# Reaching for the Stars: Discounts and Review Tier Transitions in the Video Games Market

Dmitry Sorokin (NYU)

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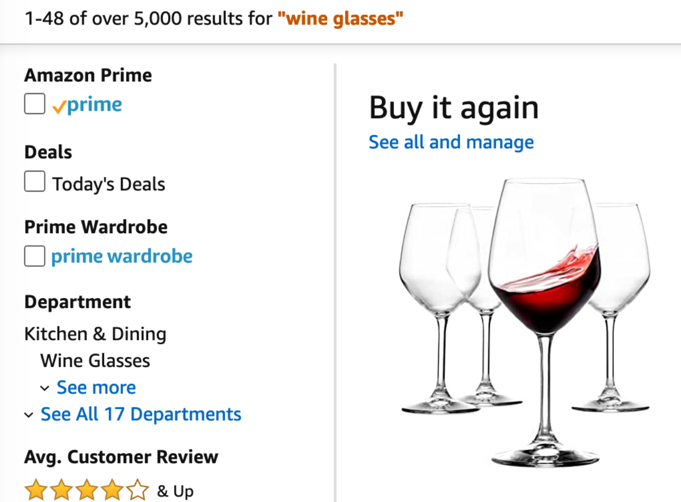
# Economics of Attention



# Economics of Attention

- Online consumer reviews help to simplify choice in many markets
  - Individual consumers leave reviews
  - Reviews are often aggregated into **review tiers** (★★★★☆)
  - Future customers rely on reviews
- Firms try to manage their reviews
  - Soliciting reviews from their buyers
  - Responding to the reviews they receive
  - Leaving fake reviews
- What firms can do to affect their reviews is important for market design
  - "Zero Reviews Trap" as a barrier to entry
- I study a new form of review management
  - Can firms use price promotions to upgrade their review tiers?
  - A link between discounts and review tier **transitions**

# Why Discount?

- Consider a product that is a few reviews short of obtaining an extra star
- Would it be profitable for this product to launch a price promotion?
- The **selection effect**:
  - Customers who buy during a discount are potentially different
  - They could leave better or worse reviews
  - The sign of the selection effect is an empirical question
- The **variance effect**:
  - Randomness in the outcome of the discount
  - A good outcome catapults the product to the next review tier
  - A bad outcome might not affect the review tier
  - The opposite effect for a product close to a review tier downgrade

# Stylized Model

▸ With Formulas

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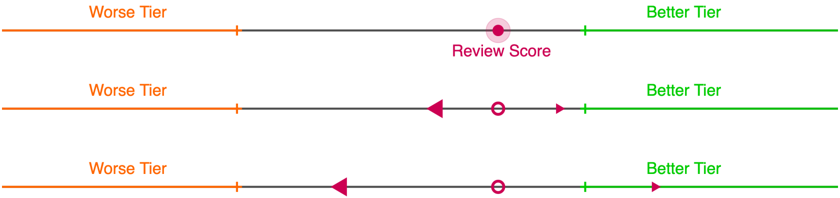

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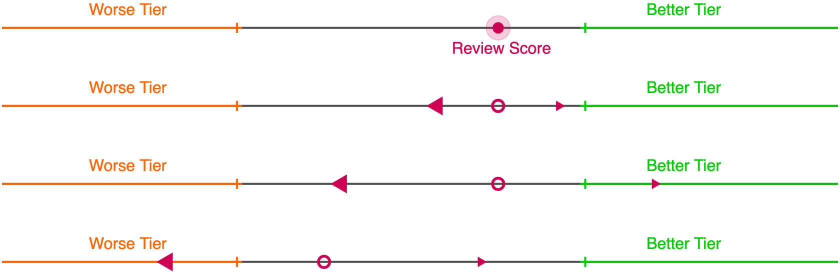

# What I do

1. Model of demand and reviewing on Steam
   - The best review tier increases sales by 23% compared the worst tier
   - Discounts are followed by a 38% spike in sales
2. Discounting around transitions
   - Products that are close to upgrading their review tier are 4-9% more likely to sell at a discount
   - Evidence that proximity to a downward transition decreases the probability to sell at a discount by up to 4%
3. Selection vs. Variance
   - The selection effect is small
   - Controlling for the selection effect, proximity to a negative transition decreases the probability of a discount by 6%
   - Consumers are more likely to leave reviews when they buy during a discount

# Literature

- Regression discontinuity with review tiers: Anderson and Magruder (2012), Luca (2016), Sorokin and Stevens (2020)
  - How random is assignment around the cutoffs?
- Promotions: is the selection effect negative?
  - Ifrach et al. (2017), Acemoglu et al. (2019)
  - Byers et al. (2012), Li (2016), Zhu et al. (2019), Cabral and Li (2015)
- A negative selection effect poses a puzzle:
  - Zegners (2017): free pricing leads to bad reviews
- Design of recommendation systems in digital markets
  - Vellodi (2020): reviews as barriers to entry and pricing as a way to solve it

# Roadmap for Today

1. Institutional Setting
2. Data
3. Empirical Model
4. Discounts Around Transitions
5. Selection vs. Variance

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# Steam

- In 2018 the U.S. video games market revenue matched the one of the U.S. film industry: $43.4 billion (Minotti 2019)

- *Steam* is the major online marketplace for selling video games
  - Think "App Store" for games on PC and Mac
  - 2013: 75% of all PC games sold online (Cliff 2013)
  - January 2018: over 47 million daily active users

- Until recently, virtually no competition
  - Developers: Steam is a powerful player that you can't ignore

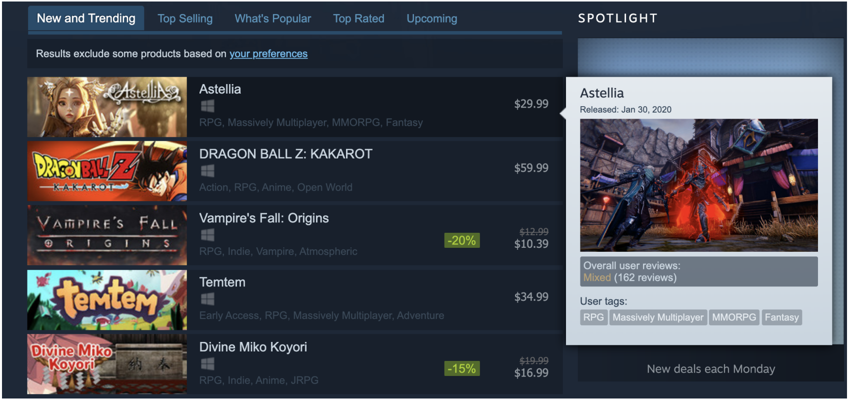
# Reviews on Steam

- Transparency and simplicity
  - Users give "thumbs up" or "thumbs down"
- A **Review Score** is the fraction of positive reviews among all reviews
  - A game with 6 good reviews out of 10 total reviews has a score of 60%
- **Review Bins** based on the score:

| Review Bin | N. of Reviews | Score |
|---|---|---|
| No Score | [0, 10) | - |
| Negative | Any | [0, 40) |
| Mixed | Any | [40, 70) |
| Mostly Positive | Any | [70, 80) |
| Positive | [10, 50) | [80, 100) |
| Very Positive | More than 50 | [80, 100) |
| Overwhelmingly Positive | More than 500 | [95, 100] |

# Visibility and Reviews

- Labels better than "Negative" have a similar contribution to visibility
- The effect is through the information that reviews convey

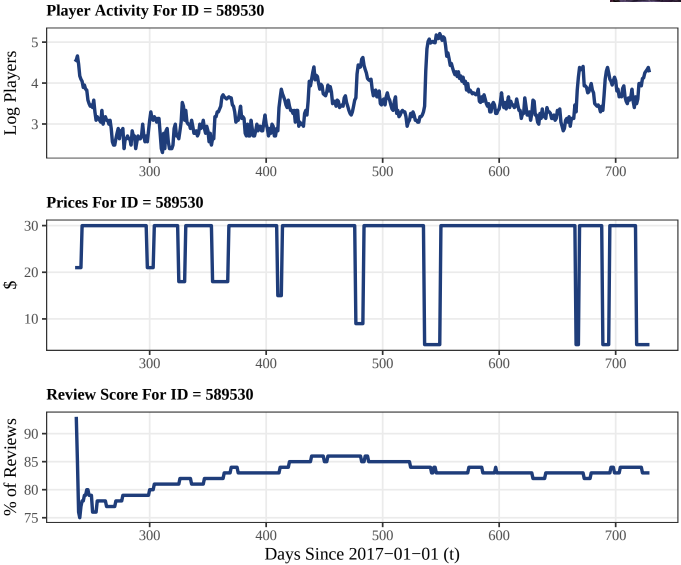


# Roadmap for Today

# Data

- Main source: SteamDB.com, a third party website
- Player count: the maximum number of concurrent players on any given day
- Price history: daily observations of prices
- Review history:
  - Cumulative numbers of positive and negative reviews on any day
  - Review score and review labels are reverse-engineered

# Example Game

# Sample

▸ Descriptive Stats

- Single player, not free-to-play games
    - → Games with stable quality: no more than 5 small patches
- Released in 2017 or later
    - → Stable review system
- At least 4 concurrent players on the median day
- This leaves us with 906 games, about 319,000 observations

# Transitions

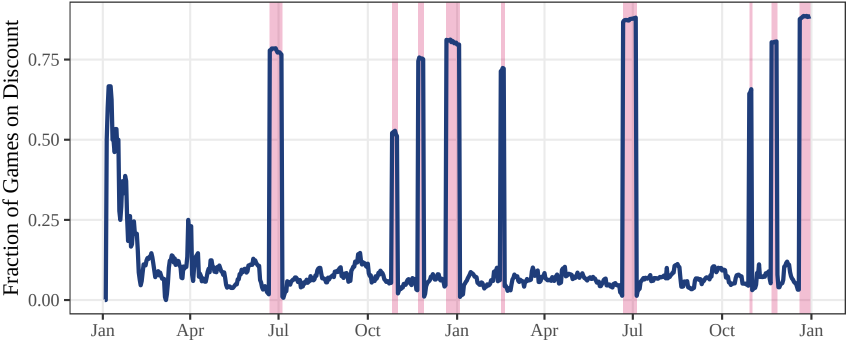
▸ Transitions Stats

- 596 games have transitioned, 1688 unique transitions
  - → 1225 are followed by at least 7 days in the new bin
- Every tier is well-represented in the data Transitions Matrix

# Discounts

- Nominal prices rarely change, but instead products go on discounts
  - 6331 discounts vs. 43 price changes
  - Consumers can set up discount notifications

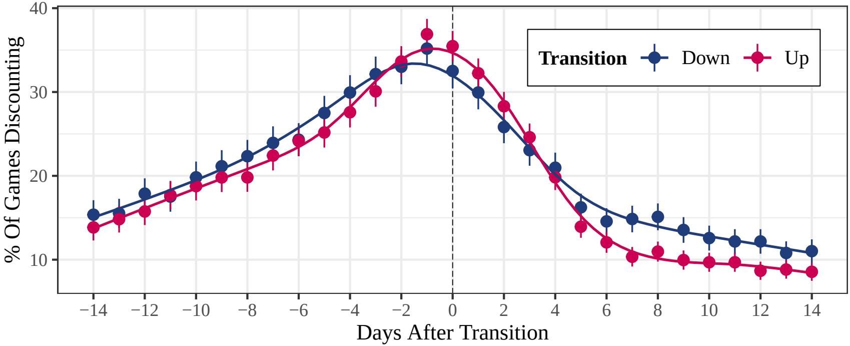
- Custom and Curated discounts
  - Seasonal sale: 64% of the sample



# Discounts Around Transitions

▸ Regression

- Transitions between review bins are preceded by discounts
- Extra day closer to the transition $\iff$ the probability of discount $\uparrow$3%
- Extra day after the transition $\iff$ the probability of discount $\downarrow$7%



# Roadmap for Today

1. Institutional Setting
2. Data
3. **Empirical Model**
4. Discounts Around Transitions
5. Selection vs. Variance

# Empirical Model of Demand and Gaming

- How impactful are discounts on Steam?
- How much do various review labels matter for sales?
- Data limitation: no sales data
  - → I use the model to infer demand parameters from product usage
- Prerequisite for a model of reviewing

# Arrival of Customers

- Game $i$ on day $t$ sells to $B_{it}$ new buyers
  - $B_{it} \sim P(\lambda_{it})$, $\lambda_{it} = \lambda_i(1 + x_{it}'\beta)$
  - $x_{it}$: price, review information, age, seasonality
  - $Q_{it}^D(x_{it}) = \mathbb{E}[B_{it}] = \lambda_i(1 + x_{it}'\beta)$ is the demand function
- Active players, $A_{it}$: bought the game and keep playing
- Game $i$ on day $t$ forever loses $E_{it}$ active players
  - $E_{it} \sim Binomial(A_{it-1}; 1 - \psi_i)$
- The evolution of $A_{it}$ is then

$$A_{it} = A_{it-1} + B_{it} - E_{it} \tag{1}$$

# Identification Challenges: Unobserved Buyers

- Both the number of buyers and the number of exiters are unobserved

$$A_{it} - A_{it-1} = B_{it} - E_{it}$$

- Key: entry is in absolute numbers, but exit is proportional to player count
  - Exit rates are identified from the spikes in the player count Show me!
  - Entry rates are identified from the level at which the player count settles
  - Crucial heterogeneity in $\psi_i$

# Identification Challenges: Causal Effects

- Time varying unobserved demand shifters correlated with the observables
  - Sample selection $\implies$ fixed quality
- Identifying assumption: conditional on the controls, the unobserved factors are not correlated with the review tier
  - Rely on the panel structure of the data
  - "Compare" sales between the periods spent in different review tiers

# Estimation

▸ Details

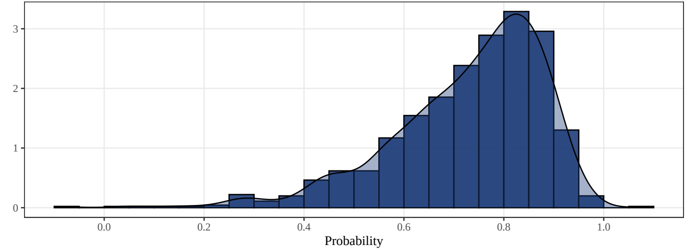
$$A_{it} = A_{it-1} + B_{it} - E_{it}$$

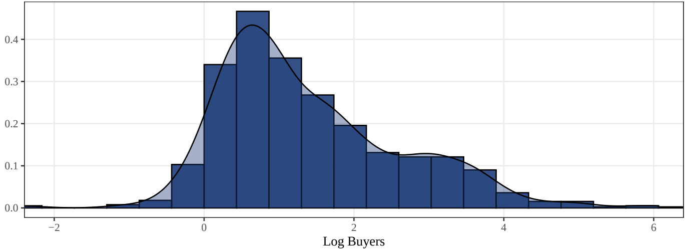
- $\mathbb{E}\left[A_{it} \mid A_{it-1}, x_{it}\right] = \psi_i A_{it-1} + \lambda_i(1 + x_{it}'\beta)$
- The model implies the following regression equation:

$$A_{it} = \psi_i A_{it-1} + \lambda_i(1 + x_{it}'\beta) + u_{it} \quad (2)$$
$$0 = \mathbb{E}\left[u_i \mid A_{it-1}, x_{it}\right] \quad (3)$$

- Parameters: $\theta = (\{\psi_i, \lambda_i\}_{i=1}^n, \beta)$, $\dim(\theta) = 2n + k$
- Conditional on $\beta$, $\psi_i$ and $\lambda_i$ could be obtained by OLS
- Minimize the concentrated sum of squares with respect to $\beta$

# Results: Distributions of $\hat{\lambda}_i(1 + \bar{x}_i\hat{\beta})$ and $\hat{\psi}_i$



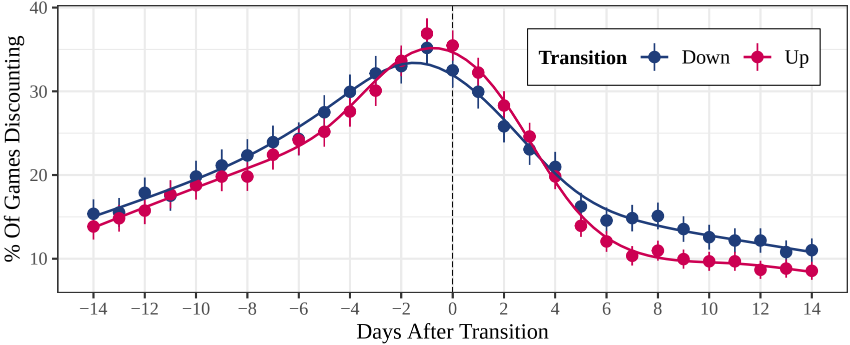
# Results: Demand Parameters $\hat{\beta}$

| | |
|---|---|
| Price | $-0.342^{***}$ |
| | (0.010) |
| New Discount | $0.230^{***}$ |
| | (0.013) |
| Seasonal Sale | $-0.006$ |
| | (0.004) |
| No Score | $-0.128^{***}$ |
| | (0.019) |
| Negative | 0.005 |
| | (0.020) |
| Mostly Positive | $0.019^{**}$ |
| | (0.008) |
| Positive | $0.054^{***}$ |
| | (0.010) |
| Very Positive | $0.052^{***}$ |
| | (0.010) |
| Overwhelmingly Positive | $0.100^{***}$ |
| | (0.013) |
| Observations | 355900 |
| $R^2$ | 0.850 |

# Roadmap for Today

# Discounts and Realized Transitions

▸ Regression



# Discounts and Realized Transitions

- Realized transitions are preceded by discounts
- It is merely a correlation
  - Discounts could be causing transitions
  - In fact, they better be, for my story to hold up!
- Firms that give a discount, but do not transition, are not accounted for
  - Firms avoiding a bad transition and not making a good one
- Solution: **potential transitions**
  - Remember the stylized model!
  - How close the game is to a transition is a state variable
  - Discount today can not cause the potential of transition

# Potential Transitions

- The goal is to see if proximity to a transition increases the probability of discounting
- Define a measure of proximity to a transition
- For each game:
  - ➜ How many positive (negative) reviews are needed for a positive (negative) transition
  - ➜ Calculate the speed of positive (negative) review arrival
  - ➜ Days to potential transition if only receiving one type of reviews
  - ➜ Example

# Empirical Strategy

- One has to study proximities to positive and negative thresholds together
  - A firm close to an upgrade might be willing to give a discount
  - A firm close to a downgrade might be willing to stay put

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- Let $T_{it}^{+} \in \{0, 1\}$ indicate if proximity to a $+$ transition is less than 14 days
- Let $T_{it}^{-} \in \{0, 1\}$ indicate if proximity to a $-$ transition is less than 14 days

# Empirical Strategy

- One has to study proximities to positive and negative thresholds together
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  - A firm close to a downgrade might be willing to stay put

- Let $T_{it}^{+} \in \{ 0, 1 \}$ indicate if proximity to a $+$ transition is less than 14 days

- Let $T_{it}^{-} \in \{ 0, 1 \}$ indicate if proximity to a $-$ transition is less than 14 days

- Estimate

$$disc_{it} = \beta^{+} T_{it}^{+} + \beta^{-} T_{it}^{-} + X_{it}\beta + f_i + \tau_t + \varepsilon_{it}, \qquad (4)$$

  - $disc_{it} = \mathbb{1}\{discount_{it} > 0\}$
  - $X_{it}$: log proximities to transitions, log review count, score, review bin dummies, time without a discount, age
  - $f_i$: game effect
  - $\tau_t$: day of the week and week effects

# Results

- Close to an upgrade: 4-9% increase in the daily probability of a discount
- Close to a downgrade: 4% decrease in the daily probability of a discount

| | *Dependent variable:* | |
|---|---|---|
| | Discount Probability | |
| | 14 days | 7 days |
| Close to Pos. Transition | $0.015^{***}$ | $0.007^{**}$ |
| | (0.003) | (0.003) |
| Close to Neg. Transition | $-0.006^{**}$ | 0.001 |
| | (0.003) | (0.004) |
| Observations | 295,228 | 295,228 |
| $R^2$ | 0.428 | 0.428 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

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# Selection vs. Variance

▸ Model

- Attenuation of the effect of the proximity to a negative transition on the probability of the discount
  - → Positive selection effect vs. negative variance effect
- Estimate the difference in review sentiment on and off a discount

$$\Delta score_i = \begin{bmatrix} \text{Expected Score} \\ \text{on a Discount} \end{bmatrix} - \begin{bmatrix} \text{Expected Score} \\ \text{off a Discount} \end{bmatrix}$$

- Using the estimates of the selection effect, check for the variance effect:
  - → Products on the verge of a review slump should discount less

# The Variance Effect

- Estimate

$$disc_{it} = (\beta_0^+ + \Delta score_i \beta_1^+) T_{it}^+ + (\boldsymbol{\beta_0^-} + \Delta score_i \beta_1^-) T_{it}^- + X_{it}\beta + f_i + \tau_t + \varepsilon_{it}$$

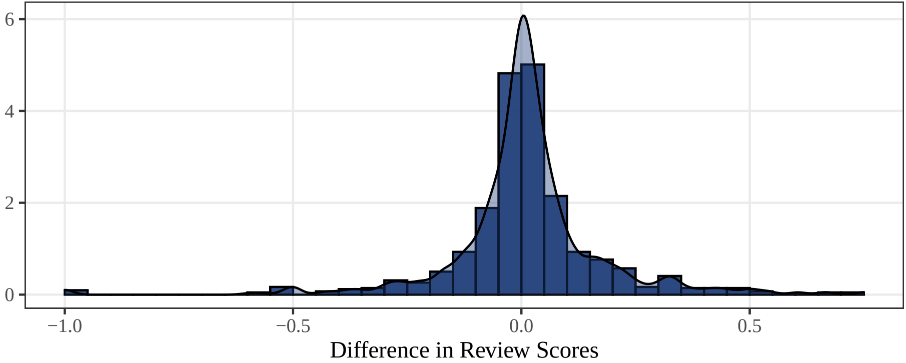
- $\boldsymbol{\beta_0^-}$ measures the effect of proximity to a negative transition when the selection effect $\Delta score_i$ is zero

- Additional test: do consumers who buy during a discount leave reviews with a higher probability?

# Results: $\Delta score_i$

Estimation

- Can not reject the hypothesis that the selection effect is negative ($p = 0.14$)
- Reject the hypothesis that users are less likely to leave a review during a discount ($t = 9.16$)
  - They are 24-40% more likely to do so



| | *Dependent variable:* | |
|---|---|---|
| | Discount Probability | |
| | Controlling for $\Delta score_i$ | Not controlling for $\Delta score_i$ |
| Pos. Transition | $0.014^{***}$ | $0.015^{***}$ |
| | (0.003) | (0.003) |
| Neg. Transition | $-0.009^{***}$ | $-0.006^{**}$ |
| | (0.003) | (0.003) |
| Selection × Pos. Tr. | 0.009 | - |
| | (0.013) | |
| Selection × Neg. Tr. | 0.019 | - |
| | (0.015) | |
| Observations | 290,628 | 295,228 |
| $R^2$ | 0.434 | 0.428 |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

# Conclusion

- I estimate a model of demand and reviewing behavior
  - The best review tier increases sales by 23% compared to the worst tier
  - Discounts are followed by a 38% spike in sales
- Proximity to a review transition affects discounting
  - Review upgrade: 4-9% more likely to sell at a discount
  - Review downgrade: 4% more likely to sell at a discount
- Two major effects at play: the selection and the variance effects
  - The selection effect is small on Steam
  - The variance effect decreases the probability of a discount by 6% for products close to a negative transition

# Game Sizes at 180 Days

Back

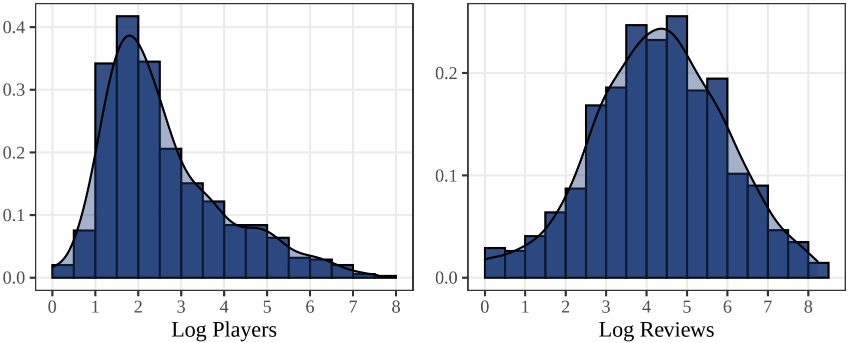



Figure: Distribution Of the Number of Reviews and Players at 180 Days.

# Reviews

◂ Back

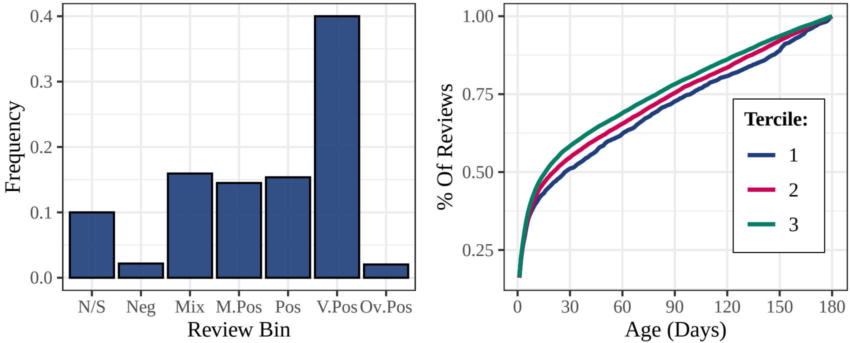



Figure: Distribution Of the Number of Reviews and Players at 180 Days.

# Stats Before Transitions

Back

Table: Average Discount, Age, and Review Count Two Weeks Before A Transition

| Statistic | N | Mean | St. Dev. | Pctl(25) | Pctl(75) |
|---|---|---|---|---|---|
| Mean Discount (%) | 1,225 | 10 | 14 | 0 | 15.9 |
| Age | 1,225 | 142 | 157 | 8 | 226 |
| Reviews | 1,225 | 130 | 343 | 26 | 81 |

# Transition Matrix

Back

| Probabilities | | | | | | | Counts | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Neg | Mix | M. Pos | Pos | V. Pos | Ov. Pos | | Neg | Mix | M. Pos | Pos | V. Pos | Ov. Pos |
| 0 | 100 | 0 | 0 | 0 | 0 | Negative | 0 | 58 | 0 | 0 | 0 | 0 |
| 24 | 0 | 76 | 0 | 0 | 0 | Mixed | 60 | 0 | 189 | 0 | 0 | 0 |
| 0 | 43 | 0 | 25 | 33 | 0 | M. Positive | 0 | 245 | 0 | 141 | 188 | 0 |
| 0 | 0 | 40 | 0 | 60 | 0 | Positive | 0 | 2 | 207 | 0 | 310 | 0 |
| 0 | 0 | 84 | 0 | 0 | 16 | V. Positive | 0 | 0 | 220 | 0 | 0 | 43 |
| 0 | 0 | 0 | 0 | 100 | 0 | Ov. Positive | 0 | 0 | 0 | 0 | 25 | 0 |

# Discounts Around Transitions

Back

| | |
|---|---|
| Days to Transition | 0.005*** |
| | (0.0005) |
| Days After Transition | −0.011*** |
| | (0.0005) |
| Negative | −0.007 |
| | (0.011) |
| Mostly Positive | 0.005 |
| | (0.006) |
| Positive | 0.044*** |
| | (0.009) |
| Very Positive | 0.014 |
| | (0.009) |
| Ov. Positive | 0.020 |
| | (0.016) |
| Score | −0.0005* |
| | (0.0003) |
| Log Reviews | −0.010*** |
| | (0.002) |
| Age | 0.0003*** |
| | (0.00001) |
| Const | 0.903*** |
| | (0.021) |
| Observations | 32,112 |
| $R^2$ | 0.396 |
| Time Effects | Weekdays, Week |
| Game Effects | × |
| Polynomial($t$ W/O Discount) | $d = 2$ |

# Proximity to a Transition: Example

Back

- Consider a game with 19 positive and 6 negative reviews
  - Score = 76%, "Mostly Positive"
  - Needs 5 positive reviews to transition to "Positive": $24/30 = 80\%$
  - Needs 3 negative reviews to transition to "Mixed": $19/28 \approx 67\%$
- If at age of 200 the game has 80 positive and 20 negative reviews, then
  - Average of 0.4 positive and 0.1 negative reviews per day
  - Needs $5/0.4 = 12.5$ days of only positive reviews
  - Needs $3/0.1 = 30$ days of only negative reviews

# Reviews

◂ Back

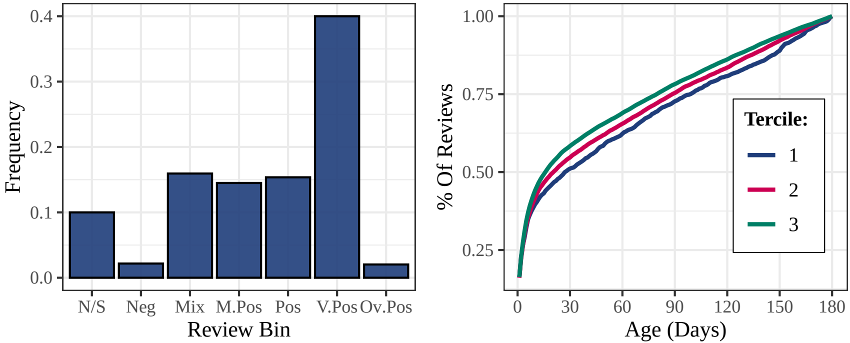



Figure: Distribution Of the Number of Reviews and Players at 180 Days.

# Demand: Identification of $\beta$

- Goals: prediction of customer arrival and the effect of reviews on sales
- Unobserved factors $\tilde{x}_{it}$ that are correlated with the observed ones can lead to the OVB

$$A_{it} = \psi_i A_{it-1} + \lambda_i(1 + x_{it}'\beta) + \lambda_i \tilde{x}_{it}'\beta + \tilde{u}_{it}$$

- Solution:
  - Sample selection ruling out changes in quality
  - $\lambda_i$ controls for time invariant features
  - Time effects to account for day of the week seasonality and big seasonal sales
  - Other controls: age, price, number of reviews, review score
- Review labels don't exhibit enough variation within games
  - Extrapolate changes in customer inflow from games that switch labels

# Demand: Estimation

- The NLLS estimator $\hat{\theta}$ is the solution to

$$\min_{\theta} \sum_{i=1}^{n} \sum_{t=2}^{T_i} w_i (A_{it} - \psi_i A_{it-1} - \lambda_i (1 + x_{it}' \beta))^2 \tag{5}$$

- Conditional on $\beta$, the problem is OLS
  - Solve for $\hat{\lambda}_i(\beta)$ and $\hat{\psi}_i(\beta)$
  - Concentrate $\lambda_i$ and $\psi_i$ out

- Solve the concentrated out minimization problem

# F.O.C. for the NLLS Problem

Back

$$
\begin{aligned}
\psi_i &: \sum_{t=2}^{T_i} (y_{it} - \psi_i y_{it-1} - \lambda_i (1 + x_{it}'\beta)) y_{it-1} &&= 0 && (6) \\
\lambda_i &: \sum_{t=2}^{T_i} (y_{it} - \psi_i y_{it-1} - \lambda_i (1 + x_{it}'\beta))(1 + x_{it}'\beta) &&= 0 && (7) \\
\beta &: \sum_{i=1}^{n} \sum_{t=2}^{T_i} w_i (y_{it} - \psi_i y_{it-1} - \lambda_i (1 + x_{it}'\beta)) \lambda_i x_{it} &&= 0 && (8)
\end{aligned}
$$

# Stylized Model

Back

- A product has of a review status $s \in (0,1)$ can give a discount at cost $c$
- Status goes up by $x$ with prob. $p$, down by $x$ with prob. $1-p$
  - Upgrade: $s$ exceeds 1. Downgrade: $s$ goes below 0.
- Payoffs from downgrade, no change, or upgrade: $u^L < 0 < u^H$
- Give the discount if $\mathbb{E}\left[U(s+X)\right] = pU(s+x) + (1-p)U(s-x) - c > 0$
- If $s > 1/2$, then

$$\mathbb{E}\left[U(s+X)\right] = \begin{cases} -c & x < 1-s \\ pu^H - c & x \in [1-s, s) \\ pu^H + (1-p)u^L - c & x \geqslant s \end{cases} \tag{9}$$

# Arrival of Reviews

Back

- A buyer at $t-k$ leaves a positive (negative) review with probability $r_{it}^{+}$ ($r_{it}^{-}$)
- Good reviews $G_{it} \sim P(\cdot\,; r_{it}^{+}\lambda_{it-k})$, bad reviews $B_{it} \sim P(\cdot\,; r_{it}^{-}\lambda_{it-k})$
  Review Arrival
- The **like rate** and the **dislike rate** are linear functions of observables

$$r_{it}^{+} = w_{it}'\rho_i^{+} \qquad r_{it}^{-} = w_{it}'\rho_i^{-} \tag{10}$$

- $w_{it} = [1, disc_{it-k}, \ldots]'$, $\rho_i^{+} = [\rho_{i0}^{+}, \rho_{i1}^{+}, \ldots]$

# The Selection Effect

- Probabilities of a like and a dislike off a discount: $\rho_{i0}^{+}$ and $\rho_{i0}^{-}$
- During a discount: $\rho_{i0}^{+} + \rho_{i1}^{+}$ and $\rho_{i0}^{-} + \rho_{i1}^{-}$
- Review score: probability of a like conditional on a review
- Measure the selection effect by the difference between the expected scores on and off a discount

$$\Delta score_i := \frac{\rho_{0i}^{+} + \rho_{1i}^{+}}{\rho_{0i}^{+} + \rho_{1i}^{+} + \rho_{0i}^{-} + \rho_{1i}^{-}} - \frac{\rho_{0i}^{+}}{\rho_{0i}^{+} + \rho_{0i}^{-}}$$

- Test

$$H_0 : \frac{\rho_{0}^{+} + \rho_{1}^{+}}{\rho_{0}^{+} + \rho_{1}^{+} + \rho_{0}^{-} + \rho_{1}^{-}} - \frac{\rho_{0}^{+}}{\rho_{0}^{+} + \rho_{0}^{-}} \leqslant 0$$

$$H_1 : \frac{\rho_{0}^{+} + \rho_{1}^{+}}{\rho_{0}^{+} + \rho_{1}^{+} + \rho_{0}^{-} + \rho_{1}^{-}} - \frac{\rho_{0}^{+}}{\rho_{0}^{+} + \rho_{0}^{-}} > 0$$

# Reviews: Identification

Back

- Turns out, $G_{it}$ and $B_{it}$ are independent
  - → We can estimate the like and dislike rates separately
- The lag between a purchase and review $k$ is set to be the max of the impulse response function of review count to discounts Regression
- Estimation is by maximum likelihood, using the estimates $\hat{\lambda}_{it}$ in place of $\lambda_{it}$

$$\mathbb{P}(G_{it} = g) = \frac{(r^+_{it}\hat{\lambda}_{it-k})^g}{g!} e^{-r^+_{it}\hat{\lambda}_{it-k}}$$

- If discount is a dummy, a closed-form solution can be derived

$$\hat{\rho}^+_{0i} + \hat{\rho}^+_{1i} = \frac{\sum_t disc_{it-k} g_{it}}{\sum_t disc_{it-k}\hat{\lambda}_{it-k}} \tag{11}$$

$$\hat{\rho}^+_{0i} = \frac{\sum_t (1 - disc_{it-k}) g_{it}}{\sum_t (1 - disc_{it-k})\hat{\lambda}_{it-k}} \tag{12}$$

# Reviews: Estimates

| | (1) | (2) |
|---|---|---|
| Constant (Like) | 0.074*** | 0.067*** |
| | (0.002) | (0.001) |
| Discount (Like) | 0.032*** | 0.017*** |
| | (0.003) | (0.001) |
| Constant (Dislike) | 0.015*** | 0.013*** |
| | (0.001) | (0.000) |
| Discount (Dislike) | 0.004*** | 0.002*** |
| | (0.001) | (0.000) |
| Young (Like) | | 0.296*** |
| | | (0.015) |
| Old (Like) | | −0.045 |
| | | (0.001) |
| Young (Dislike) | | 0.067*** |
| | | (0.006) |
| Old (Dislike) | | −0.008 |
| | | (0.000) |
| Observations | 355077 | 355077 |

# Identification of $k$

Back

| | Dependent variable: | | |
|---|---|---|---|
| | New Reviews | New Reviews(%) | Score (0-100) |
| Discount 0 Days Ago | 1.094*** | 1.801*** | −0.159 |
| | (0.122) | (0.135) | (0.152) |
| Discount 1 Day Ago | 3.254*** | 4.282*** | −0.557*** |
| | (0.276) | (0.228) | (0.184) |
| Discount 2 Days Ago | 1.377*** | 1.969*** | −0.470*** |
| | (0.139) | (0.100) | (0.176) |
| Discount 3 Days Ago | 0.743*** | 1.197*** | −0.370** |
| | (0.110) | (0.072) | (0.170) |
| Discount 4 Days Ago | 0.622*** | 0.847*** | −0.401** |
| | (0.096) | (0.066) | (0.166) |
| Discount 5 Days Ago | 0.418*** | 1.023*** | −0.395** |
| | (0.104) | (0.125) | (0.161) |
| Discount 6 Days Ago | 0.071 | 0.396*** | −0.368** |
| | (0.086) | (0.063) | (0.159) |
| Discount 7 Days Ago | −0.120* | 0.254*** | −0.336** |
| | (0.072) | (0.076) | (0.155) |
| Weekdays + Week Effects | ✓ | ✓ | ✓ |
| Game Effects | ✓ | ✓ | ✓ |
| Observations | 350,819 | 350,819 | 350,819 |
| $R^2$ | 0.059 | 0.105 | 0.154 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |