Exposure Doesn't Pay the Bills
Artistic Production on Streaming Platforms Under Algorithmically-Induced Audience Uncertainty

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Abstract

Content streaming platforms like YouTube and TikTok play an important part in the lives of many. This paper contributes to existing literature by exploring the optimal quality-quantity tradeoff of a content creator on a streaming platform. This paper creates a model of how a creator's revenue evolves when audience size is determined by an unpredictable album. Solving this model using dynamic programming predicts the emergence of a three-phase quality strategy. Small creators who are unlikely to be discovered choose high quality, budding creators choose low quality to quickly grow a following, and established creators return to high quality. This paper contributes to the growing streaming literature by focusing on what drives the content creator's decisions.

Contents

1   Introduction

YouTube, the video streaming giant, reported 28.8 billion dollars in ad revenue in 2021.[1] YouTube's ad revenue alone is greater than Visa, Kraft Heinz, and Starbucks.[2]

YouTube and Spotify, among their industry peers like Instagram and TikTok, lie at the intersection of two burgeoning markets: streaming platforms and social media. Services like YouTube, Spotify, Instagram, and TikTok, which I will refer to as *platforms*, provide a rich opportunity for economic analysis. For this analysis, a platform will mean any online service that connects individuals media creators to media consumers.

Platforms are fundamentally a marketplace. *Content creators*, firms, are given an opportunity to connect with consumers who wish to consume their products. In this way, streaming economies are *two-sided markets*, markets in which both the buyer and sellers connect through a third party. In our case, the streaming platform serves as the point of connection. One key distinction between a physical marketplace and a digital platform is that consumption is usually nonrivalrous. One consumer's decision to listen to an artist's newest release on Spotify has no negative impact on another consumer's ability to consume that product. However, one consumer's choices do indeed affect others. We expect that a platform's algorithm measures one user's engagement and uses that and other factors to decide whether or not to show a product to a different consumer. Different from many other markets, a consumer may not know what kind of content they wish to consume and use the platform as a content discovery tool. Furthermore, a content creator's inventory is limited only by the bandwidth of the platform and the number of consumers who wish to consume their product. The number of willing consumers is a content creator's audience and is central to the analysis conducted below.

Audience evolution is another key component of streaming markets. Of course, consumers can seek out content directly if they know that a creator exists, but that does not fully describe consumer-creator matching on a platform. A central component of streaming markets is the *algorithm*. By algorithm, I mean a platform's way of analyzing a release by a content creator and deciding which consumers will be shown that release. Consumers are required to self-select products they wish to purchase. However, platforms use their algorithm to show content to consumers they may not have initially been aware of. Algorithms are also a way of encoding a content creator's reputation over time. When deciding whom to show a content creator's work to, an algorithm looks at a subset of a creator's history of releases. These past releases serve as a reputation even when a consumer has not yet been exposed to a creator. A consumer might think, "I don't know what this video will be, but if the algorithm is recommending it, I will probably enjoy it." Many platforms market their algorithmically selected content in that way. TikTok's "For You Page" is where a user can find algorithmically selected content that TikTok suspects will be good *for you*.

All successful content creators must acknowledge the importance of a platform's algorithm and adapt

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[1]Compiled from the 2021 reports available here
[2]Data were taken from *Fortune*, available here

to its changes. A useful anecdote comes from Stevie Wynne Levine, Chief Creative Officer of Mythical. Mythical is a YouTube conglomerate with over 75 million subscribers across its channels and 25 billion total views on its videos. In reference to how their team analyzes the algorithm, Wynne Levine tells Business Insider:

> It's something that we do not only every day, but three, four times a day. We analyze each video that we've put out for that day and how we can improve impressions and views. So definitely not something that we set it and forget it, because it's constantly evolving. (Whateley (2020), para 12)

The above discussion reveals that content creators have a unique economic problem that is worthy of study. Recent literature has focused on the optimal behavior of consumers and platforms, but content creators have been mostly omitted in the literature on streaming platforms. Work that has tackled artists' optimal behavior has focused on fine art in non-digital markets.

In this paper, I will explore how content creators must balance the inherent quantity-quality tradeoff present in making content for a platform. A higher number of releases offers a content creator more opportunities for the random component of the algorithm to make their content viral. However, investing in greater quality encourages consumers who do know about an artist's content to stream that content more. Again using YouTube as an example, their "Creator Academy" which is intended to teach content creators how to make more effective content, acknowledges but does not provide clear guidance on this quality-quantity tradeoff. Simon Whistler, a popular content creator and the presenter of this video says that "…if you have more videos out there, chances are your watch time overall is going to be higher" YouTube Creators (2018). Watch time, in this context, is the cumulative time that viewers have watched your content divided by the number of unique viewers and is an important predictor of algorithmic success.

I construct a model of artist/content creator behavior in which artists must decide on a quantity and quality of art to release in every period. Their quantity choice affords them some number of chances at algorithmic exposure. Additionally, the algorithm will also factor in how many times past audience members consumed an artist's work when deciding audience size. An artist's underlying talent (ability to produce the same quality/quantity at a lower cost) will govern optimal production, and I will show how revenue and quality develop over time.

I hypothesize that artists early in their career, where new audience members make up a large share of their total audience, are more likely to produce low-quality content, and then switch to a low-volume, high-quality strategy later in their career. The interaction of artist decisions in the streaming economy and algorithmic uncertainty is novel to this paper. Additionally, I will show that a three-stage quantity strategy is employed by an agent. Upon simulating results, I will see that sufficiently small initial talent prevents audience accumulation over time.

The remainder of this paper is broken into seven sections. In the Literature Review, I discuss how related literature has informed the construction of the model. The Relevant Institutional Characteristics

section discusses YouTube in more depth and how it informs the modeling decisions in this paper. In The Model section, I discuss assumptions about the properties of consumers, producers, and algorithms, and assemble the primary model used throughout. In The Artist's One-Period Maximization Problem, I analyze the simplest implementation of the model in one period to gather preliminary results. In the Dynamic Programming Model section, I reframe the established model as a recursive dynamic programming problem which will allow for multi-period analysis. I also discuss the necessary assumptions and calibrations in this section. The Dynamic Programming Results contains the main results of the paper. The Conclusion summarizes and discusses future avenues for research.

2 Literature Review

2.1 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 signaling 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 the market characteristics that incentivize 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. Their model provides evidence that even when a firm's brand offers no intrinsic consumer utility, the information contained in branding makes it worthwhile for both firms to invest in and consumers to pay a premium for branding. 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. Shapiro confirms the results of Klein and Leffler while expanding on the fragility of branding. Shapiro finds that even when a firm can charge more for a branded product than an unbranded alternative, there is no market power earned, only a higher price.

2.2 Superstar Literature

The branding literature is related to the "superstar" literature. The superstar literature, however, lies closer to cultural economics because it focuses primarily on markets for art and entertainment. Rosen, the pre-

eminent author in the superstar literature, characterizes a superstar market as having a: "relatively small numbers of people (who) earn enormous amounts of money and dominate the activities in which they engage" (Rosen (1981a), p. 845). 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.

2.3   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 I will follow the characterization given in Thomes (2013). He characterizes a streaming economy 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 changes hands on both sides of this market. Researchers have focused on various aspects of the streaming economy as it has evolved.

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. This paper takes the artist's behavior as given, and does not tackle the conditions under which artists will choose to produce content for the platform.

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.[3] The analysis below examines how artists should optimally produce once they have already committed to making content for a streaming platform.

Hiller & Walter (2017) has elements from Thomes (2013) and Bender et al. (2021) by modeling an economy with digital purchases in addition to free and paid subscriptions on a streaming service. The au-

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[3]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

thors 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. I will examine this quantity-quality tradeoff below, but with the key difference of uncertain audience size.

2.4   This Paper's Contribution to the Literature

The preceding discussion reveals a few unexplored areas that this paper will investigate. One, previous literature has focused on the 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. 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.

In particular, this paper seeks to answer a few key questions informed by related literature but unique to a streaming environment. First following the work of Rosen (1981a) I will explore how a streaming market influences the convexity of profits in talent. I will explore whether or not a platform with high unpredictability has more or less convexity of revenue in talent.

Additionally, following the work of Bender et al. (2021), I will explore whether or not the introduction of a multi-period model allows artists with small initial followings to pursue a high-quality strategy, unlike Bender's one-period model.

3   Relevant Institutional Characteristics

The model constructed below is based most closely on YouTube, and I will now discuss some aspects of YouTube's structure that I used to ground the model. The two most relevant parts of the YouTube streaming environment are the algorithm and the way that artists get paid per stream.

First, the algorithm. The content consumer has three primary ways of discovering content: direct search, the subscriptions page, and the "home" page. Using direct search, consumers can search for a style of video or the name of a creator if they already know what they are looking for. On the subscription page, a consumer sees all of the videos from the content creators they are "subscribed" to. Subscription is free and simple and allows a consumer to stay up to date on a content creator's newest releases. That being said, YouTube has pushed users towards the final option, the "home" page. This page, now the default when you open YouTube on mobile or desktop shows an algorithmic amalgam of the content creators you've subscribed to and new creators. There can be videos you have finished before, videos you have started but not finished, or videos you have never seen. The content is unpredictable but responsive to the media you

have recently viewed.[4]

The "home" page motivates the analysis conducted below. There is some cohort of your audience that may remember you, and seek out your content directly. However, the rest of your viewership may come and go depending on how frequently the algorithm shows your content. There exists endless online discussion of how to optimize your content for "the algorithm." Various methods exist like catchy thumbnail images, adequate video length for the genre, upload time, etc.

In addition to the algorithm and consumer content discovery, there is the matter of monetization. YouTube does not widely publish the rates at which they compensate their content creators, but prevailing wisdom indicates that content creators make well less than fifty cents for every time a viewer watches an ad during their video. There is little available information on when YouTube shows a viewer an ad before or during a video. I will assume that there is a linear relationship between the number of views and the advertisement revenue generated from content.[5] Creators do not have much control over which advertisements are shown on their videos. YouTube shows ads based on characteristics it has compiled on the viewer.[6] Since creators can't control the ads, they instead must focus on the algorithm that gets their videos to viewers.

YouTube monetization is a complex concept that depends on whether or not copyright-protected content is used in a video. Creators may also experience "demonetization" if YouTube automatically flags content as inappropriate for children. Partially because of demonetization, many YouTube content creators opt to seek out sponsors directly and advertise during the body of their video. Further still, many creators opt to use services like YouTube's "Channel Memberships," Patreon, or Paypal to allow viewers to pay for their services directly, often in exchange for additional or personalized content. All of these characteristics are ignored in the proceeding analysis so that attention is focused on the interaction of the content creator and the algorithm

Finally, I will note that many other platforms have similar characteristics, but YouTube's size and structure make it a good base for a model.

4   The Model

The streaming market has three primary actors: the end consumer, the streaming platform, and the artist. For this analysis, I will assume that the behaviors of the consumer and the streaming platform are exogenous. I will limit attention to the artist who must choose a quality, z_t, and quantity, m_t, of releases to produce in every period. The streaming platform's algorithm is driven by consumer engagement (number

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[4]A discussion of how content is placed on a user's YouTube home page is available here: https://www.youtube.com/watch?v=69tpVNunQEU

[5]Some additional explanations for variations in revenue per stream are given in the "Why is my CPM Changing?" tab here.

[6]Google operates ad placement on YouTube, a brief discussion of which ads a viewer might see is here: https://support.google.com/youtube/answer/7403255?hl=en#:~:text=The%20ads%20you%20see%20may,Google%20services%2C%20like%20Google%20Ads

of streams per viewer) last period, n_{t-1}. The algorithm combines past user engagement with the number of new releases to decide the number of new consumers to show an artist's work to. I will assume that consumers have no ex-ante knowledge of an artist and require the algorithm to reveal an artist to them. I will call these algorithmic revelations *impressions* and denote them I_t. The term impression comes from the language that YouTube uses when defining a meaningful exposure to content.[7] Once a consumer has received an impression, their number of streams will depend on the quality of the art that the artist released in that period. If a consumer has received an impression, they are under no obligation to stream, the number of streams is fully determined by the quality of the art. Impressions only serve as a way for a consumer to be made aware of an artist's portfolio. After the consumer decides to stream, the algorithm observes the streams per impression and uses this to decide how many times to show the artist's work next period.

The artist earns a royalty every time a video is streamed, and the artist tries to maximize this discounted flow of royalties. The tradeoff between the 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 intertemporal benefit of encouraging next period's algorithm to show the art to more consumers. The artist will reach a larger audience next period because the algorithm rewards creators whose content is frequently engaged with. 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. The algorithm, in this analysis, will serve only to map the number of impressions during this period to the number of impressions given in the next period.

4.1 Consumer Behavior

I assume there is a large market of consumers with identical preferences on a streaming platform. Preferences are not themselves important, but I will assume that each consumer has the same demand function in terms of quality. This assumption does not fully depict the consumer base of a streaming platform. However, for an emerging artist in an established genre, this assumption is more realistic. To a new artist, the number of potentially-accessible consumers can seem almost limitless. Further, if an artist enters an existing genre, there is a clear sense of what is successful across the entire market, so there is some observable homogeneity in consumer preferences.

ex-ante, consumers do not know 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 $n = v(z)$ times, where z is the quality of the art. I will assume that $v_z > 0$ and

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[7]Detailed definition available here

$v_{zz} < 0$, so increases to quality always increase demand, but at a lessening rate. A notable assumption in the above modeling decision is that the quantity of releases has no influence on the number of streams by a given consumer. Consumers see the quality and might choose to stream one release all n times, or they might spread their consumption across multiple pieces of art.

4.2   Artist Behavior

The artist's problem is to maximize their discounted stream of profits over multiple periods. The artist generates revenues from per-stream royalties and faces a cost according to their quality and quantity. 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 times r. The artist chooses to produce m pieces at the same quality, z. I will assume that the artist's combination of m and z incurs cost $C(m, z; \kappa)$ where κ is the artist's underlying talent that makes production easier. I will impose some standard assumptions on C. Namely, I will assume $C_m > 0, C_z > 0, C_{mm} > 0, C_{zz} > 0, C_{z\kappa} < 0, C_{m\kappa} < 0$. The assumptions say that increases to quality or quantity increase cost and additional units of quantity or quality are more costly than the previous. The cross partial derivatives say that increasing talent decreases the marginal cost in each of the inputs. For κ to be meaningful as a talent parameter, we should require that at every input, an additional unit of talent makes the next unit of production less costly. 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. The only partial derivative without an immediate sign choice is the quantity-quality cross partial derivative, $C_{mz} = C_{zm}$. A positive cross partial derivative says that a one-unit increase in quality increases the marginal cost of an additional unit of quantity. We can also interpret this as a one-unit increase in quantity increases the marginal cost of an additional unit of quality. More broadly, the sign of this partial derivative determines whether or not the quality and quantity are complementary. For this analysis, I will assume that $C_{mz} \geq 0$. This assumption is reasonable considering that an artist only has finite time in every period, so every minute they spend using more of one, decreases the time they have for the other.

4.3   Audience Evolution and Algorithmic Behavior

First, a distinction between audience and streams. For this analysis, an artist's audience at time t, A_t, is the number of consumers who are aware of an artist's work. Again, these audience members are under no obligation to stream, but they will be able to observe an artist's quality to inform their consumption decisions.

I impose three heuristics on how an artist's audience evolves. First, some proportion of last period's audience should be retained between periods. Second, a streaming platform should have an algorithm to determine the number of new audience members that an artist has. Finally, there is some unforecastable random noise present in how the algorithm behaves, at least in the eyes of the artist.

I first assume that every period, a fraction δ of the audience "forgets" about an artist and needs reimpression to consume an artist's work again. As such, the share of last period's audience that endures is $(1 - \delta)$. We can think of $(1 - \delta)$ as the share of audience members who naturally remember an artist or as the fraction of consumers who are forced to remember an artist from reminders by the streaming platform. On different platforms, δ might be very different. Low bonding interactions, like buyers and sellers on eBay, might have a higher δ as people do not have any personal connection to the seller who sold them a product. On the other end of the spectrum, certain content creators form close connections with their audience, something that consumers would not soon forget. In this case, δ might be small. That discussion reveals one limitation of the model presented in this paper: good content may be more memorable. As stated the model does not factor the quality of a release into the fraction of the audience that is retained into next period. While this effect is not included directly, the effect is captured in the impressions function which I will define later.

Now I will characterize how new consumers can be added to an artist's audience. I assume that the streaming platform's algorithm governs the number of new impressions for each release by an artist. For the algorithm to be a meaningful tool, it should not be entirely random. It should use some measure of engagement to dictate the number of impressions in the next period. For this model, the algorithm uses last period's number of streams per audience member as the measure of engagement. By construction, at time t, the algorithm will use $v(z_{t-1})$, so the algorithm is indirectly incorporating quality.

There are multiple ways to interpret the uncertainty in the algorithm. One such way is to interpret a streaming platform's algorithm as an imperfect instrument that measures talent. An alternate way to interpret algorithmic uncertainty is in the context of producer uncertainty. In this case, the artist understands the average effects of the algorithm, but the streaming platform intentionally or inadvertently obfuscates exactly how the algorithm behaves so there is always some artist uncertainty about the true number of impressions in the next period.

Tom Scott (2017) gives an engaging look into why YouTube's algorithm is unpredictable. He notes that when a streaming platform reveals information about its algorithm, get-rich-quick content creators produce inferior content that is only intended to exploit these trends. He also notes that many algorithms are constructed using machine learning with huge training data sets that have too many inputs to be easily understood.

An additional concern when modeling an uncertain algorithm is that artists with higher talent may be correlated with the unforecastable boosts from the algorithm. However, most artists, at least professional content creators, can observe any information in the algorithm that might benefit them when making their product. By definition, the most algorithmically favored products are shown the most. As such, I will assume that artists have ample opportunity to analyze successful content and arbitrage away any useful information. This assumption says that there are no frictions in obtaining information about the algorithm. Certainly, dedicated media teams have a better ability to spot algorithmic trends than single producers,

but this relationship is outside the scope of this paper. Further analyses could explore this relationship in more detail, but this model will assume that talent and algorithmic uncertainty are independent.

With the aforementioned assumptions, I construct the algorithm as follows. First, denote the impression algorithm for an artist's ith art piece in period t as $I(n_{t-1}) + \varepsilon_{it}$ where ε_{it} is a mean zero independent identically distributed random variable. Both I and ε have units of the number of additional people in the audience. Assuming the algorithm is a useful, if imperfect, measure of quality, I will assume that $I_n > 0$. So increases to engagement increase the expected number of impressions per release. In this construction I am assuming that errors are independent within artists across time, so an artist does not have a bias on how they expect the algorithm to treat their releases.

For each art piece that an artist produces in the present period, they must submit this work through the algorithm which is subject to random noise. If the artist releases m pieces in a given period, the total number of impressions from the audience is then 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 $m\mathrm{Var}(\varepsilon)$. Increasing the number of releases increases the expected audience, but also 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:

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

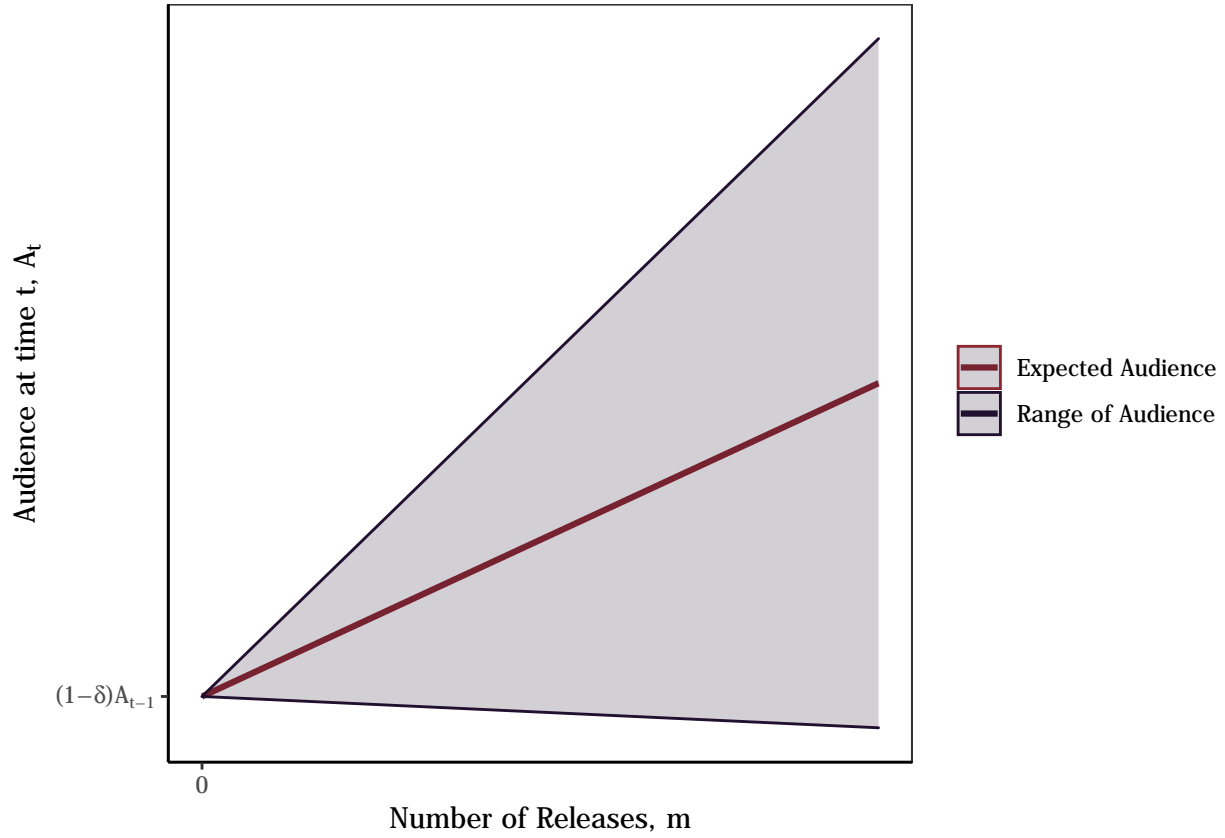We can visualize audience development as follows:

Figure 1: *Increases to quantity produced increase expected audience and variance of outcomes*

Figure 1 shows that if an artist chooses to release no art in a given period, they can guarantee that they receive the depreciated audience they had last period. However, the more releases by an artist, the higher expected audience size this period, but this comes with more and more risk. Figure 1 shows that a creator's audience may decrease below those who depreciated naturally. One possible explanation for a negative number of impressions is a platform removing an artist from an existing viewer's home page. Removal from the home page makes a creator less accessible and effectively reduces the audience size below those who naturally depreciate. Another possible concern with this method of audience development is that increasing releases now may be beneficial to future periods. In particular, more videos might serve as a portfolio of videos for new viewers to go back and watch once they discover a creator. In this analysis, I will exclude this possible intertemporal benefit of quantity. In a quickly evolving genre, old releases may not be well-aligned with current preferences. This serves as one possible justification for why the intertemporal quantity benefit can be excluded.

5 The Artist's One-Period Maximization Problem

We can assemble the above pieces into the one-period revenue maximization problem. The timing of the model is as follows, the artist chooses m and z, then the random variables in the algorithm are realized, then consumers stream the artist's work according to $v(z)$. In the case where there is only one period, we can interpret n_{t-1} as the total amount of reputation that an artist has earned throughout their career up to now. Similarly, A_{t-1} becomes the entire audience that has been retained. In a one-period model, objects in the equation of motion represent a lifetime's work, not just one period.

As such, we can express the artist's problem as:

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

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

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

The implicit function theorem produces some interesting comparative statics in terms of the parameters and state variables of the model. I summarize the results below

Table 1: *Signs of partial derivatives for the one-period model*

X	$\partial m/\partial X$	$\partial z/\partial X$
r	–	–
δ	0	+
A_{t-1}	0	–
n_{t-1}	–	–
κ	–	–

The first column gives the relationships between increasing the parameters and state variables and the optimal choice of quantity, m. 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.

Since z does not affect the future engagement measures (because for now 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, r, increases, the artist will be able to recoup the same amount of revenue selling fewer units, so they will choose to lower their z due to its increasing costliness.

5.1 One Period-Binary Choice Example

I will now explore the case in which the artist can only choose from one of two options. To collapse the problem to a binary choice set, instead of using a cost function, I will add a budget constraint, $C(m, z) = Y$ which implicitly defines z in terms of m. I 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 z_h. In the other case, the artist can produce 2 goods, each at a lower quality z_l. The artist will then choose:

$$\max \{r\left((1-\delta)A_{t-1} + I(n_{t-1})\right) v(z_h), r\left((1-\delta)A_{t-1} + 2I(n_{t-1})\right) v(z_l)\} \tag{4}$$

The artist's optimal production choice can be summarized as

$$\begin{cases} z_l & v(z_h) < \left(1 + \frac{I_0}{I_0 + (1-\delta)A_0}\right) v(z_l) \\ \text{Either} & v(z_h) = \left(1 + \frac{I_0}{I_0 + (1-\delta)A_0}\right) v(z_l) \\ z_h, & v(z_h) > \left(1 + \frac{I_0}{I_0 + (1-\delta)A_0}\right) v(z_l) \end{cases} \tag{5}$$

An alternate way of formulating the above statement comes in the following example. Suppose that demand for the high-quality product is 10% higher than demand for the low-quality product. Further suppose that the expected this-period impressions is 5% higher for a low-quality product than a high-quality product. In this case, the artist will choose to pursue high-quality because the demand percentage is larger than the audience percentage. This percent-to-percent comparison generalizes to any set of initial parameters.

The denominator in the above expression is the expected audience size when the artist chooses the high-quality option. As such, we can interpret the fraction as the percent of expected audience that is earned by the algorithm (and not coming from past audience). Holding other factors equal, an artist with a larger initial audience, A_0, is more likely to have a smaller premium to induce high-quality production relative to a new artist where most of their audience is algorithmically generated. Therefore, established artists are more likely to produce high-quality content. In contrast, new artists are likely to produce a greater number of lower-quality art and rely on the algorithm to get their art into the hands of new consumers. However, the new creator's preference for low-quality comes from their risk neutrality and zero expected algorithmic shock. A risk-averse creator may favor the high-quality strategy because it comes with lower risk.

5.2 One Period with Talent

Since the talent parameter κ enters through the cost function, it is not represented in the analysis above. I will now modify the model slightly, allowing κ to enter into the binary choice problem. Instead of constraining the artist to produce only one or two items at qualities z_l or z_h, I will now examine the case in which the artist still chooses to produce items of qualities z_l or z_h, however, the artist's talent dictates the number of releases they can produce. In particular, let $m_l(\kappa)$ be the number of low-quality releases that an artist of talent κ can produce in one period. Similarly, define $m_h(\kappa)$ be the number of high-quality releases the same artist could produce in one period. In the eyes of a given artist (who only has one talent), they only have two production options, however, artists with differing talents face different (though still binary) production options.

The functions $m_l(\kappa), m_h(\kappa)$ should mirror reality in their properties. Namely, these functions should satisfy the following for all κ: $m_l(\kappa) > m_h(\kappa)$. This condition guarantees that more low-quality products can be produced than high-quality ones. Furthermore, both $m_l(\kappa)$ and $m_h(\kappa)$ should be increasing in κ and should have diminishing marginal product, $m_h''(\kappa), m_l''(\kappa) < 0$.

We can formulate the artist's one-period maximization problem as:

$$\max \left\{ r\left((1-\delta)A_{t-1} + m_h(\kappa)I(n_{t-1})\right)v(z_h), r\left((1-\delta)A_{t-1} + m_l(\kappa)I(n_{t-1})\right)v(z_l) \right\} \tag{6}$$

With optimal choice of quality satisfying:

$$\begin{cases} z_l & v(z_h) < \left(1 + \frac{(m_l(\kappa)-m_h(\kappa))I_0}{m_h(\kappa)I_0+(1-\delta)A_0}\right)v(z_l) \\ \text{Either} & v(z_h) = \left(1 + \frac{(m_l(\kappa)-m_h(\kappa))I_0}{m_h(\kappa)I_0+(1-\delta)A_0}\right)v(z_l) \\ z_h, & v(z_h) > \left(1 + \frac{(m_l(\kappa)-m_h(\kappa))I_0}{m_h(\kappa)I_0+(1-\delta)A_0}\right)v(z_l) \end{cases} \tag{7}$$

Proposition 1. *Increasing talent increases the relative utility of the low-quality strategy whenever the semielasticity of low-quality production in κ is greater than the semielasticity of high-quality production in κ. This condition is equivalent to:*

$$\frac{\partial \ln(m_l(\kappa))}{\partial \kappa} > \frac{\partial \ln(m_h(\kappa))}{\partial \kappa}$$

A proof of this result is available in the appendix.

We can interpret these semielasticities as follows: the low-quality option gains relative value whenever a one-unit increase in κ allows for a greater percentage change in the available low-quality units than high-quality units. These semielasticities relate one-unit changes to the input, κ, to percentage changes in the output, m_l and m_h. For example, consider a one-unit increase in talent. If this increase in talent allows the creator to produce 10% more low-quality work and 5% more high-quality work, then the utility of the low-quality strategy increased more than the high-quality strategy. This does not directly imply which strategy the creator will choose, but it does say that the low-quality option became more attractive relative to before

the talent increase.

If instead this one-unit increase in talent only allowed for 5% more low-quality production and 10% more high-quality production, the high-quality strategy is now comparatively more attractive relative to their talent before.

The result implies that increases to talent push an artist towards low-quality production whenever low-quality production is cheap. We should not innately have a sense of whether or not $\frac{\partial \ln(m_l(\kappa))}{\partial \kappa} > \frac{\partial \ln(m_h(\kappa))}{\partial \kappa}$ holds in reality. One could argue that an additional percent of low-quality production may be harder because you produce more low-quality goods, so additional units may be more difficult. Alternately, high-quality production may be harder because these goods are inherently harder to produce.

5.3 Conclusions From A Binary Choice Model

While the analysis above is limited to one period, it still provides useful information for the main conclusions of the paper. In particular, the binary choice model showed that there exists an initial audience threshold such that artists greater than a certain initial audience pursue a high-quality strategy. Artists below this threshold choose to pursue a low-quality strategy. This audience-based strategy switch will be mirrored in the dynamic model, but the results up to this point have not relied on functional form assumptions for demand or audience evolution.

Additionally, in this binary choice model, the mechanism for the strategy switch is readily apparent. Here, the agent chooses a quality depending on the ratio of demand and audience from high and low-quality releases. Creators' production decisions are driven by two main uncontrollable factors, consumer preferences for quality and the importance of the algorithm. Going forward I will leverage the comparison of demand to algorithm when explaining the results of the dynamic model.

6 Dynamic Programming Model

I will now use dynamic programming as a final method of analyzing the model constructed in 4. I will assume that the content creator has an infinite number of future periods subject to a discount rate. As such, that allows us to recursively state the Bellman condition for the content creator as follows:

$$V(n, A) = \max_{m,z} \{rE[A']n' + \rho E[V(n', A')]\} \, s.t. A' = \mathcal{A}(m, n, A, \varepsilon), n' = \nu(z), f(m, z) = \kappa \qquad (8)$$

I will briefly refresh previously established notation and introduce everything new. Moving Left to right in the expression above, we have the following. The function $V(n, A)$ is the optimal discounted lifetime revenue after the creator has maximized their lifetime utility subject to the equations of motion. The parameter r is the revenue that an artist earns for every stream. $E[A']$ represents the expected audience size this period. A' has a random component but is generated by the audience function and equation of motion,

$\mathcal{A}(m, n, A, \varepsilon)$, which takes quantity, last period's streams per capita, last period audience, and a random component respectively.

Last period's streams per capita, n, requires careful interpretation. For a brand new artist, they will not have earned a "last period's streams per capita" instead, this n, represents how favorable the streaming *platform* is to new creators. A high n implies that the platform treats new artists as though they produce high-quality content. However, we can alternately interpret the model as one snapshot in time for an established artist. In this case, n will actually represent last period's streams per capita which is a function of last period's quality.

Next, n' represents the number of streams for every audience member this period. n' is a function of quality, z, according to $n' = v(z)$. ρ is the discount factor between consecutive periods. Next, $E[V(n', A')]$ gives the expected lifetime utility starting next period given that we start with state variables that have evolved according to the equations of motion. Finally, $f(m, z) = \kappa$ gives a constraint that prevents a creator from producing as much quality and quantity as they want while allowing κ to be a meaningful talent parameter by increasing a creator's production options. This production constraint takes the place of the cost function in 2. This relationship has the notable benefit of reducing the policy space, the possible choices of m and z, to one dimension instead of two by solving for z in terms of m and κ. A one-dimensional policy space allows for more efficient maximization techniques and reduces the overall number of points that need to be checked. While some information is lost by omitting a cost function, the computational upsides make the tradeoff worthwhile.

The specification above is subtly different from that proposed in 4. The specification does not directly include the impressions function $I(m, n, \varepsilon)$, but its effect will be replicated in the functional form specification of $\mathcal{A}$.

The code for the value function iteration is a heavily modified version of the framework proposed in Sargent & Stachurski (n.d.). Their website[8] provides an excellent Python or Julia introduction to quantitative economics. They solve their dynamic program through value function iteration which I mirror in this analysis. There are three consequential differences between their code and the code required to solve the dynamic program stated in 8. First, the state space will need to be manually bounded. Next, the random component requires discrete approximation of expected values. Finally, the multidimensional state space from n and A requires additional modifications. Solutions to each of these problems are discussed in greater detail in the appendix.

6.1 Model Calibration

Without functional forms for $\mathcal{A}$, $v(z)$, and $f(m, z)$, it will not be possible to solve the dynamic program, as such, I will specify functional forms that have behavior consistent with economic intuition while remaining usable for value function iteration. Once these forms have been specified, I will find parameters

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[8]https://quantecon.org/

within those functions that allow for a continuum of solutions under various starting conditions instead of a corner solution for every starting condition.

6.1.1 Functional Form Specification

I propose the following logistic functional form for audience evolution, $\mathcal{A}$:

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

Where $\overline{A}$ is the audience limit (total available audience) for a creator to reach. $\overline{A}$ is also the upper bound of the function. α, β, and γ are parameters that correspond to how important streams per capita, n; number of releases, m; and the random shock, ε are to next period's audience respectively. A high value of α increases the steepness of the logistic in n. Essentially, a large α causes n even moderately far from 0 to be quickly pushed to either 0 or $\overline{A}$ depending on the sign of n. Similar interpretations exist for β and γ. Finally, I will let, $c = \frac{\overline{A} - (1-\delta)A}{(1-\delta)A}$ which is constructed so that if $-\alpha n - \beta m - \gamma \varepsilon = 0$, then the $A' = (1-\delta)A$. This mirrors the constraint in 1 which puts downward pressure on a creator's audience absent other factors. The proposed functional form meets all of the previously stated requirements. The other benefit of using this functional form is that the distribution of ε can take both positive and negative values without issue.

When initially specifying how the algorithm should function in section 4.3, I implemented a few desirable characteristics of audience evolution that this logistic satisfies. If the audience produces no new work this period and caries forward no reputation, n, from the previous period, then an artist's audience should depreciate by a factor of δ every period. Additionally, I required that an increase in quantity should have an immediate positive effect on the expected audience size. Additionally, I required that more streams per capita last period should positively affect this period's audience on average. Finally, larger values of the random component, ε, should also increase audience size holding other factors constant. When using value function iteration, the equations of motion must be bounded. The logistic proposed meets each of these requirements.

For the quantity-quality tradeoff, I propose the following functional form:

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

This form satisfies $f_m, f_z > 0$. These conditions say that increasing either quality or quantity pushes the agent closer to their constraint value κ. Furthermore, the function should never have decreasing marginal cost because additional units of one input will come at the expense of the other. This condition is stated as $f_{mm}, f_{zz} \geq 0$. This simple multiplicative form satisfies these requirements. Later in figure 5, one can see how different levels of κ allow for increased production of either input. Creators with higher talent can always produce the same (m, z) bundle as their low talent counterparts but will always have the option to increase either m, z, or both.

The final functional form I will specify before numerically solving the dynamic program is $v(z)$ which I will specify as: $v(z) = \overline{n}(1 - e^{-\lambda z})$. Where $\overline{n}$ is the maximal number of streams per viewer in any period and high λ allows lower qualities to result in higher per capita streams. This functional mixes computational requirements and economic intuition. On the computation requirements side, this function naturally bounds $v(z)$ between 0 and $\overline{n}$ which allows for a compact state space to evaluate over. On the economic intuition side, a viewer can't stream any less than 0 times, so this provides a natural lower bound. Additionally, if we assume a viewer only has finitely many hours a week to stream, additional increases to quality must eventually taper off to zero impact on the number of streams.

6.1.2 Baseline Parameters

Real streaming platforms have a continuum of creator efforts and audience sizes, as such, the parameters of the proposed model should not result in corner solutions in which all agents prefer one strategy. As such, I calibrate the model so that different starting conditions produce different optimal strategies. I look for a few factors when calibrating the model, first, the numbers should conform to some level of real-world reasonability. Next, I evaluated the possible values of A' and n' for a range of n, m, z, ε. Poorly calibrated parameters would result in a very small range of attainable A' or n' or would result in excess polarization where A' would take only two values. These two heuristics allowed me to narrow in on values for parameters that make sense for this model.

The first parameters that I specified were the ranges of the state space variables, n, A. This amounted to choosing suitable $\overline{n}$ and $\overline{A}$. For this model, I chose $\overline{n} = 5$, and $\overline{A} = 1000$. Neither of these specifications should be taken too literally and only serve as baselines to which the other parameters must conform. The discount rate, ρ, was set to 0.96 following conventional beliefs on human discounting. Next on the list of specifications are α, β, and γ from the audience evolution function $\mathcal{A}$. As an initial baseline, I set $\alpha = \beta = \gamma = 0.1$.[9] I will let the sharpness of consumer demand, λ, be 1. Finally, I set the audience depreciation, δ, to a fairly high value at 0.7, so 70% of an artist's audience depreciates every period. Such a high δ was set to reflect the quickly shifting trends on many media platforms. The royalty rate per stream, r was set to 1.

I vary is the talent parameter, κ, but as a baseline, it is set to 20. I set this to such a large value because smaller values did not allow enough differentiation between quality-quantity strategies to see the emergence of different strategies under different conditions.

7 Dynamic Programming Results

With the model specified and calibrated, I will now discuss the key insights from the baseline model and how the artist optimally behaves under their maximal lifetime revenue function. After discussing this baseline, I will explore key comparative statics on talent, variance of algorithmic uncertainty, and audience

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[9] I initially considered larger values, but this made the logistic function too sharp and pushed optimal strategies to corner solutions

depreciation rate.

7.1 Baseline Results

Recall that there are two initial state variables, A and n. As such, a creator's optimal strategy may depend both on their initial audience and initial streams per capita. The optimal strategy was reduced to one dimension, quantity, m, but quantity is inversely proportional to quality, z. When applicable, I will compare results to the signs of the first derivative from the one-period model in table 1. Below is a plot showing how the initial audience and streams per capita induce an optimal strategy m.
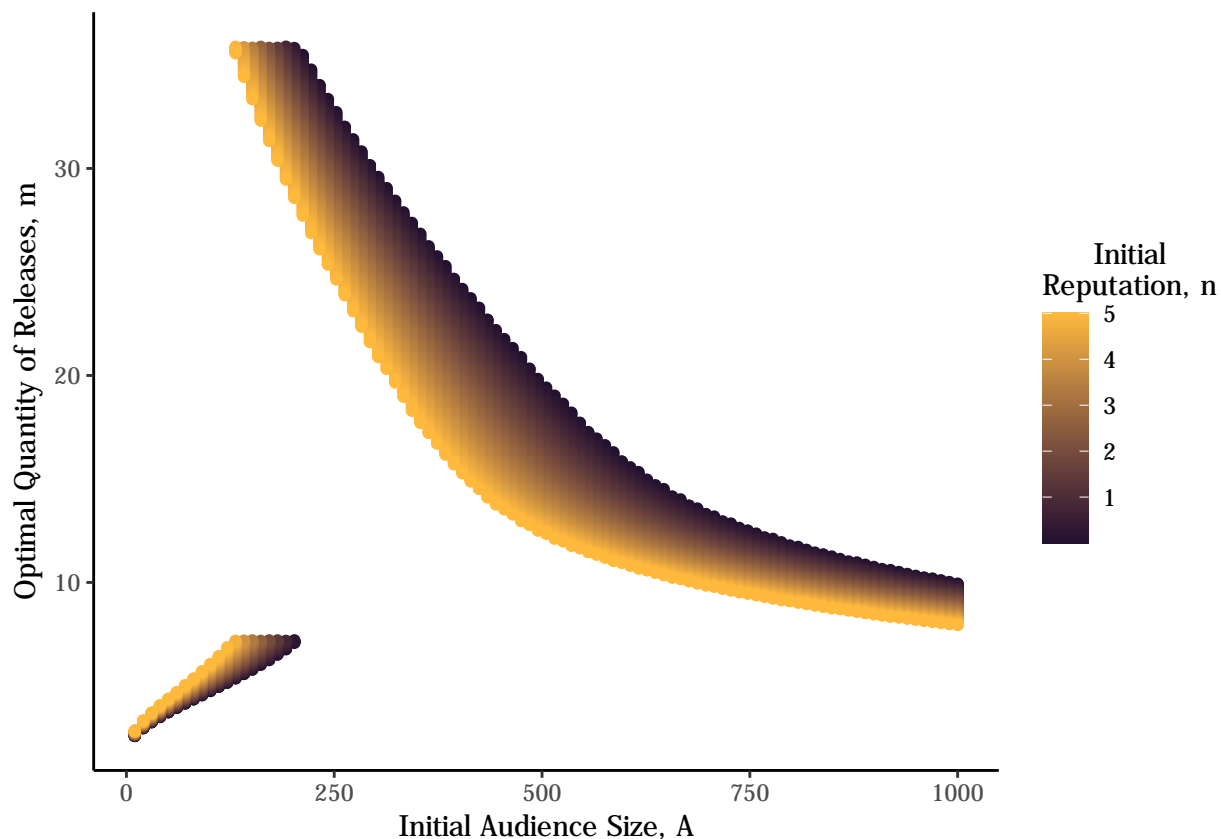
Figure 2: *Optimal quantity strategy by starting audience and reputation. Initial audience and reputation can also be intepreted as last period's values*

Figure 2 shows how the initial audience size (horizontal axis) affects the optimal choice of quantity (vertical axis) while taking into account how high a creator's initial reputation is (the color of the points). We can draw a few key interpretations from figure 2, but first a caution. This plot does not show the career trajectory of an artist. Instead, it shows the optimal choice of m given starting conditions. This plot gives the policy function of an artist who is just starting on a platform or an artist who is taking a look at their career thus far and regrouping to maximize their future utility.

Now for the interpretation. The plot above shows that for small initial audience (points on the left), the artist chooses a low volume strategy (high-quality), however, once the audience becomes sufficiently large (by this calibration around 175 audience members), there is a jump in the ideal strategy. The artist shifts from a low volume strategy to a higher quantity strategy. After this steep jump in quantity, the agent slowly transitions to a low-volume, high-quality strategy.

There is, in a way, activation energy for the artist. If the current audience for the artist is small, they will not find it worthwhile to invest in quantity, but once a sufficiently large audience has been attained, the artist will almost discretely change strategies to the higher-volume strategy.

There are essentially three regions in this plot. First, there is an initial waiting game before you switch to a high-volume strategy. I name this first region the *hobbyist* because the artist does not supply sufficient quantity to maintain a large audience and instead focuses on their quality. Then, after a sufficiently large audience, you pursue high volume. I name this second phase the *budding creator* because the creator has reached an audience, but they have not yet met their full potential. Finally, as your audience reaches its maximum, you increase quality. I call this phase the *superstar*, in part as a nod to Rosen (1981b), but mostly because these artists produce high-quality work for a large audience. In later sections, we will see that some artists go through each of these stages over the course of their careers. We may think of these second two stages as after an artist has "gone viral" and attained a sustainable following.

Another remarkable characteristic of the diagram above is the relation of starting reputation, n, on the optimal production decision. Reputation serves an artist in two ways. First, reputation serves as the number of streams per capita. Reputation, n, is also factored into the audience development next period. In the growth stage, low A, the optimal quality is decreasing in reputation. We can see this in figure 2 because the points on the left-hand side get darker as z increases. This relationship inverts once the artist has switched to the second stage of production. Once an artist has attained a large following, increases to reputation increase the quality produced in a given period. That is to say, artists with high reputations and large audiences pursue higher quality than low-reputation artists with large audiences.

In table 1, an increase to starting audience does not affect quantity choice. In figure 2, increases to audience have a non-monotonic relation with quantity. The *hobbyist*'s quantity strategy is increasing in A, but the *budding creator* and *superstar* decrease their quantity of releases for additional starting audience. The dynamic model differs from the one-period model because the audience evolution function is now non-linear in starting audience.

In the one period model, increases to initial reputation, n, decrease the optimal quality choice. This result partially holds in figure 2. In the *hobbyist* phase, increased reputation increases the quantity strategy. The two more established phases mirror the results from the one-period model in that increases to reputation decrease the optimal quantity. In the one period model, the artist decreases quantity when reputation increases because the cost function is convex. A similar principle occurs for the *budding artist* and *superstar*. For these established artists, additional audience members are difficult to attain (the audience

function is concave in m for high audience levels). As such, the creator substitutes away from quantity and toward quality because their audience is increasing from the reputation boost. Since the *hobbyist* still sees convexity of audience in quantity, an increase to reputation makes increasing quantity more desirable.

We should also look at the revenue being generated from a creator's work. We can explore this relationship by plotting $V(n, A)$ which is the expected lifetime discounted revenue for the artist.

Figure 3 shows an important monotonicity result. Increases to A (rightward movements) always increase the expected lifetime revenue of an artist. Furthermore, increases to reputation (lightening color) also move the artist's lifetime revenue upward after conditioning on the audience size. Neither of these results are surprising as both A and n serve to benefit the artist with no potential downside (unlike m or z).

The discontinuity of the policy function is also demonstrated in the value function. There is a notable jump in the value function around the point at which the artist changes their strategy. This discontinuity again points to the idea of activation energy for an artist. There is a higher level of utility that cannot be attained when your initial audience is small.
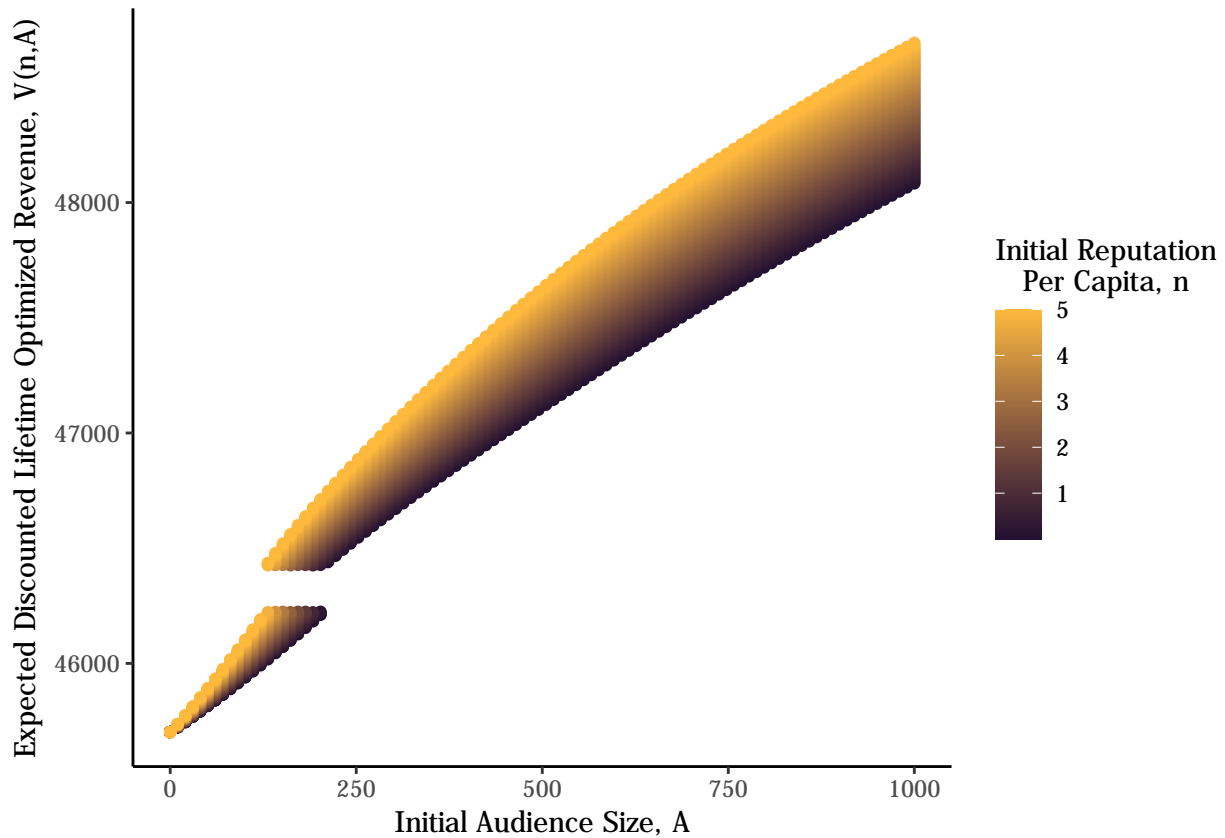

Figure 3: *Increases to initial audience or reputation increase expected lifetime revenue. Initial audience and reputation can also be intepreted as last period's values*

The discontinuity that exists both in the optimal policy and value functions is unexpected. Nothing in

this model is discretized in a way that naturally would produce a discontinuity in the policy function. To further explore what causes the discontinuity, consider figure 4.
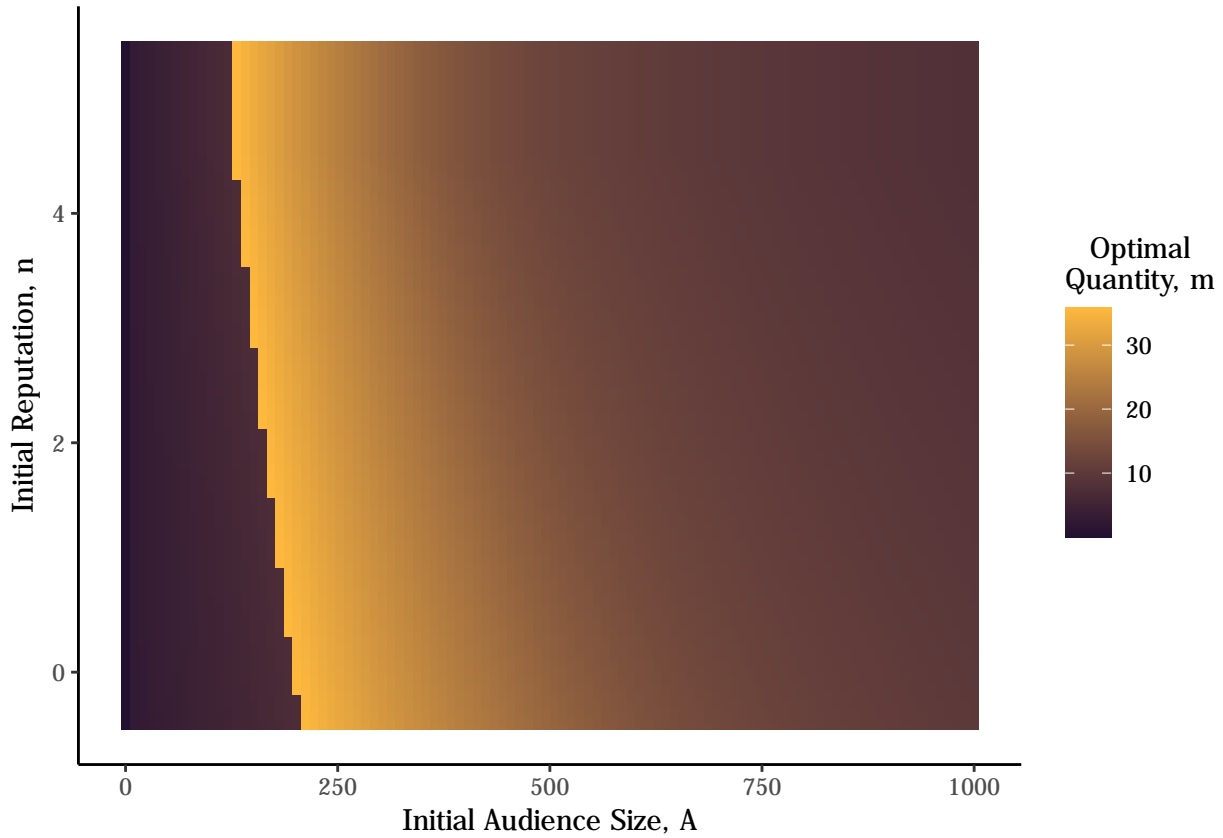

Figure 4: *Visualize the effect of starting parameters on policy discontinuity*

In figure 4, we can see that there exists a cutoff in terms of both initial audience and reputation such that below this cutoff the artist pursues a low-quality, high-quantity strategy, and above this cutoff, the artist pursues a high-quality strategy.

The reason for this cutoff is murky but seems to indicate that given a sufficiently large combination of audience and reputation, an artist will pursue a high equilibrium, and for a small audience and reputation, the artist will pursue a low equilibrium. One possible explanation for this discontinuity is the shape of the logistic curve used to generate future audience. It may be that the change in convexity (from positive to negative) of the logistic causes a sharp change in optimal strategy which is appearing as a jump in the value and policy functions. The discontinuity is difficult to justify, but it does align with the intuition that there is a considerable schism between those who have "made it" on a platform and those who have not.

7.2 Comparative statics

I now vary one parameter at a time from the baseline to explore how an artist's uncontrollable characteristics or market conditions affect optimal production decisions.

The first relevant comparative static is on the talent parameter, κ. To get an initial sense of how talent affects optimal strategy. Figure 5 shows the range of optimal values of (m, z) varying only the level of talent. The highlighted areas correspond to a realized strategy for a given set of (n, A) and κ. This plot shows that increasing an artist's talent moves the artist to move to a higher quantity strategy. One might initially think that an agent who has limited talent would try to balance their strategy between quality and quantity, but this is not the case. It is difficult to understand why the high talent creator shifts production away from quality and towards quality, but I suspect this comes from the parameters selected, and alternate parameterizations may see different behavior. Table 1 suggests, that both quantity and quality should decrease when κ increases. That result would not be possible in this dynamic model because increasing quantity necessarily decreases quality according to the production constraint.
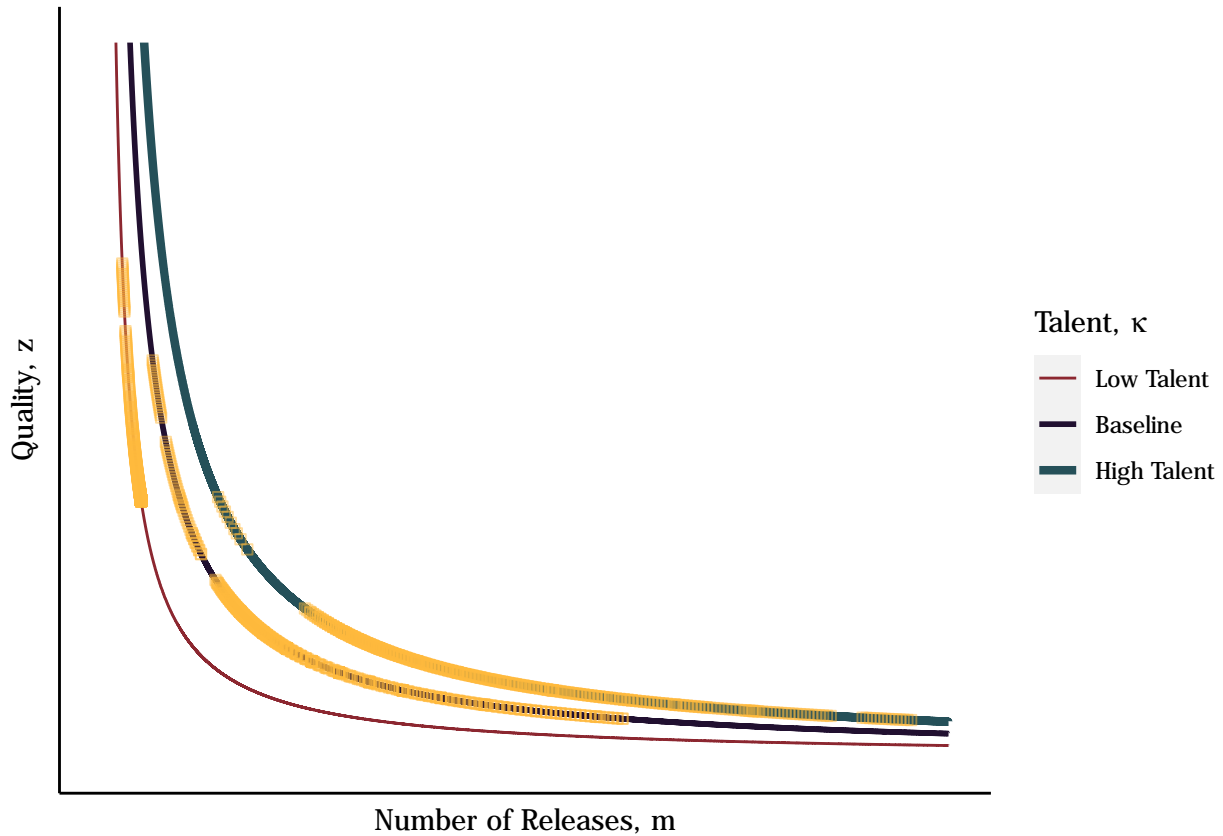

Figure 5: *The effect of varying talent on optimal strategy and revenue. Shaded areas correspond to a chosen strategy for a certain set of state variables*

The next two plots take the median of the utility and quantity strategy grouped by the initial reputa-

tion n. The variable n does not make a large difference on either outcome, so removing its influence in the plots allows the interpretation to be more direct. The next important parameter is the variance of the algorithmic shocks. A random algorithmic shock could be either positive or negative to an artist, and it is not immediately obvious whether the agent benefits on average from increased volatility. Note that in any period the agent is effectively risk-neutral because their per-period utility function is linear in revenue. However, the uncertainty introduces some curvature through its interaction with the audience evolution function, $\mathcal{A}$.
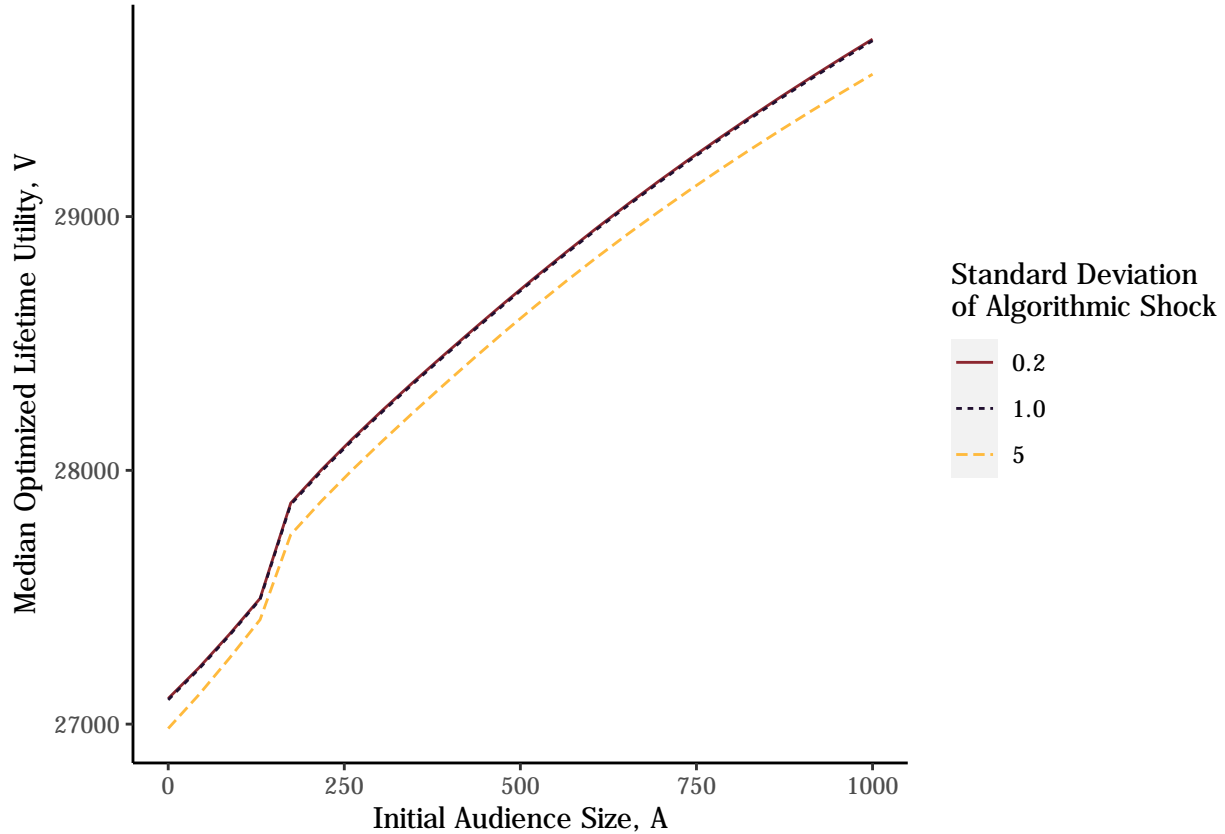

Figure 6: *Expected lifetime utility at different levels of algorithmic uncertainty and initial audience. Median over reputation, n*

Figure 6 shows how volatility affects an artist's optimized lifetime discounted revenue. The actual values of lifetime revenue are not individually important. The relative difference between the utility at the baseline and the utility at alternate values of algorithmic unpredictability does provide a useful comparison. The plot above gives the difference between the lifetime utility at the baseline standard deviation $\sigma = 1$ and alternate values. The change from 1 to 0.2 has relatively little impact on the lifetime expected utility of the agent. However, increasing the standard deviation from 1 to 5 notably decreases the expected lifetime revenue of a creator. On average, a creator loses lifetime utility by increased variance.
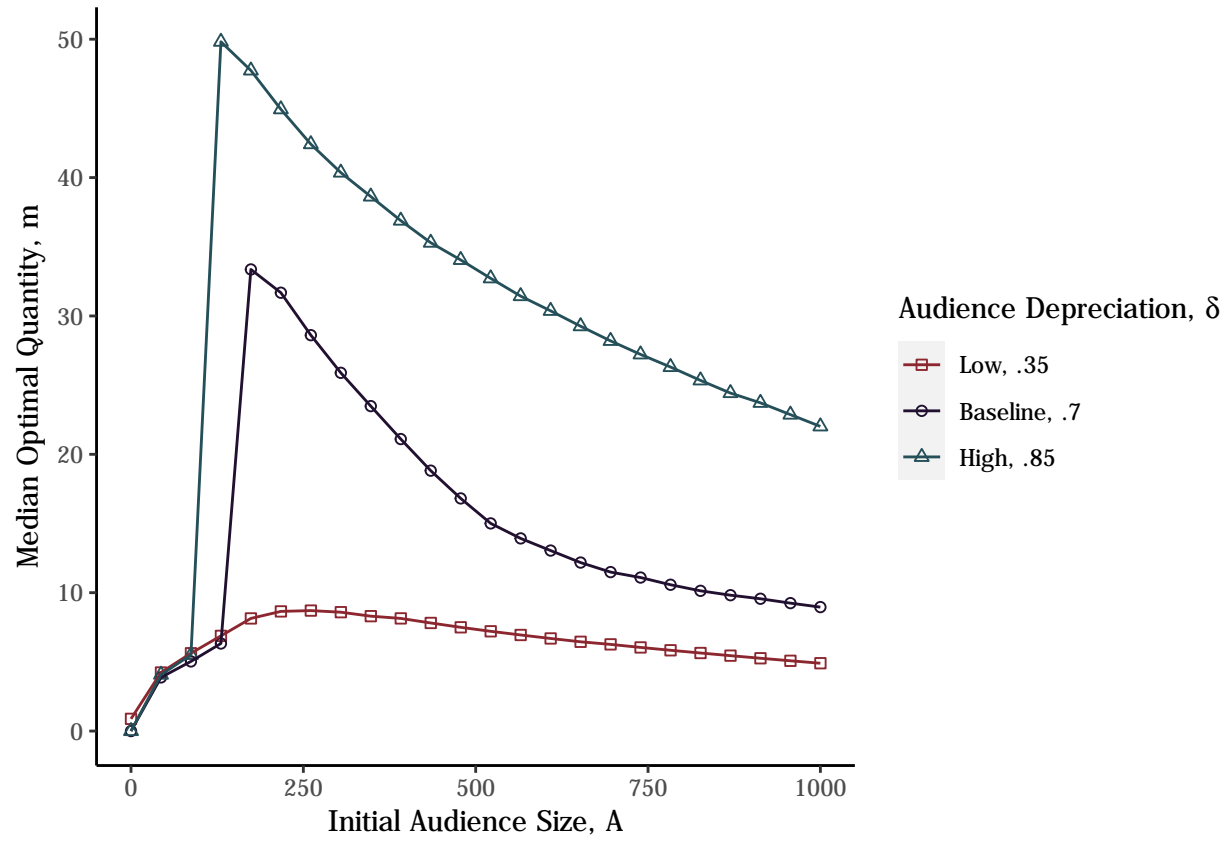
Figure 7: *Median optimal quantity as a function of initial audience size and audience depreciation rate. Median over reputation, n*

Figure 7 shows the median optimal quantity, m, for a given initial audience, A at three levels of audience depreciation rate, δ. For artists with low audience depreciation, $\delta = 0.35$, the strategy does not have a sharp jump in the optimal strategy. For a creator who loses a considerable portion of their audience every period. There is a certain audience threshold below which it is not worth investing in high quantity. This threshold I termed activation energy. The low depreciation artist never experiences this jump. They can afford to invest in quality because they know their audience sticks around. The other artists rely more on algorithmic exposures. More precisely, the quality chosen now affects the number of algorithmic impressions next period. If you can rely on your audience staying around, you are given more freedom to invest in the intertemporal benefit of quality. Creators with high depreciation do not have this same luxury. This low depreciation transitions smoothly from *hobbyist* to *superstar* without a steep jump.

The other notable effect of depreciation on optimal quantity is the steepness of the strategy jump for the high deprecation artist. The baseline and high depreciation creators move together while in the hobbyist phase, but the high depreciation artist has a greater jump in quantity than the baseline when entering the *budding creator* phase. At any audience level, the high depreciation artist has to work harder to maintain the same audience next period. As such, it is not a surprise that the high depreciation artist focuses on high quantity and not quality. What this may indicate is that in genres where the content creator is not very memorable, the content creator will focus on creating a lot of new and finding as many new audience members each period.

"How-To" videos on YouTube may be an example of a high-depreciation genre. After watching a tutorial and completing the task, a viewer has little incentive to watch that creator's other work. As such, tutorial creators may find it optimal to pursue quantity over quality. YouTube intimates this fact in a previously mentioned video by Simon Whistler speaking for YouTube's Creator Academy. He stresses the importance of concision in tutorial videos YouTube Creators (2018). A creator making short videos can make more videos than a creator making long videos.

In table 1, increases to depreciation rate make no change to quantity strategy. In figure 7 we see that for *budding creators* and *superstars* increasing depreciation also increases quantity. The difference from the one-period model has two reasons. The dynamic model is non-zero because the audience evolution function is no longer linear in the depreciation rate. The relationship is positive for established creators because high depreciation means that investing in quality has much less of a two-period benefit, so the creator substitutes toward quantity.

The talent parameter, κ, is worth additional analysis. In particular, I ask whether or not revenue is convex in talent similar to the result in Rosen (1981a). I solve the dynamic program multiple times changing only the talent parameter κ while keeping all others at their baseline.
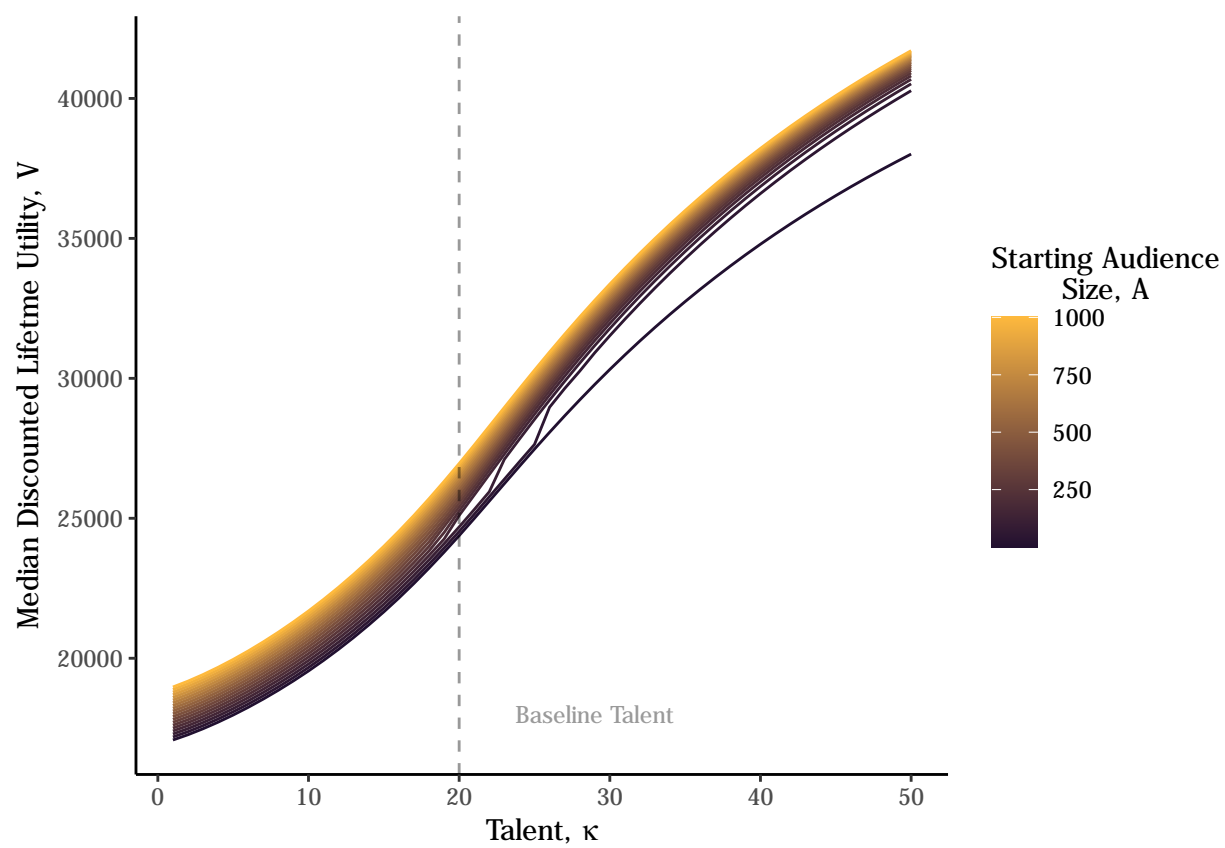
Figure 8: *Affect of Changes to Talent on Optimal Lifetime Revenue. Median over reputation, n*

In [8](), we can see that the effect of talent on lifetime revenue is nonlinear. Initially, there appears to be a convexity of revenue in talent, but then at higher levels of talent, additional talent becomes less and less meaningful. This is partially justifiable by the model specification. When talent is very large, the artist has enough of both z and m to near the maximal audience size, regardless of their starting n, A. As such, a more robust model that does not have a permanent upper bound on the audience size may see the convexity of revenue in talent for the entire range of talents.

Figure [8]() provides modest support for the generalization of Rosen's superstar theory to streaming markets. The result is especially pronounced in the transition from low to moderate talent in which small changes to talent can result in disproportionately large increases in lifetime revenue.

The effect of varying talent is not included because I found it to have a relatively small impact on the convexity of profit in talent.

7.3 Additional Simulations

The previous sections explored how changing an artist's state variables n, A affected their optimal production decision. This is useful when looking at the first-period behavior of multiple artists, but it does not give insight into the career trajectories of a single artist. Of course, algorithmic uncertainty prevents an artist from completely mapping out production decisions in every future period. However, the dynamic programming formulation allows the agent to re-optimize their quantity-quality tradeoff in every new period following the shock from the previous.

To explore these career trajectories, first I solve the dynamic program for a given set of parameters. Then I choose the number of time intervals to simulate and how many paths of shocks will be simulated. I set each simulation to the same initial audience and streams per capita, (n, A). From there the artist chooses an optimal quality and quantity based on the solved dynamic program. Then a new shock is randomly generated for the artist, and their production choice is combined with the shock to determine this period's revenue and audience. Next period's audience will likely not be what the artist was envisioning, so they have an opportunity to choose a new optimal quantity and quality. The artist experiences a shock that brings them to the current period, but the revenue they have this period will be affected by a shock they have not yet observed. Artists across simulations do not interact in any way.

Repeating this process for 1000 artists each over 100 periods produces a sufficient data set to find the average career for a set of starting parameters. First, I consider the case where both starting audience and starting reputation are very near zero.
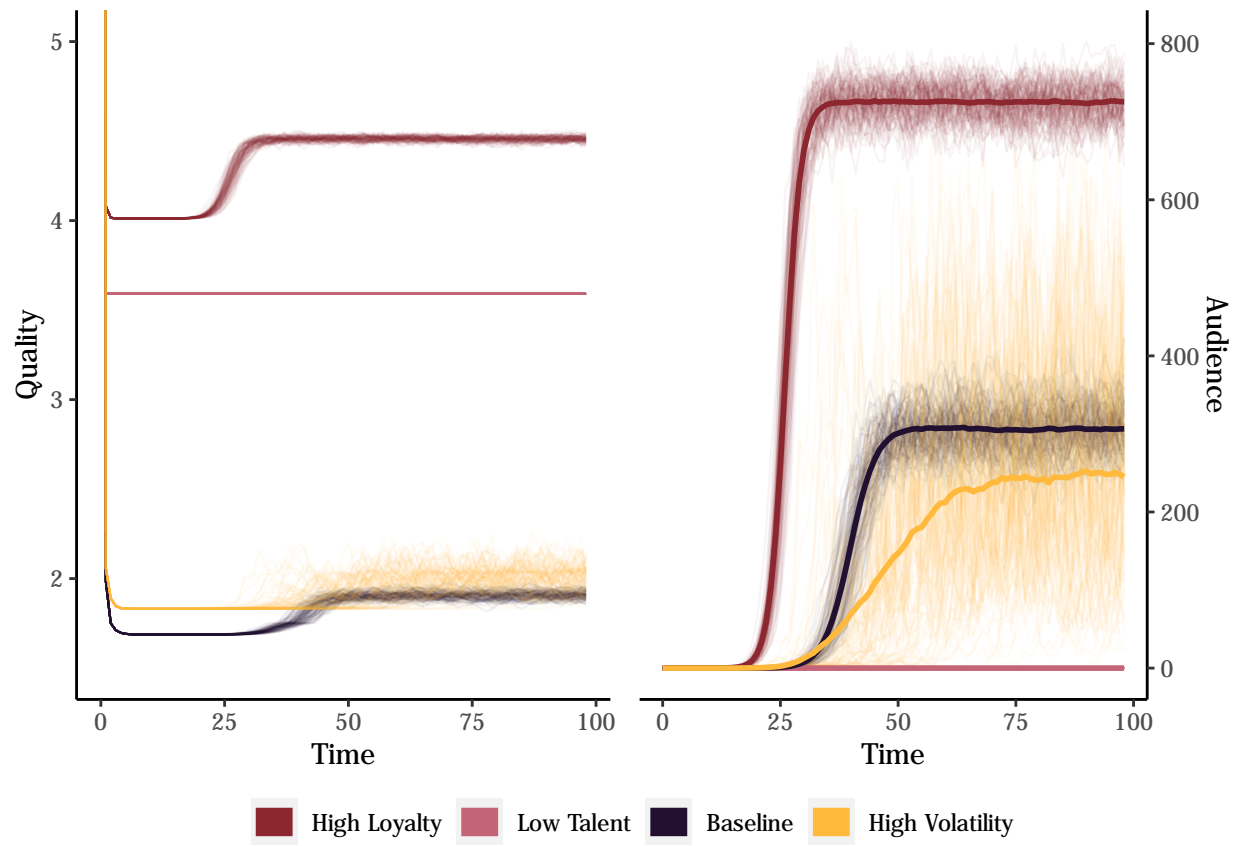
Figure 9: *Baseline Simulation, $n_0, A_0 = 0, 0$*

In figure 9, we can see a few facts. The right plot is a creator's audience over time. Three of the selected creator profiles maintain a considerable audience over time: baseline, high loyalty, and high volatility. Matching the results from the comparative statics, increased loyalty benefits the creator by increasing the audience over time. Again like the comparative statics, additional unpredictability decreases the creator's average audience over time. Of course, with additional unpredictability, some creators outperform the baseline for a while, but the average is below the baseline. The high-unpredictability creator may not gain an audience for many periods, but no creators are permanently prevented from going viral. A model with a reservation utility may see these unlucky creators drop out eventually, but that is not possible here.

Shifting focus to the left of the plot, we can see the three previously discussed stages emerge for the successful artists. In the first few periods, the creator's quality is very high when they are in the *hobbyist* phase. The successful artists then remain steady at a lower quality for a while while they are in the *budding creator* phase and accumulating audience. Eventually, as the creator becomes a *superstar*, the creator ramps up quality as their audience stabilizes. The high volatility creator profile's three-stage strategy is less obvious, but it is still present. For the high volatility case, different creators go through the different phases at different times.

The unsuccessful creator starts with a high-quality level, lowers it, but never gains enough of a following to truly enter the *budding creator* phase. The low talent creator does experience shocks, but their audience is so small that it makes almost no change to their strategy or audience. This plot shows that algorithmic shocks are insufficient to develop an audience. All creators start with the same audience and reputation, but we do not see any simulations of the low talent profile gaining a large audience by chance.

The quality chosen by an artist does not immediately determine audience size. In fact, the two most popular artists, high loyalty and baseline, have the highest and lowest quantity strategy respectively. This result shows that multiple types of artists can be popular on a platform.

This plot answers one of the initial questions of the paper, whether or not multiperiod models allow for small artists to invest in high-quality production. This simulation shows that artists who start small will be able to produce a high level of quality in the later periods of the simulation.

The final notable characteristic of figure 9 is that there appears to be an ergodic equilibrium in audience size and strategy over time. That is, after a certain audience size is reached, the artist will on average maintain their current audience and strategy over time. There may be random fluctuations in audience and resulting optimal strategy, but both ultimately revert to values around their averages. This result should not be taken too literally because there are no genre dynamics in this model. In reality, we expect certain media markets to rise and fall over time according to current tastes. This model holds consumer preferences as constant over time.

The artist is not just maximizing their discounted audience over time, they are maximizing their discounted revenue which is proportional to the number of total streams per period. As such, one may be concerned that the plot above does not adequately describe the careers of an artist over time. However, a

plot of the total number of streams per period looks almost identical to the plot above of audience size in every period. In our model, this means, that artists optimally focus on growing their audience. Investing in a small audience who streams frequently is not optimal.

Next, I will explore how changing an artist's starting parameters affects their career trajectory.
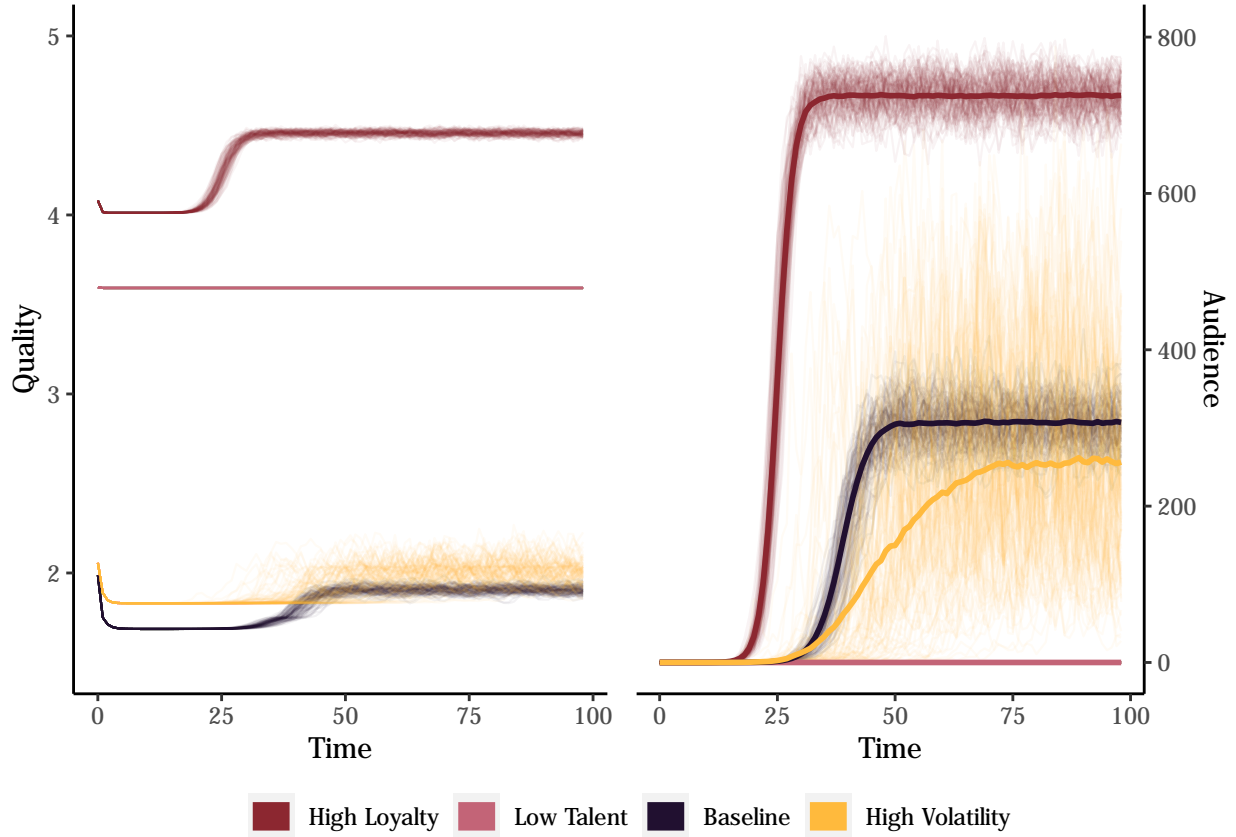
Figure 10: *Higher Initial Reputation Simulation, $n_0, A_0 = 5, 0$*

In figure 10, we can see the effect of a high starting reputation on audience and quality over multiple periods. There are a few questions that this plot immediately answers. First, we might ask if a high starting reputation allows low-talent artists to "fake it" and maintain a large audience. In this model, the answer is no. Despite an initial boost to reputation, this level of reputation cannot be maintained by low-talent artists, so their audience and revenue are quickly lost.

The other question that this plot answers is whether or not different starting conditions allow an artist to reach a different equilibrium. Again, the answer is no. The equilibrium level of audience for all creator profiles is equal to that in figure 9.

The initial boost to reputation allows the successful artists to mostly skip the *hobbyist* phase. We can see that the hobbyist phase is skipped because the initial drop in quality is much smaller, so the strategy discontinuity is not being used.

8 Conclusion

This paper constructs a model to explore the optimal behavior of a content creator on a streaming platform with an uncertain algorithm. I began by asking if small creators are able to invest in high-quality production in a multi-period. I was also interested in discovering whether or not a creator's revenue is convex in their talent. Starting with a one-period binary-choice example and then moving to dynamic programming, I found the following results.

First and foremost, this model predicts that different talent and reputation produce of three types of artists: *hobbyists*, *budding creators*, and *superstars*. Hobbyists pursue high-quality production and do not reach a large audience. After a certain audience is reached, budding creators focus on high-volume production to grow their audience. Superstars have large audiences and switch to a higher-quality strategy maintaining their current audience becomes a priority. The multiperiod model allows even small creators to eventually pursue a high-quality strategy.

In this model, content creators are more likely to invest in the intertemporal benefit of high-quality production when they are confident most of their audience will be retained next period. As such, a platform wishing to create a community of high-quality creators may find it optimal to keep consumers connected to the creators they have found in the past.

Another interesting result from the model is the relationship of algorithmic unpredictability to the career path of an artist. A more unpredictable algorithm decreases the expected lifetime discounted revenue of an artist. However, even if an artist experiences multiple negative shocks, they will not be prevented from eventually gaining a following.

Lower talent also decreases lifetime utility. Even if an algorithm gives a bonus to new artists, low-talent artists cannot "fake it" until they "make it." Talent plays an important role in predicting lifetime utility. For low-talent artists, initial gains to talent are very useful. These low-talent creators face a convex value function in talent. However, the additional benefits of talent decrease, and very talented artists face decreasing marginal expected lifetime revenue in talent.

Future research could use a technique like web scraping to collect data and construct a panel of a creator's followers and view count over time. These data could further calibrate the model presented above. Other avenues for further research include generalizing the model presented above to allow for direct competition between creators for views. This would allow for the size of the audience to be limited endogenously, not exogenously. More nuanced research of what determines a creator's audience over time would allow for more generalizable models and results. Further attention should also be paid to optimal platform design by the companies who create streaming services. More freely-accessible and publicly-available analysis of a platform's optimal algorithmic uncertainty, audience depreciation, and consumer-creator matching would be extraordinarily valuable both financially and economically.

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Appendix

Proof of Proposition I

By 7 the low-quality strategy becomes more desirable relative to the high-quality strategy when the following quantity increases:

$$\left(1 + \frac{(m_l(\kappa) - m_h(\kappa))I_0}{m_h(\kappa)I_0 + (1-\delta)A_0}\right)$$

Therefore, the low-quality strategy gains desirability from increases to κ whenever the derivative of the above expression is greater than zero. The κ derivative is:

$$\frac{(m_l'(\kappa) - m_h'(\kappa))I_0\left(m_h(\kappa)I_0 + (1-\delta)A_0\right) - (m_l(\kappa) - m_h(\kappa))I_0\left(m_h'(\kappa)I_0\right)}{(m_h(\kappa)I_0 + (1-\delta)A_0)^2}$$

The denominator is always positive, so positivity on the derivative only requires the numerator to also be positive. Expanding and simplifying that expression gives the following inequality:

$$(m_l' - m_h')(1-\delta)A_0 + (m_l'm_h - m_lm_h')I_0 > 0$$

Now suppose that $(m_l'm_h - m_l\overline{m'}) > 0$, and by construction $m_l > m_h$. Note that for an arbitrary $a, b, x, y \in \mathbb{R}^+$, when $ax - by > 0$, $x > \frac{b}{a}y$. The condition $x > y$ is weaker than and is implied $x > \frac{b}{a}y$ whenever $b > a$. Letting $a = m_h, b = m_l, x = m_l', y = m_h'$, shows that both terms in the above inequality must be positive, so the whole derivative must also be positive. Finally,

$$m_l'm_h - m_lm_h' > 0 \iff \frac{m_l'}{m_l} > \frac{m_h'}{m_h} \iff \frac{\mathrm{d}\ln(m_l)}{\mathrm{d}\kappa} > \frac{\mathrm{d}\ln(m_h)}{\mathrm{d}\kappa}$$

This completes the proof.

Notes Value Function Iteration Implementation

The first difference between Sargent & Stachurski (n.d.) and the model used in this paper is that the state space is multidimensional. The control variables, m and z can be reduced to a one-dimensional relationship according to $f(m, z) = \kappa$. In this way, the artist is only choosing one variable in every period. That being said, the state variables, n and A cannot be reduced to one dimension. Therefore, the set of potential input points at which the value function must be numerically maximized is two-dimensional. Resolving this difference amounted to little more than careful index chasing, array reshaping, and waiting much longer for computations.

The next substantial difference between Sargent & Stachurski (n.d.)'s work and the problem at hand is the presence of uncertainty. Computing the expected audience size required that I first assume a distribution for the random variable ε. I chose a normal distribution because it has mean zero and its variance can

easily be rescaled. The normal distribution is continuous and requires discretization to compute an estimated expected value. To fairly compute the expected value, I create N evenly spaced numbers between 0 and 1. I then evaluate the inverse cumulative density function of the distribution at each of those N points. Therefore, the sampling of the distribution evenly represents where samples are likely to lie. From there, I compute discrete expected value by finding the total probability mass between two evaluation points, then computing the audience conditional on a given ε. Then I multiply the mass and the audience and sum each of these pieces together.

The final substantial difference between Sargent & Stachurski (n.d.)'s work and mine is the boundedness of the equation of motion. In their case of cake eating, a consumer can consume anything between 0 and the total cake remaining. The state variable sent to next period is simply the starting cake less consumption that period. In my case, the relationship between two periods comes from $v(z)$ and $A' = A(m, n, A, \varepsilon)$. Absent the requirements of dynamic programming, there is no reason for most new creators to see any upper limit to their audience size or streams per viewer. However, to prevent both functions from growing off to infinity, any output lying outside of a chosen range is brought back to the maximum or minimum of this range. This weakens results, however, if sufficiently high and low bounds are chosen, the omitted values contribute relatively little to overall results. I give the audience evolution function a logistic shape that naturally has upper and lower bounds. Further, I give $v(z)$ a shape that bounds it between 0 and a choice of maximal $\overline{n}$ for all $z \in [0, \infty)$.