Exposure Doesn't Pay the Bills:

Aristic Production under Algorithmic Uncertainty in Streaming Markets

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Outline

1. Intro and Motivation
2. Model
3. Findings
4. Questions

Intro and Motivation

- YouTube's 2021 Q3 Ad Revenue is $7.2B[1]
- Streaming Platforms are driven by **content creators**
- Content creation can be a full time job
- Creators make content, but algorithm decides who sees it

[1] Source

Motivation, continued. My Niche in the Literature

- Artist's problem on streaming platforms
  - Choose ideal quantity and quality each period
- Role of algorithmic uncertainty on producers
- Effect of time on quality

The Model

What should a model describe?

Consumer Behavior:

- Artist discovery
- Consumption based on quality

Artist/Content Creator:

- Maximize royalties from streams
- Quality-quantity trade-off under audience uncertainty

Streaming Platform:

- Algorithmic consumer-artist matching
- Useful but imperfect matching

Putting the pieces together

Audience Evolution

$\mathcal{A}(m, n, A, \varepsilon)$

Consumer demand

$\nu(z)$

Putting the pieces together:

Per-period revenue:

$$\mathcal{A}(m, n, A, \varepsilon)\nu(z)r$$

Subject to:

$$f(m, z) = \kappa$$

Insights from a binary-choice one period model

- There is a strategy cutoff dependent on A:
  - Established artists choose high quality, new artists choose more exposure
- If algorithm is very favorable to new artists, both may choose high quality
- *This doesn't rely on functional form assumptions*

Dynamic Problem and Main Results

Solving Dynamically Using Recursion:

$$V(n_{-1}, A_{-1}) = \max_{m,z} \{E[Anr + \rho V(n, A)]\}$$

$$s.t.$$

$$A = \mathcal{A}(m, n_{-1}, A_{-1}, \varepsilon), \text{ Audience Evolution}$$

$$n = \nu(z), \text{ Consumer Demand}$$

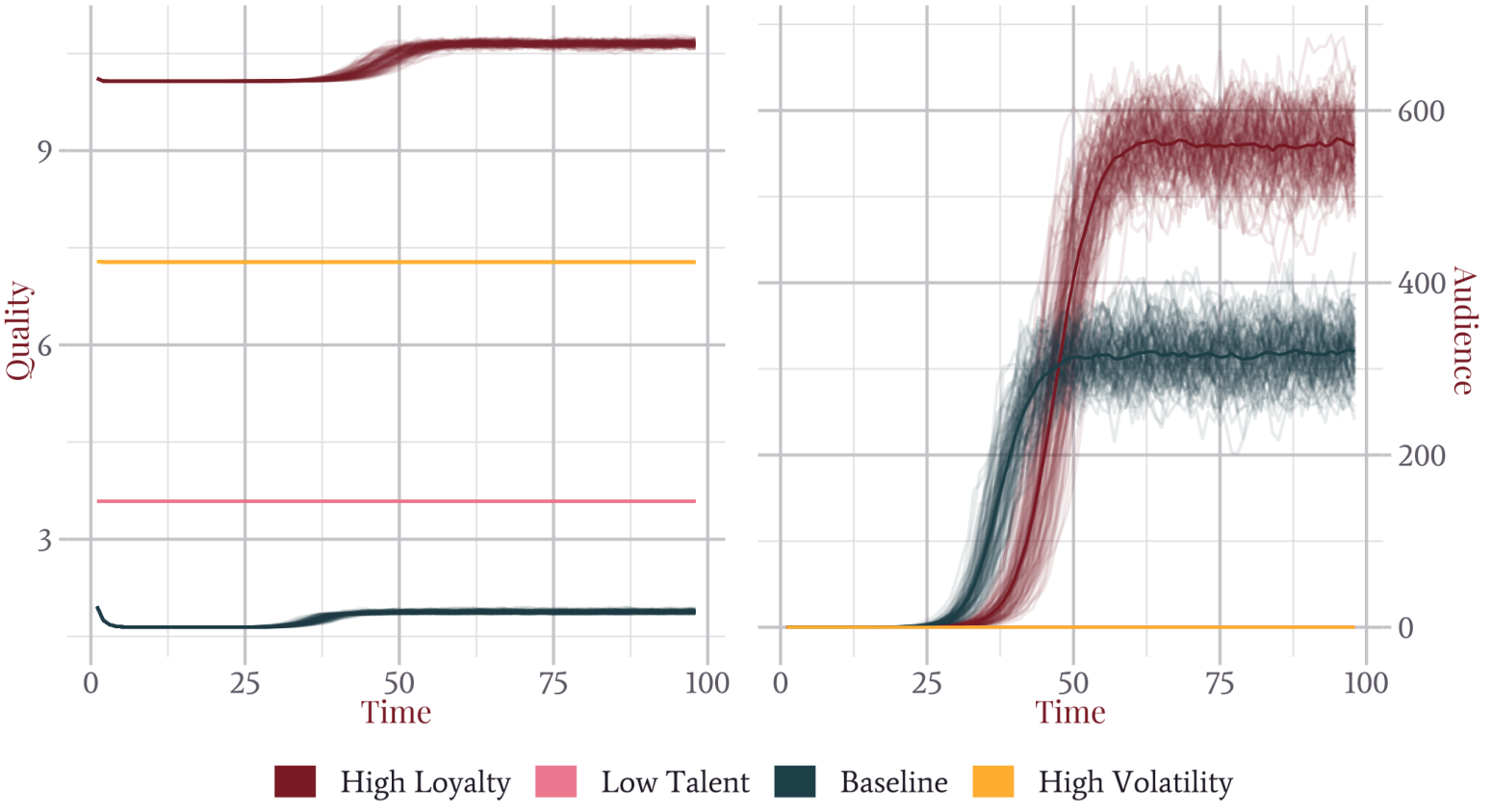
$$f(m, z) = \kappa, \text{ Tradeoff}$$

Solving for V and optimal m, z:

$$V(n_{-1}, A_{-1}) = \max_{m,z} \{E[Anr + \rho V(n, A)]\}$$

- In this form, we have preexisting solving techniques!
- Solutions computed numerically
- Calibrated baseline for boundedness, interior solutions
  - Should not interpret magnitude of numbers, only differences from baseline

Three variations from the baseline:



Conclusion

- Quality does not determine audience
- Successful artists shift from lower to higher quality
  - After they "go viral"
- Agents who do not understand the algorithm will not maintain audience
- Talent can also filter out artists
- Future research:
  - How does talent influence distribution of revenue
  - Fit with data

Thanks, Questions?

Aguiar, L. and J. Waldfogel (2018). "Quality Predictability and the Welfare Benefits from New Products: Evidence from the Digitization of Recorded Music". In: Journal of Political Economy 126.2. http://www.journals.uchicago.edu/doi/full/10.1086/696229, pp. 492–524. ISSN: 0022-3808. DOI: 10.1086/696229.

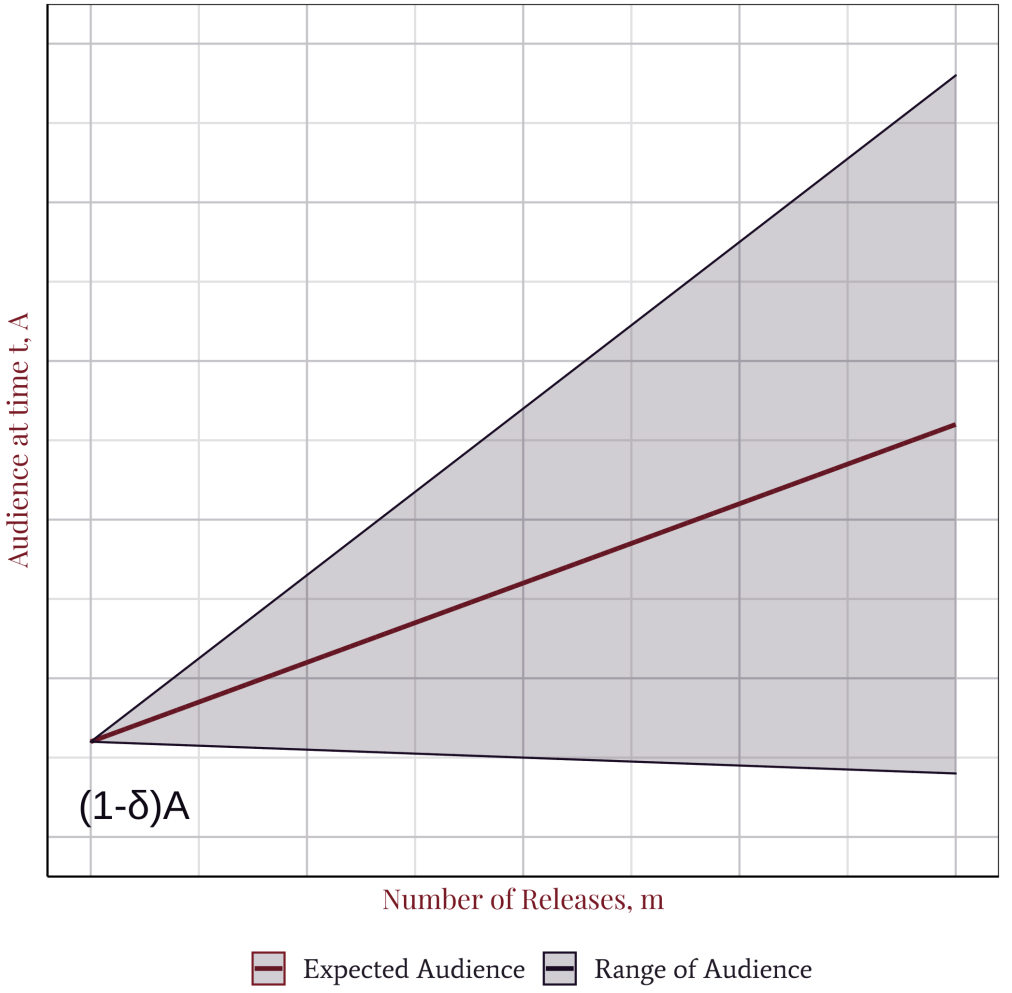
Klein, B. and K. Leffler (1981). "The Role of Market Forces in Assuring Contractual Performance". In: The Journal of Political Economy.

MacDonald, G. M. (1988). "The Economics of Rising Stars". In: The American Economic Review 78.1. https://www.jstor.org/stable/1814704, pp. 155–166. ISSN: 0002-8282.

Shapiro, C. (1983). "Premiums for High Quality Products as Returns to Reputations". In: The Quarterly Journal of Economics 98.4. https://www.jstor.org/stable/1881782, pp. 659–679. ISSN: 0033-5533. DOI: 10.2307/1881782.

Thomes, T. P. (2013). "An Economic Analysis of Online Streaming Music Services". In: Information Economics and Policy 25.2. https://www.sciencedirect.com/science/article/pii/S0167624513000103, pp. 81–91. ISSN: 0167-6245. DOI: 10.1016/j.infoecopol.2013.04.001.

Visualizing Audience Uncertainty:



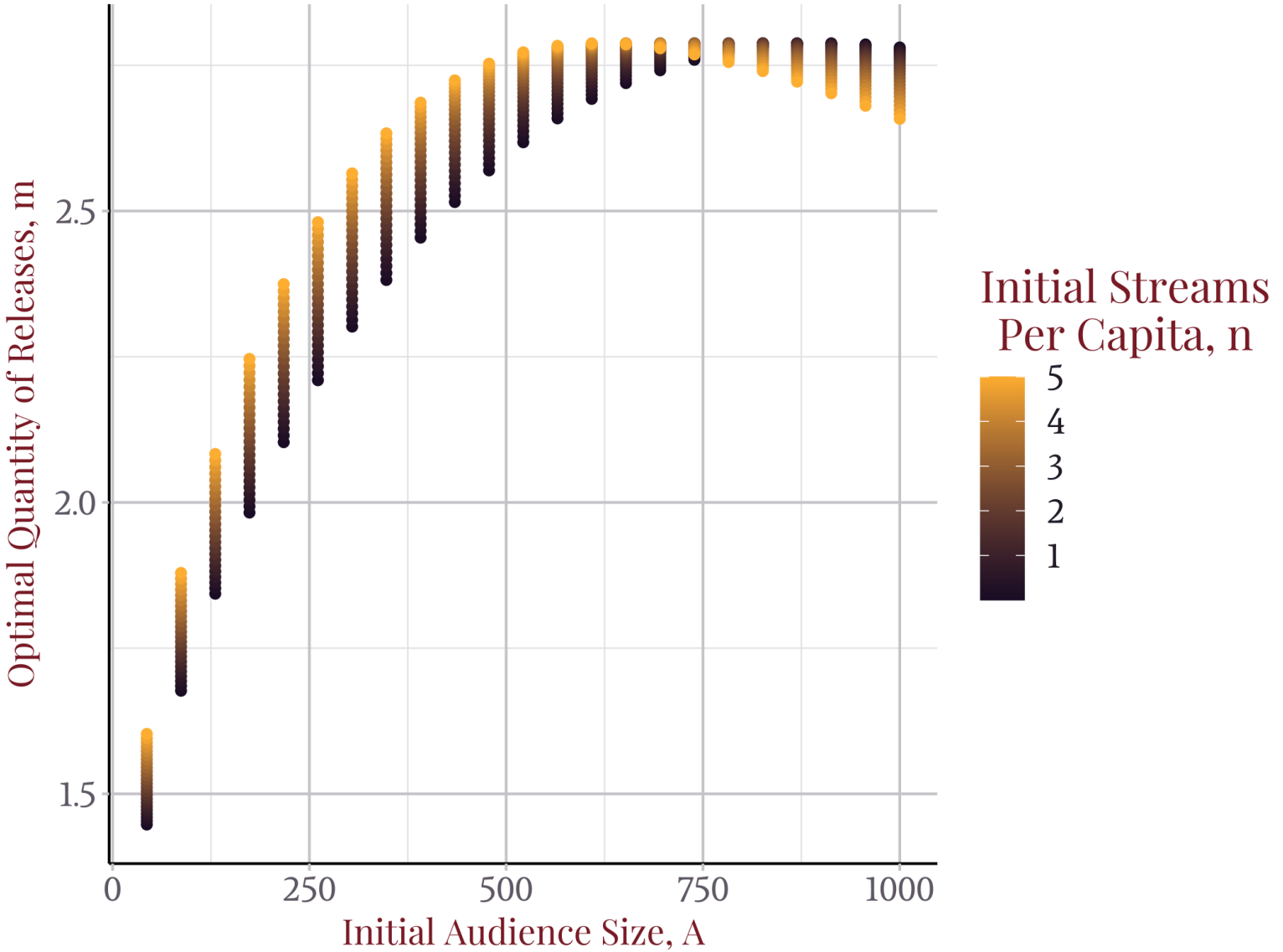
Functional Forms

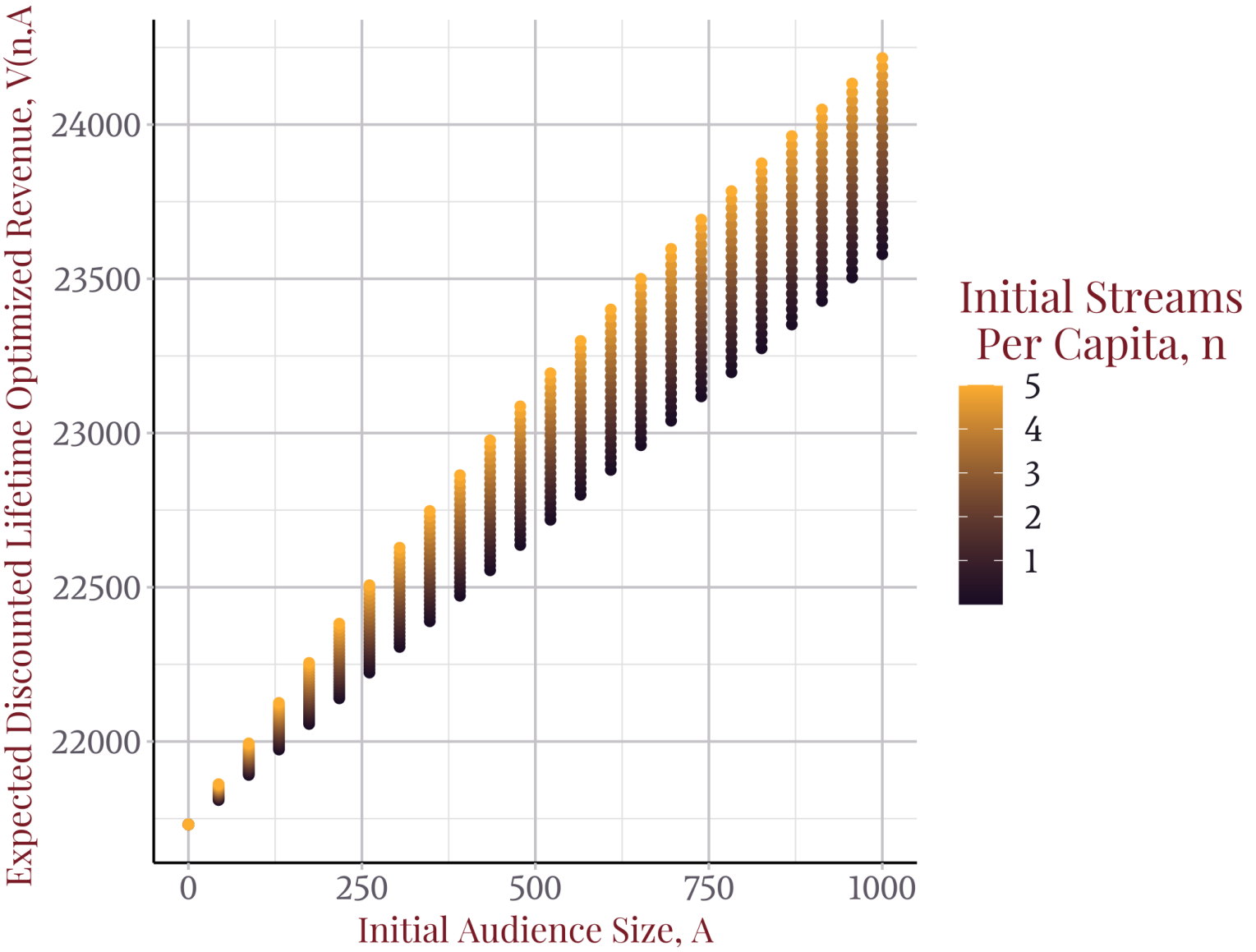
$$\mathcal{A}(m,n,A,\varepsilon)=\frac{\overline{A}}{1+ce^{-\alpha n-\beta m-\gamma\varepsilon}},c=\frac{\overline{A}-(1-\delta)A}{(1-\delta)A}$$

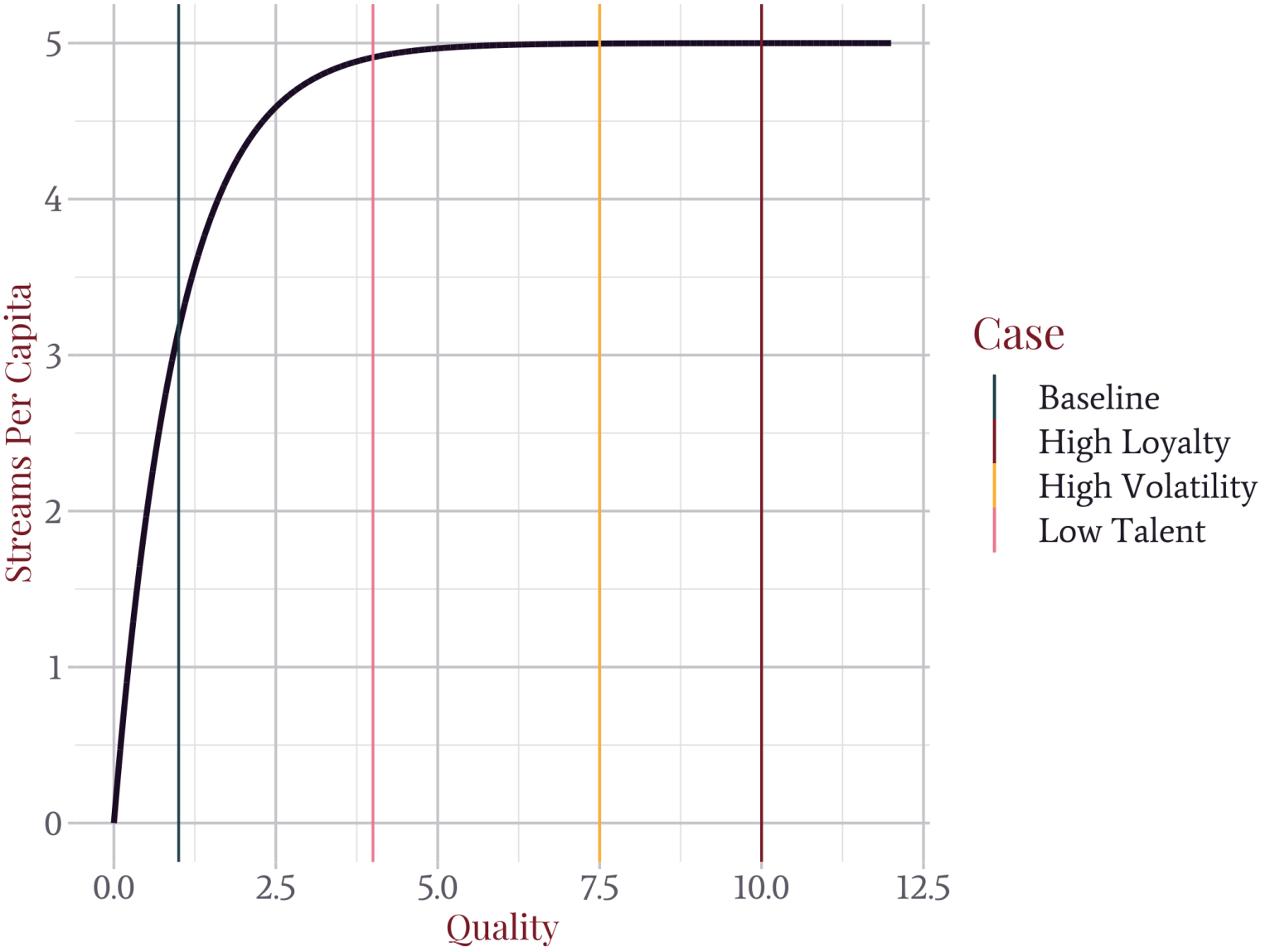
$$f(m,z)=mz$$

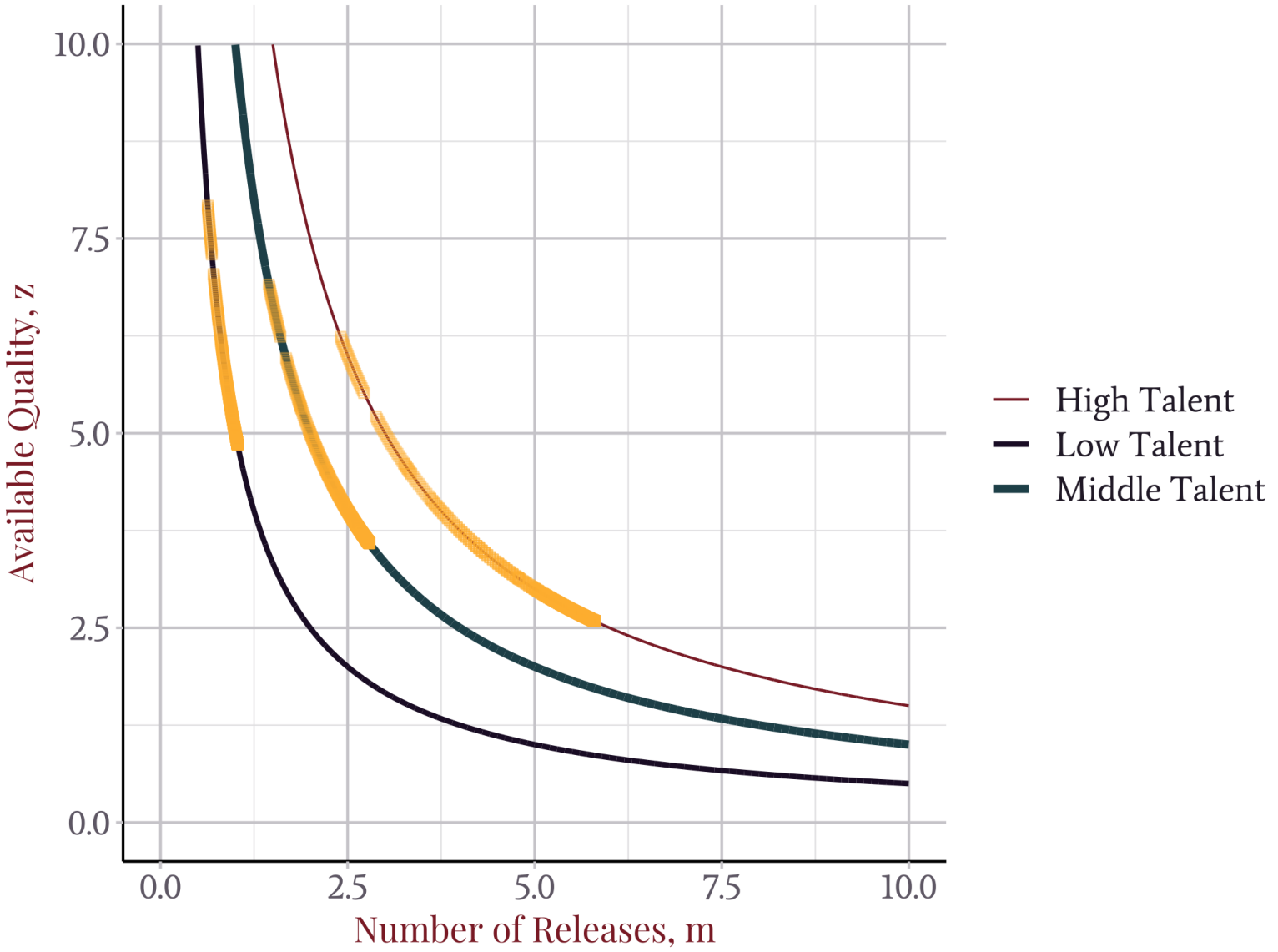
$$n(z)=\overline{n}(1-e^{-\lambda z})$$

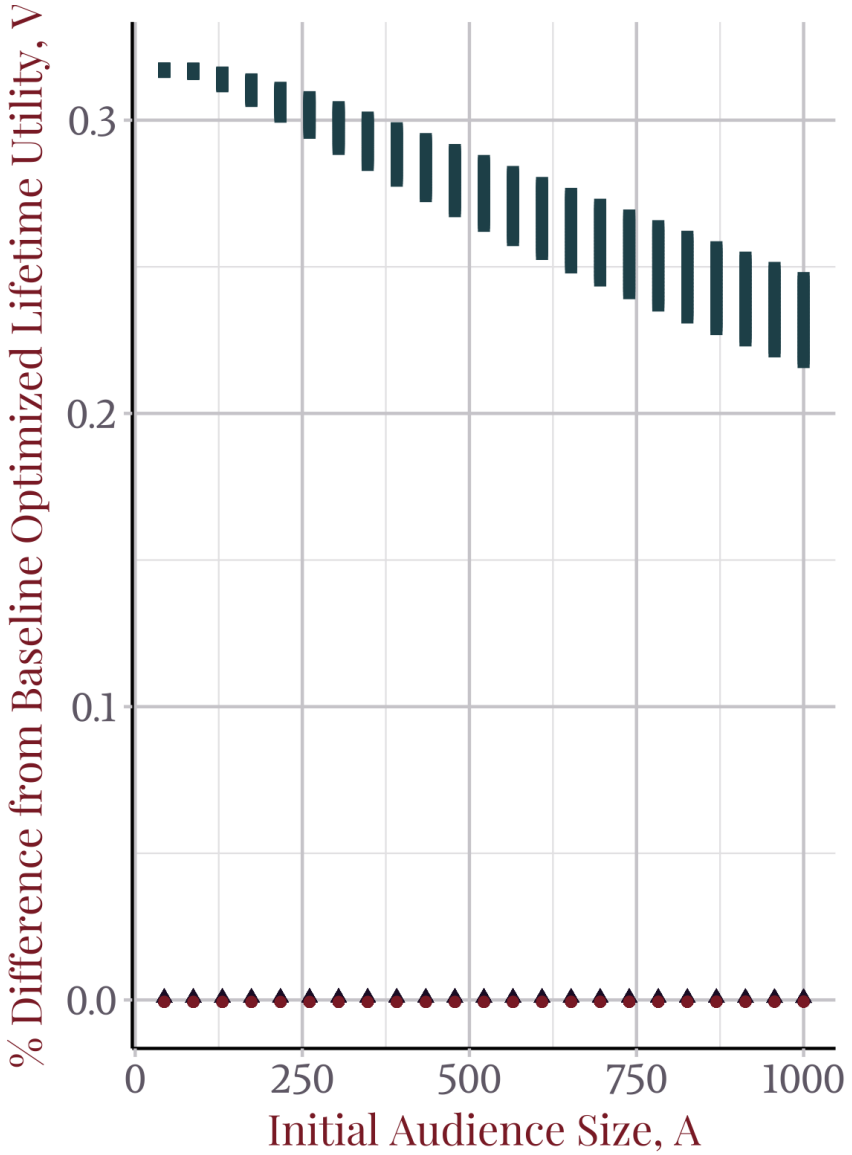
$$\varepsilon\sim N(0,\sigma^2)$$

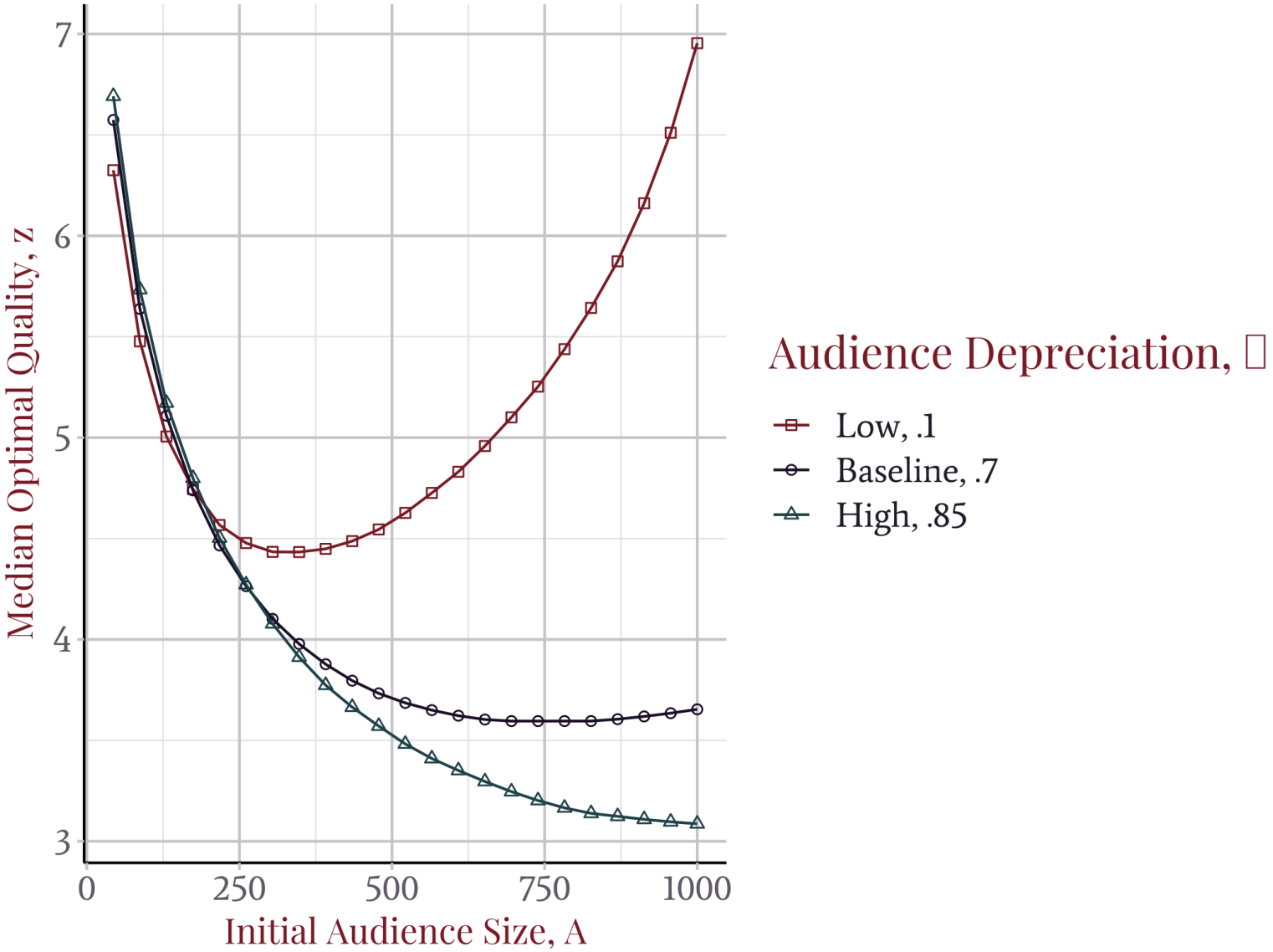

Optimal Quantity of Releases, m
2.5
2.0
1.5
0
250
500
750
1000
Initial Audience Size, A
Initial Streams Per Capita, n
5
4
3
2
1


Expected Discounted Lifetime Optimized Revenue, V(n,A
24000
23500
23000
22500
22000
0
250
500
750
1000
Initial Audience Size, A
Initial Streams Per Capita, n
5
4
3
2
1


Streams Per Capita
5
4
3
2
1
0
0.0
2.5
5.0
7.5
10.0
12.5
Quality
Case
Baseline
High Loyalty
High Volatility
Low Talent


10.0
7.5
5.0
2.5
0.0
Available Quality, z
0.0
2.5
5.0
7.5
10.0
Number of Releases, m
High Talent
Low Talent
Middle Talent


% Difference from Baseline Optimized Lifetime Utility, V
0.3
0.2
0.1
0.0
0
250
500
750
1000
Initial Audience Size, A
Algorithmic Uncertainty,
0.0
1.0
10


Median Optimal Quality, z
7
6
5
4
3
0
250
500
750
1000
Initial Audience Size, A
Audience Depreciation,
Low, .1
Baseline, .7
High, .85