Demand-Based Pricing and Learning in the Market for New Digital Music

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Music Market

- Shift to internet-based purchasing (iTunes, Amazon.com):
  - Easier to sample: listen before buying.
  - More information available: decisions of previous consumers (listens and purchases).
- How do consumers find new music to listen to?
  - If consumers have a common component of utility, they may rely on information from other consumers to help decide which songs to listen to (i.e., observational learning).

Observational Learning in the Online Music Market

- Possible long run outcomes:
  - Songs die (no consumers listen or purchase).
  - Songs survive (consumers listen, a fraction purchase).
- Bad outcomes (bad herds):
  - A good song dies.
  - A bad song survives.
- This is an empirical study of bad herds in an online music market.

Amie Street Music

Enhance discovery of new artists:

- Demand-based pricing (iTunes and Amazon.com use fixed prices).
- Information on the number of times people listened and purchased.

Research Questions

1. How prevalent are bad herds in the Amie Street market?
   1. What is the probability that good a song dies?
   2. What is the probability that a bad song survives?
2. What is the effect of demand-based pricing on the probability of bad herds, compared to fixed pricing?

Strategy

- Develop a model of how consumers choose to listen to and purchase songs in this market.
- Simulate the model to produce long run outcomes of songs and match the outcomes to the data.
- Calculate the likelihood of bad herds in this market.
- Use the model to predict the likelihood of bad herds using a fixed price.

Main Results

- In the Amie Street market: 60% of good songs die and 0% of bad songs survive.
- If Amie Street employed a fixed price of 99 cents: 100% of good songs die and 0% of bad songs survive.

Related Literature

- Observational learning:
  - Theoretical: Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), Smith and Sorensen (2000),
  - Empirical: Sorensen (2006), Chevalier and Mayzlin (2006), Cai, Chen, and Fang (2009), Conley and Udry (2010).
- Optimal pricing with observational learning: Bose et al. (2006, 2007)
- Music: Waldfogel (2009, 2011), Hendricks and Sorensen (2009), Hendricks, Sorensen and Wiseman (2012).

Road Map

Data Source: Amie Street Music

- Active from 2006 until September 2010.
- Goal: to be "the place to discover new music".
- Featured unknown and indie bands.

Pricing Scheme: Demand-Based Pricing

- All songs start at 0.
- The first 13 purchases of a song are free.
- The 14th purchase costs 13 cents.
- The price increases 1 cent for every additional purchase, up to 98 cents.
- The price never decreases.
- Price is a measure of aggregate purchases (i.e., 28 cents=28 purchases).

Song Information

A consumer observes:

- Song title, album title, artist name, etc.
- Album's release date: signal of the number of consumers that have arrived.
- Current price: signal of the number of consumers that have purchased.
- Number of listens: signal of the number of consumers that have listened.

Data Collection

- Wrote webscraper to collect weekly data for a subset of songs.
- Download period: March - September 2010.
- Data:
  - Price (purchases).
  - Listens.
  - Band/song attributes: genre, release date, song name, etc.

Subsample: Unknown Songs

Goal is to include only unknown songs:

- Folk artists.
- New artists
  - Last 1,000 artists who posted prior to the collection period.
  - 300 artists who posted during the collection period.
- For each artist, selected the album with the earliest release date.
- For each album, selected the first song listed.

Subsample: Songs in a Long Run Outcome

- Focus on songs that have reached a long run outcome.
- Two outcomes:
  - Songs die below 98 purchases: no one listens for two consecutive weeks.
  - Songs survive to 98 purchases: consumers continue to listen.
- Songs move quickly to one of these two outcomes (2 weeks).

Subsample: Songs in a Long Run Outcome

- Of songs that had two weeks of inactivity, 85% were never listened to again.
- Of songs that made it to 98 purchases, 82% never had two weeks of inactivity.
- Assume other songs are still in transition.
- Include songs with:
  - At least 98 purchases.
  - Less than 98 purchases and no one listened in the final two weeks of the collection period.

Aggregate Data

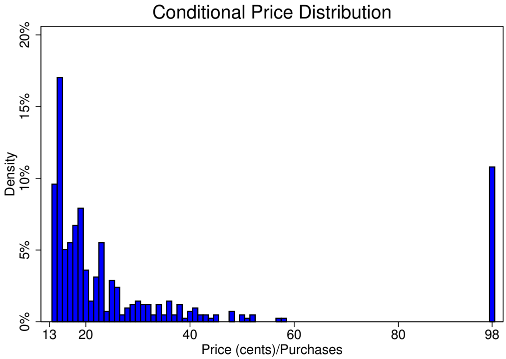
Focused on the aggregate data for this subset of songs:

- A snapshot of the price and listen distribution at the end of the collection period.
- Two reasons: (1) Speed of transition and (2) Left truncation for some songs.

Data Summary

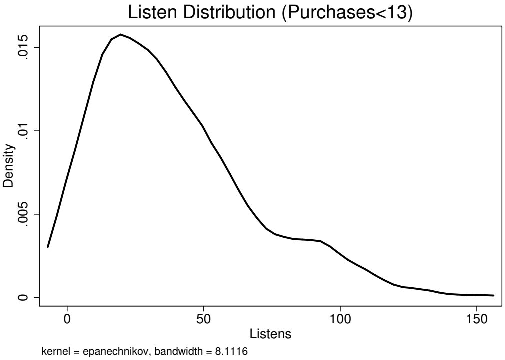
- 944 songs.
- Aggregate joint distribution of price and listens for songs that died.
- Number of songs that made it to 98 purchases.
  - Do not use listen information for 98 cents songs.
- Most of the analysis is focused on the dead songs.

Price/Purchase Distribution for Songs Bought at Positive Price



50% of songs were not purchased for a price>0.

Conditional Listen Distribution



98 cent song averaged 16 listens per week after 4 weeks of being on the website.

Model

- Consumer utility.
- Information.
- Formation of beliefs.
- Long run outcomes.

Consumer Utility

- Consumers arrive at a song in an exogenous order and are subscripted by their arrival order i.
- Consumer i has the following utility for the song:

$$w_i = X + u_i - p_i$$

- Common component: $X = \begin{cases} H & \textit{with probability } 1-\lambda \\ L = 0 & \textit{with probability } \lambda \end{cases}$
- Idiosyncratic component: $u_i \sim N(0, \gamma^2)$.

Listening

- Consumer does not know $X + u_i$.
- Can learn this value by listening to the sample of the song.
- Listening to the song costs the consumer c.
- Assume a consumer will not purchase a song without listening to it first.

Information

Before making listening decision, consumer i:

- Observes the number of listens, l_i, and the price, p_i.
  - Updates the social belief: $\mu_i = Pr(X = H|(l_i, p_i))$.
- Receives a private signal $\sigma_i = Pr(X = H)$.
  - $\sigma_i \sim \begin{cases} beta(1, \delta_1) & if\ X = H \\ beta(1, \delta_0) & if\ X = 0 \end{cases}$
  - $\delta_0 > \delta_1$.
- Private belief: $\rho_i = Pr(X = H|(l_i, p_i), \sigma_i) = \frac{\sigma_i \mu_i}{\sigma_i \mu_i + (1-\sigma_i)(1-\mu_i)}$

Formation of Beliefs: Example

Define:

- $\pi_i((l_i, p_i), X)$: the probability of observing (l_i, p_i) in state X.
- $\hat{\sigma}_i(l_i, p_i)$: the cutoff value for the private signal given (l_i, p_i).
    - $\rho_i E[w_i|H, w_i \geq 0] + (1 - \rho_i)[E[w_i|L, w_i \geq 0] \geq c$
- $\alpha_i((\hat{\sigma}_i(l_i, p_i), X)$: the probability consumer i listens when they observe (l_i, p_i) in state X.
- $\beta_i(X, p_i)$: the probability consumer i purchases in state X, given they listened.

Formation of Beliefs: Example

Consumer 4 observes $(2,1)$: there are three possible actions of consumer 3, given X:

1. Consumer 3 observed $(2,1)$ and didn't listen. The probability of this event is:

$$\pi_3((2,1),X)(1-\alpha_3(\hat{\sigma}_3(2,1),X))$$

2. Consumer 3 observed $(1,1)$ and listened but didn't purchase. The probability of this event is:

$$\pi_3((1,1),X)\alpha(\hat{\sigma}_3(1,1),X)(1-\beta(X,1))$$

3. Consumer 3 observed $(1,0)$ listened and bought. The probability of this event is:

$$\pi_3((1,0),X)\alpha(\hat{\sigma}_3(1,0),X)\beta(X,0)$$

Formation of Beliefs: Example

- $\pi_4((2,1),X)$ is the sum of these three probabilities.
- $\mu_4 = Pr_4(X = H|(2,1)) = (1-\lambda)\frac{\pi_4((2,1),H)}{\pi_4((2,1),H)+\pi_4((2,1),L)}$
- $\rho_4 = Pr(X = H|(2,1),\sigma_4) = \frac{\sigma_4\mu_4}{\sigma_4\mu_4+(1-\sigma_4)(1-\mu_4)}$

Listen/Purchase Decision

- Consumer 4 will listen if:

$$\rho_4 E[w_4|H, w_4 \geq 0] + (1 - \rho_4)[E[w_4|L, w_4 \geq 0] \geq c \rightarrow \alpha_4((\hat{\sigma}_4(2,1), X)$$

- She will buy if:

$$X + u_4 \geq p_4 \rightarrow \beta_4(X, 1)$$

Possible Long Run Outcomes

- The probability a consumer will listen converges to 0.
  - Beliefs ρ such that no σ will induce listening.
    - $\sigma \in (0, 0.999)$.
  - Songs less than 98 purchases.
  - For H songs, this is a bad herd.
- The probability a consumer will listen converges to a constant.
  - Songs made it to 98 purchases.
  - For L songs, this is a bad herd.

Identification of Bad Herds

For any parameters, I can calculate the beliefs about a song at a given (l_i, p_i).

- The distribution of beliefs for songs with less than 98 purchases determines the probability of good songs dying.
- The distribution beliefs for songs that reach 98 purchases determines the probability of bad songs surviving.

Simulation

- The vector of parameters to be estimated is:

$$\theta = [\gamma, c, H, \lambda, \delta_0, \delta_1]$$

- Given this vector of parameters I can simulate the life of a song to its long run outcome.
  - Step 1: Calculation of belief matrix.
  - Step 2: Simulate $I = 700$ consumers and their choices.

Simulation

- A single simulation produces:
  - (l, p) for a dead song.
  - $p = 98$ for a surviving song
- Simulate market $2,000$ times:
  - (l, p) distribution for dead songs.
  - Number of songs reaching 98 purchases.
- Match these moments to moments in the data to estimate the parameters of the model.

Moments

- Unconditional price distribution for dead songs.
- Unconditional listen distribution for dead songs
- Joint distribution for dead songs.
- Mean and standard deviation of purchases for songs less than 98 cents.
- Mean and standard deviation of listens for songs less than 98 cents.
- % of songs that reach 98 cents.

Estimates

Parameter Estimates						
Parameters	γ	c	H	λ	δ_1	δ_0
Estimate	\$0.99 (0.042)	\$0.36 (0.052)	\$2.60 (0.154)	0.91 (0.011)	4.2 (0.94)	9.7 (2.91)

Standard errors (numerically calculated) in parentheses.

Model Fit: Purchase Distribution

c=\$0.36 and γ=\$0.99

Purchases	Distribution
0-13	45.7% (52.3%)
14-20	27.3% (29.4%)
21-40	13.6% (15.6%)
41-60	9.7% (2.7%)
61-97	3.8% (0.0%)

Note: data in parentheses.

Model Fit: Listen Distribution

H=\$2.60

Listens	0-25	26-75	76+
Distribution	27.7% (29.6%)	56.8% (51.4%)	15.5% (19.0%)

Note: data in parentheses.

Model Fit: Joint Distribution

δ_0=9.7 and δ_1=4.2

Purchases\ Listens	0-25	26-75	76+
0-13	22.8% (16.9%)	22.9% (28.6%)	0.0% (6.9%)
14-20	4.9% (10.0%)	22.4% (12.2%)	0.0% (7.1%)
21-40	0.0% (2.6%)	11.4% (9.1%)	2.2% (3.9%)
41-60	0.0% (0.1%)	0.1% (1.6%)	9.5% (1.0%)
61-97	0.0% (0.0%)	0.1% (0.0%)	3.7% (0.0%)

Model Fit: 98 cent Songs

λ=0.91

- Number of 98 cent songs:
  - Data: 5.4% songs reached 98 downloads.
  - Model: 4.6% of songs reached 98 downloads.

Outcomes

- Artist discovery:
  - Probability of good song dying: 60%.
- Consumer welfare:
  - Probability of bad song surviving: 0%.
  - Short run consumer surplus per consumer per song (700 consumers): 8 cents.
- Expected long run revenue for high quality song per consumer:
  - price*long run purchase probability*(1-probability of dying): 37 cents.

Demand-Based Pricing vs Fixed Pricing

- What would these outcomes be if Amie Street used a fixed-pricing scheme?
- Counterfactual:
  - Same learning environment.
  - Price fixed at 99 cents.

Demand-Based Pricing vs Fixed Pricing

What would these outcomes be if Amie Street used a fixed-pricing scheme?

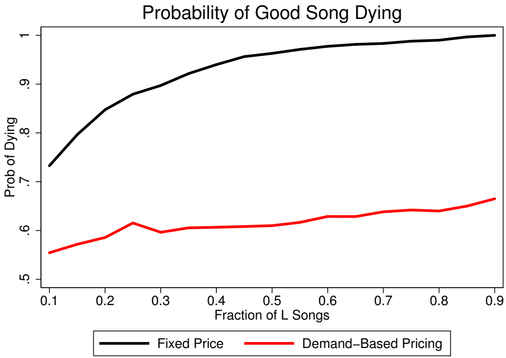
	Amie Street	Fixed Price (99 cents)
Probability a Good Song Dies	60%	100%
Probability a Bad Song Survives	0%	0%
Expected Short Run Consumer Welfare	\$0.08	\$0
Expected Long Run Revenue (per consumer)	\$0.37	\$0

Lower Fixed Price

	Amie Street	Fixed Price(50 cents)
Probability a Good Song Dies	60%	98%
Probability a Bad Song Survives	0%	0%
Expected Short Run Consumer Welfare	\$0.08	\$0.00
Expected Long Run Revenue (per consumer)	\$0.37	\$0.02

Filtering out the Low Quality Songs

What would the probability of a bad song dying look like when the overall quality of music is increased?



Amazon.com

- Should Amazon use demand-based pricing?
  - Does Amazon rely on consumers to learn elsewhere?
  - Overall quality of music.
  - Could exploit the learning effects of pricing.

Conclusion

- Empirically estimated the likelihood of bad herds in an online market for digital music.
  - 60% of good songs die and 0% of bad songs survive.
- Compared how different pricing schemes affect the likelihood of bad herds.
  - Demand-based pricing can reduce the probability that good songs die.
- Extensions:
  - Heterogeneous listening costs.
  - Song Heterogeneity.
  - Other counterfactuals: learning environment.