Exposure Doesn't Pay the Bills

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1 Literature Review

In this paper I will examine how an artist's production decisions and reputation are influenced by algorithmically uncertain audience size in the digital streaming economy. This topic is tethered to multiple lines of research each of which informs the construction of the model below. I discuss connections to the branding literature, the superstar literature, and the novel streaming literature.

1.1 Branding Literature

An artist concerned with growing their audience faces many similar incentives to a new firm trying to develop a brand. One can view a brand as a set of signals about the quality of a firm's product. Branding becomes an important consideration when consumers do not have ex ante knowledge about the quality of the product they are purchasing. As such, consumers rely on the signals presented by a firm's brand to inform their consumption decisions. The branding literature begins with the signalling literature pioneered in Spence (1973). In this paper, Spence finds that observable characteristics, both impactful and superficial, can have substantial effects on the hiring decisions of a potential employer. More directly, Klein & Leffler (1981) presents a simple model that identifies key characteristics that a market must possess in order for firms to invest in branding and selling a high quality product. Central to their model is consumer reputation formation. They propose a rather draconian baseline in which consumers' trust can never be regained upon a firm choosing to deceive them. A key finding is that with sufficient differentiation between high and low quality products, some firms may choose to invest in their reputation into perpetuity. Shapiro (1983) generalizes the model proposed by Klein and Leffler to a case where reputation can exist on a continuum of values and can evolve in a less austere manner. The authors describe the characteristics of a market equilibrium and find that again so long as there is sufficient price difference between low and high quality products, producers may choose to invest in building a brand.

The application of the branding literature to the problem posed in this paper lies in the way that streaming platforms' alogrithms reveal information and content to consumers. Generally streaming platforms allow users to choose their own content, but many platforms like Youtube, Spotify, and Apple Music also algorithmically provide content based on the consumer's revealed preferences. When this content is previously unknown to the consumer, we can view the platform as relying on its branding to present desirable content to the user.

1.2 Superstar Literature

A related strand of literature to branding is the superstar literature which itself lies more towards cultural economics. The use of the word superstar in an economic context was popularized in Rosen (1981a) in his seminal exploration of why art markets have tremendously skewed income distributions even when the underlying talent pool may be much less skewed. In his paper, he presents a model where consumers can perfectly observe talent ex ante. In this framework, Rosen finds that small increases in underlying artistic talent can have disproportionately large increases in resultant revenue in market equilibrium. This leads to revenues being concentrated among only a few artists. Art market concentration is further explored in MacDonald (1988) which takes an alternate modeling approach and introduces uncertainty in the talent of an artist. This uncertainty is market-wide where neither the consumer nor the artist knows their talent until they have performed. This model also intersects with the branding literature because it explores how an artist's perceived talent evolves over multiple periods based on the quality of their performance.

The superstar literature is important to this analysis because it emphasizes the artist's production decisions and how they affect market revenues. As I will discuss later, much of the recent literature on streaming economies has focused on the streaming platform and the end consumers, so the superstar literature gives a more nuanced view of how artistic production can be modeled and optimized.

1.3 Streaming Literature

The third and most closely related field of study is the streaming literature. The advent of streaming has garnered considerable attention from both theoretical and empirical angles. Streaming platforms can take many forms, but they can be broadly characterized as an internet-based two-sided media marketplace. The streaming platform is in the middle of this two sided marketplace. The first side of the marketplace is the streaming platform accepting media from content creators. The other side of this marketplace is the streaming service delivering this content to consumers. Usually money is changed hands on both sides of this market. Researchers have focused on various aspects of the streaming economy as it has evolved. I will begin by giving an overview of some of the key topics addressed by theoretical papers. After discussing theory, I will mention some relevant empirical studies that analyze how digitization has affected the distribution of artist popularity—a central question of the research at hand.

Early papers in the streaming literature investigate how streaming may curb pirating, the (usually free) illegal download of unlicensed music, like on Napster. One such early paper is Thomes (2013) which takes the perspective of the music streaming platform when deciding how to price its paid subscription service relative to its free-with-ads alternative. Thomes endogenizes the demand for advertisements which governs the streaming platform's revenue from its free-with-ads service. The author finds that if both a free and paid option exist, a streaming platform's profit is maximized when consumers are very permitting of advertising. This result is a product of high ad tolerance leading to a maximal advertising market size. The author further shows that if there is a piracy alternative that carries some risk of punishment, the streaming platform will make their free-with-ads alternative as desirable as possible which crowds out piracy from the market due to its inherent risk. The first claim, that profit is maximized when ad tolerance is high, seems not to have held up empirically. Spotify claimed that 93% of its 2020 quarter two revenue comes from premium subscribers.[1] This paper provides a valuable description of the incentives of the streaming platform when designing its features and pricing, but the analysis below will take these features as given to focus on the artist's problem.

Another more recent paper that takes the streaming platform's perspective is Bender et al. (2021). This paper analyzes competition between permanent digital MP3 sales and streaming platforms. It analyzes consumer demand, and how the platform should optimally set its royalty to attract artists to the platform. The authors find that it is the most popular artists that might choose to hold out and sell their work only via permanent download, a result seen anecdotally with the Beatles who kept their music off of streaming services for a famously long time.[2]

Hiller & Walter (2017) incorporates elements from both Thomes (2013) and Bender et al. (2021) by modelling an economy with digital purchases in addition to free and paid subscriptions on a streaming service. The authors investigate the artist's decision to produce one high-quality piece of art versus multiple comparatively lower-quality pieces. The authors find that the streaming economy fosters an environment in which profit-maximizing artists focus on generating high-quality singles instead of lower-quality albums. The quality quantity trade-off will be examined in the analysis below but with the key difference of uncertain audience size. The proceeding analysis acknowledges the fact that releasing more content may increase an artist's chance of reaching a larger audience.

Another driving question of this research pertains to the debate of whether or not streaming platforms have created a "long tail" of products. I will now summarize some empirical work that analyzes this topic.

The term long tail was popularized in Anderson (2006). The principle of the long tail is that digitization of commerce allows consumer's access to a wider variety of products—far more than a brick and mortar store could every stock. The greater variety of products allows consumers to pinpoint the product that best suits their preferences. A diverse product set results in many products having a small number consumers. As such, the distribution of consumers per product should have much longer tail than pre-digitization. The streaming economy is an excellent example of where this long tail might exist as Spotify can stock hundreds of times more songs into a server than a vinyl record store could ever stock in-store. The long

[1] Calculated from Spotify's published shareholder letter, available here: https://s22.q4cdn.com/540910603/files/doc_financials/2020/q2/Shareholder-Letter-Q2-2020_FINAL.pdf

[2] A discussion of the Beatles decision to stream their music is available here: https://www.fastcompany.com/3054965/its-official-the-beatles-are-coming-to-spotify-apple-music-and-more

tail hypothesis would suggest a diffusion of revenues across many artists. However, Rosen (1981a), finds that revenue should be concentrated among only a few artists. This disagreement suggests a fundamental shift in the way we should model the modern art market.

That being said, opinions are mixed as to whether or not the long tail hypothesis holds empirically. Elberse (2008) initially pushed back against the idea of a long tail. She cites data from Quickflix (a now-defunct Australian pay-per-view movie streaming platform) which showed that a small number of DVDs comprised a large portion of sales. The proceding analysis in this paper will model a different type of streaming platform, one in which customers have unlimited access to content either for free or for a monthly subscription fee.

A more recent alternate perspective on the long tail, Aguiar & Waldfogel (2018), posits that the benefits of the long tail may come from producers and not consumers. Aguiar and Waldfogel argue that digitization substantially lowers the entry cost of new firms. Lower entry costs marry well with uncertainty about whether or not a firm will be successful. Lower entry costs allow firms with lower expected profit into the market. When their true talent is realized, firms may have profit well above their expectation. They test this hypothesis using digital music sales to estimate demand and use this to infer consumer surplus. They compare their findings to the the hypothetical case in which firm performance is perfectly predictable. They robustly show that variety is much more important in the more realistic uncertain case. They argue that the value of variety provides evidence that there exists a long tail of producers.

1.4 This Paper's Contribution to the Literature

The preceding discussion reveals a few key unexplored area that this paper will investigate. One, previous literature has focused on behavior of the streaming platform and the end-user. This analysis contributes to the comparatively-understudied role of the artist in the streaming economy. Two, this paper will endogenize audience development, a similarity to the branding and superstar literature not yet applied to the streaming literature. Third, this paper will contribute the debate of the long tail in the streaming literature by exploring the equilibrium distribution of artist talent. Finally, This paper will also contribute to the presently-unexplored role of unpredictable algorithms on streaming platforms in shaping an artist's career and optimal behavior.

2 The Model

Modeling the streaming economy requires us to describe three primary actors: the end consumer, the streaming platform, and the artist. For the purposes of this analysis, I will assume that the behavior of the consumer and the streaming platform are exogenous. I will limit attention to the artist who must choose a quality and quality of art to produce. The streaming platform's algorithm will then show that art to consumers based on last period's consumer engagement with an artist and the number of pieces an artist releases this period. I will assume that consumers have no ex ante knowledge of an artist and require the algorithm to reveal an artist too them. I will call these algorithmic revelations, impressions. Once a consumer has received an impression, their number of streams will depend on the quality of the art that the artist released that period. The algorithm observes the streams per impression and uses this to decide how many times to show the artist's next period work.

The artist earns a royalty every time a song is streamed, and the artist tries to maximize this discounted flow of royalties. The trade-off between quantity of releases and the quality of those releases will be central to their maximization problem. Increases to quality ensure that once a consumer receives an artist's work, they will consume that product more. Increasing quality also has the inter-temporal benefit of encouraging next period's algorithm to show the art to more consumers. On the other hand, the artist can increase their quantity at the expense of quality. The algorithm will have more pieces to show to consumers (increasing the probability that a given consumer discovers an artist), but it also leaves audience size more up to the random component of the algorithm.

2.1 Hypotheses

Before describing the model in detail, I will first lay out possible results based on the literature presented above. The first hypothesis pertains to "long tail" theory described in Aguiar & Waldfogel (2018). Following the superstar literature and in particular Rosen (1981b), I will measure the long tail of outcomes by examining the convexity of the expected profit function in an artist's underlying talents. Weighing the long tail theory with Rosen's findings of convexity of profit in talent, I pose the following:

> *Hypothesis 1: Unpredictability of a streaming platform's content matching algorithm will decrease the convexity of profits in talent.*

The second hypothesis relates to audience development over multiple periods. Similar to the work of Bender et al. (2021), I will examine how the choices of established artists differ from artists with smaller starting audiences.

> *Hypothesis 2: Artists will smaller initial audiences will be more likely to choose a low-quality, high-quantity strategy relative to established artists.*

The final hypothesis pertains to how the previous hypothesis changes over time. The quality quantity tradeoff becomes less clear cut when quality informs next period's audience. As such I propose:

> *Hypothesis 3: Artists with small initial audiences will prioritize quality more in a multi-period setting than they will in a one-period environment.*

2.2 Consumer Behavior

I assume there is an infinitely large market of consumers with homogeneous preferences on the streaming platform. This assumption does not fully depict the consumer-base of a streaming platform, but for an emerging artist in an established genre, this assumption is more realistic. Ex ante, consumers have no knowledge of a given artist and require the algorithm to reveal an artist to them. Upon receiving an impression of an artist, the consumer gains knowledge of all of an artist's work from that period, not just the piece they were exposed to. I will assume that after an impression a consumer will stream the artist's work $n(z)$ times, where z is the quality of the art. I will assume that $n_z > 0$ and $n_{zz} < 0$, so increases to quality always increase demand, but at a lessening rate. A notable assumption in the above modelling decision is that the quantity of releases has no influence on the amount of streams by a given consumer. Consumers see the quality and might choose to stream one song all n times, or they might spread their consumption across multiple pieces of art.

2.3 Artist Behavior

The artist's problem is to maximize the royalties they receive from their audience streaming their music. In particular, I will assume that each stream earns the artist an amount r, so the total revenue in each period is the total number of streams time r. The artist chooses to produce m pieces each of which at the same quality z, though this assumption could relaxed to allow for heterogenous products. I will assume that the artist's combination of m and z also incur a cost $C(m, z; \kappa)$ where κ is the artist's underlying talent that makes production easier. We can interpret the previous equation as a budget constraint with Y in dollar units, and $f(m, z)$ as a cost function. I will impose some standard assumptions on C. Namely, I will assume $C_m > 0, C_z > 0, C_{mm} > 0, C_{zz} > 0$. The assumptions say that increases to quality or quantity also increase cost, and additional units of quantity of quality are more costly than the previous. I will further assume $C_\kappa < 0$ and $C_{\kappa\kappa} > 0$, so increases to underlying talent lower costs, but additional increases to talent are less and less impactful.

2.4 Audience Evolution and Algorithmic Behavior

There are three drivers of audience evolution: last period's audience, the new audience algorithm, and the unforecastable random noise present in the algorithm. I will assume that every period, a fraction δ of the audience "forgets" about an artist and needs reimpression in order to consume an artist's work again. As such, the share of last period's audience that endures is $(1-\delta)$. The other two components are related to the algorithm. I assume that the streaming platform's algorithm governs the number of new impressions for each song released by an artist. A key metric on many streaming platforms is the click through rate which is the number of clicks on an item divided by the number of impressions of that item. It is essentially the probability that a random consumer will click on an item when it is shown to them. The analogous metric in this model is $\overline{n}$, the average number of consumer streams per impression across an artist's entire portfolio. As such, the algorithm will take last period's n, incorporate some random noise and use that to decide the number of impressions in the present period. I will denote this impression algorithm for an artist's ith art piece is $I(\overline{n}_{t-1}) + \varepsilon_{it}$ where ε_{it} is a mean zero independent identically distributed random variable. For each art piece that an artist produces in the present period, they must submit this work through the algorithm which is subject to the random noise. Assume homogenous product quality, the artist's total number of impressions is given by $mI(n_{t-1}) + \sum_{i=1}^{m} \varepsilon_{it}$. As such, the expected number of impressions is simply $mI(n_{t-1})$ with variance $m\text{Var}(\varepsilon)$. Increasing the number of releases increases the expected audience, but equally increases the variance of outcomes. Putting all of these pieces together, the equation of motion for audience size at time t, A_t, is given by:

$$A_t = (1-\delta)A_{t-1} + mI(n_{t-1}) + \sum_{i=1}^{m} \varepsilon_{it} \tag{1}$$

2.5 The Artist's One-Period Maximization Problem

We can assemble the above pieces into the respective one-period revenue maximization problem. The timing of the model is as follows, the artist chooses m and z, then the random variable in the algorithm is realized, then consumers stream the artist work according to $n(z)$. As such, we can express the artist's problem as:

$$V(m,z) = \max_{m,z} \left\{ E\left[rA_t n(z) - C(m,z;\kappa)\right] \text{s.t.} A_t = (1-\delta)A_{t-1} + mI(n_{t-1}) + \sum_{i=1}^{m} \varepsilon_{it} \right\} \tag{2}$$

Substituting in with A_t allows us to solve this problem as an unconstrained maximization problem with the following first order conditions:

$$\begin{aligned} \frac{\partial V}{\partial z} &: r\left[(1-\delta)A_{t-1} + mI(n_{t-1})\right] mn'(z) - C_z(m,z;\kappa) = 0 \\ \frac{\partial V}{\partial m} &: rI(n_{t-1})n(z) - C_m(m,z;\kappa) = 0 \end{aligned} \tag{3}$$

I will now use the implicit function theorem to interpret some comparative statics in terms of the parameters of the model. I summarize the results below

	∂m	∂z
$/\partial r$	$\downarrow$	$\downarrow$
$/\partial \delta$	0	$\uparrow$
$/\partial A_{t-1}$	0	$\downarrow$
$/\partial n_{t-1}$	$\downarrow$	$\downarrow$

	∂m	∂z
$/\partial\kappa$	$\downarrow$	$\downarrow$

Since z does not affect the future engagement measures (because I only consider one period), the artist will try to substitute away from using z in production because it is more costly. As such, when the royalty rate increases, the artist will be able to recoup the same amount of revenue selling fewer units, so they will chose to lower their z due to it's increasing costliness.

We have a similar result for changes to the quantity produced. Again, producing more quantity incurs costs that the artist substitutes away from when given more slack by the other parameters. Interestingly, the previous period's audience makes no impact on the artist's choice to produce a greater quantity. This comes from the fact that prior audience is sunk in m. Since m can only influence the number of new listeners, the artist need not consider how much of the previous audience they've retained.

2.6 One Period-Binary Choice Example

To fix ideas, I will now explore the case in which the artist can only choose from one of two options. In order to collapse the problem to a binary choice set, instead of using a cost function, I will use a budget constraint, $C(m,z) = Y$ which implicitly defines z in terms of m. As such, let's consider the case where the artist is choosing to produce either 1 or 2 products. If the artist chooses $m = 1$, they can produce one higher quality good at quality $\overline{z}$. In the other case, the artist can produce 2 goods, each at quality $\underline{z}$. The artist will then choose:

$$\max\left\{r\left((1-\delta)A_{t-1} + I(n_{t-1})\right)n(\overline{z}), r\left((1-\delta)A_{t-1} + 2I(n_{t-1})\right)n(\underline{z})\right\} \tag{4}$$

The artist's optimal production choice can be summarized as

$$\begin{cases} \underline{z} & n(\overline{z}) < \left(1 + \frac{I_0}{I_0+(1-\delta)A_0}\right)n(\underline{z}) \\ \text{Either} & n(\overline{z}) = \left(1 + \frac{I_0}{I_0+(1-\delta)A_0}\right)n(\underline{z}) \\ \overline{z}, & n(\overline{z}) > \left(1 + \frac{I_0}{I_0+(1-\delta)A_0}\right)n(\underline{z}) \end{cases} \tag{5}$$

We can interpret the result above as follows. When demand for high quality goods is sufficiently high $n(\overline{z}) > 4n(\underline{z})$, the artist will always expend the extra effort to produce the high quality good, regardless of the starting parameters of the model. However, if consumers have sufficiently little differentiation between high and low quality goods ($n(\overline{z}) < 2n(\underline{z})$), the artist will always choose to produce the low quality good regardless of the starting parameters. The indeterminate portion of the above, always has an ideal choice, but it is not easily characterized, however can make some statements. First note that if there is no audience retention, $\delta = 0$, or if there is no starting audience, $A_0 = 0$ then, there is no indeterminate region. The artist weakly prefers the high quality option whenever $n(\overline{z}) \geq 2n(\underline{z})$, and will choose the low quality otherwise. Further, whenever $\frac{(1-\delta)A_0}{I_0} > 1$, the agent will make the high quality product whenever $n(\overline{z}) \geq 2n(\underline{z})$ and produce the low quality product otherwise. **I can't prove this, but Desmos shows it here:** DESMOS LINK. This result has an elegant interpretation. The fraction $\frac{(1-\delta)A_0}{I_0}$ is the ratio of retained audience to new audience per song released. Whenever the artist is established and experiences less growth growth than audience retention $\frac{(1-\delta)A_0}{I_0} > 1$, the artist is likely to prioritize high quality instead of higher quantity. Growth-oriented artists, who are gaining more consumers than they retain ever period will likely prioritize lower quality and greater exposure.

2.7 Two Period Binary Choice

I now explore the case where the artist has the same options as before, one or two products at quality $\overline{z}$ and $\underline{z}$ respectively. However, in this case, I examine the artist's behavior over two periods. In this case, their choice of z in the first period influences the number over impressions that the algorithm produces next period. I will now introduce some new notation. Let $\overline{I}$ be the impressions awarded to the artist when their choice of quality $\overline{z}$ induces consumption $n(\overline{z})$. Define $\underline{I}$ analogously. Since, we have already characterized the one period case, the artist's problem is essentially reduced to choosing the optimal amount of impressions this period taking as given optimal behavior next period.

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