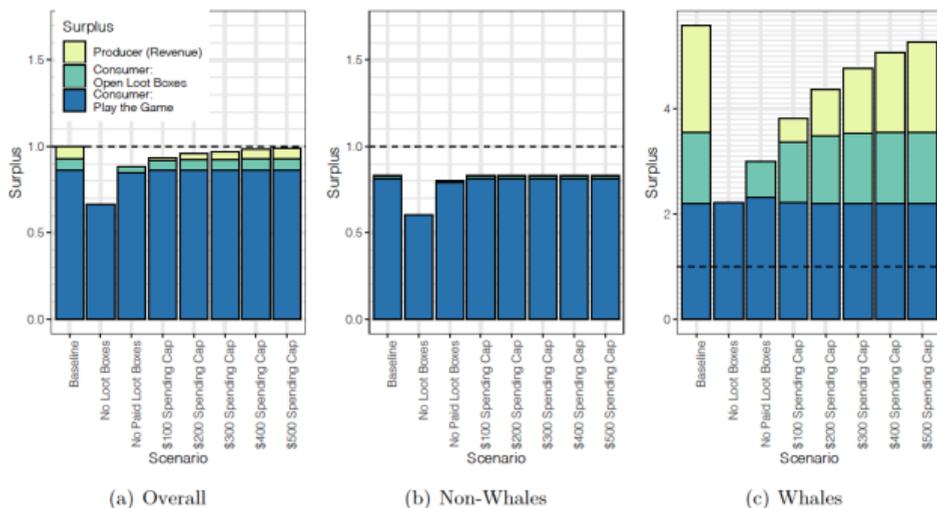


3. A ban on paid loot boxes:

- ▶ Zero revenue (by construction)
- ▶ Regular players get 2.1% less CS from playing stages
- ▶ 🐳 get 50% less CS from opening loot boxes

Counterfactuals: Welfare Effects of Policies

Figure 10: Revenue and Consumer Surplus under Loot Box Bans and Spending Caps



4. \$100-\$500 spending limits:

- ▶ Regular players not affected (never spend above \$100)
- ▶ 🐙 get the same CS from playing
- ▶ \$100-\$500 caps:
 - 🐙 get 84%-99.9% of CS from loot boxes vs. baseline
 - the firm gets 24.3%-86.5% of PS

Conclusions

1. Loot boxes bring different types of value for regular and high-spending players
 - ▶ Mostly (90%) complementary to the game for regular players → “part of a game of skill”
 - ▶ Mostly (97%) direct values for high-spending players → “a stand-alone game”
2. Current game design (complexity) trades-off the engagement from regular players and revenues from high-spending players
3. Use the estimates to evaluate loot box bans and spending limits (per consumer) on consumer and producer surplus

Thank you!