Music Ex Machina: How Spotify's Recommendations Shape Music Production*

Max E. Schnidman†

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Abstract

I examine how recommender systems have influenced the music industry and shaped music production over the last decade. Using a structural model of Spotify's recorded music industry, I analyze consumer behavior, platform recommendations, and rightsholders' decisions. Results indicate that streaming services and recommender systems correlate with a 40-second decrease in average song length on Billboard's Hot 100. The model estimates a fixed cost of $79,000 for songs entering Spotify's Top 200, with an 8% price-cost margin. Counterfactual analysis shows that without recommender systems, songs would be 50 seconds longer on average, but consumer welfare would be 13% lower. While reducing music variety, these systems have increased song quantity and overall consumer welfare.

Keywords: Recommender Systems, Economics of Platforms, Digital Economics, Music Economics

JEL Codes: D82, L15, L82, Z11

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†University of Virginia, mes7jw@virginia.edu

1 Introduction

Recommender systems, designed to match consumers with products they will like, have transformed how consumers search for and acquire products. Such systems are prevalent in many online marketplaces, including Amazon, TikTok, and Netflix, and they have become a key feature of the digital music industry.[1] Music streaming platforms, where consumers can access a vast catalog of music for a fixed monthly fee, have become the primary way that consumers access music, with streaming accounting for 84 percent of the recorded music industry's $16bn revenue in 2023.[2] Notably, these platforms use recommender systems to generate algorithmic playlists to surface music for users, These playlists are where users discover the majority of new music. I investigate how these recommender systems affect the music industry, and how they have shaped the sound of music over the last decade.

Recommender systems are a form of advertising for content on digital platforms, but they are unique in that the producer does not actually design or purchase the advertisement.[3] Antitrust authorities have begun to investigate the effects of these systems on competition, and several pieces of legislation have been passed to regulate them. Examples include the Digital Markets Act and Digital Services Act in the EU, and the recent US Department of Justice investigation into the RealPage rent pricing algorithm.[4] These systems come with a number of economic tradeoffs. Consumers can more easily find music they may like and discover new artists, and artists can reach a wider audience than ever before (Aridor and Gonçalves 2022). Platforms can use these algorithms to steer consumers towards profit-maximizing products, rather than products that consumers actually prefer (Reimers and Waldfogel 2023). Additionally, these systems may have inherent biases, providing recommendations that are not representative of the population or that are harmful to certain groups (Melchiorre et al. 2021). I focus on the equilibrium effects of these systems, where

1. Amazon, TikTok, Netflix
2. RIAA 2023 Year-End Music Industry Revenue Report
3. Platforms do have sponsored recommendations, but Spotify, the platform I study, did not introduce these sponsored recommendations until after the timeframe of my data.
4. Digital Markets Act, Digital Services Act, DOJ escalates price-fixing probe, Politico, March 2024

producers respond to the recommender system by changing their product design, and how these changes affect consumer welfare.

To capture these equilibrium effects, I build a structural model of the recorded music industry to estimate the supply of and demand form recorded music on Spotify. This model has three sets of agents: consumers, Spotify, and rightsholders (producers). Consumers receive songs from Spotify's recommender system and choose whether to listen to them during their streaming session under a nested logit framework. Spotify's recommender system computes the probability that a consumer listens to a particular song, based on the song's characteristics and the consumer's preferences, and delivers the song to the consumer. Rightsholders choose whether to release songs to Spotify given the demand for the song, which is the joint probability the recommender system surfaces the song and the consumer listens to it. They are forward-looking agents, looking to maximize expected profit, so they consider the future revenue the song generates when deciding whether to release it. In an oblivious equilibrium, rightsholders release songs so long as the expected revenue exceeds the fixed cost of release, which is given by the expected revenue of the worst-performing (or marginal) song.

To estimate this model, I use three sources of data: the Music Streaming Session Dataset (MSSD), data scraped from Spotify Charts, and the Spotify API. The MSSD contains 160mn consumer-level streaming sessions from July to September 2018, including song characteristics, consumer characteristics, length of the listen (binned), and whether they got the song from a recommender system, or other sources. Spotify Charts is a webpage reporting the daily top 200 songs on Spotify for every country in which they operate. It also includes stream counts, and the song ID. The Spotify API allows me to query the song characteristics of each song on Spotify Charts.

I find that song characteristics, such as length, tempo, and danceability, have changed significantly since 2010. I estimate that the introduction of streaming services and recommender systems correlate to a 40-second decrease in the average length of songs on Billboard's Hot 100. Additionally, music industry executives have confirmed that they have changed the kind of music they release to better fit the recommender system's objectives (e.g., shorter, more danceable songs).

My structural model estimates that a wedge exists between consumer demand and recommender systems, and that producers respond to this wedge by targeting the recommenders' objectives jointly with consumer preferences. For example, while consumer are likelier to listen to longer songs, the recommender system is likelier to surface shorter songs, and producers respond by releasing shorter songs. I also estimate the fixed cost of releasing music on Spotify. My estimate for a song that enters Spotify's Top 200 is $79,000, and my estimate for the average song is $45. In both cases, however, the price-cost margin is small, at approximately 8% for a song that enters the Top 200, and approximately 7% for the average song.

My counterfactual analysis focuses on changing Spotify's recommender system to see how it has affected song characteristics. Specifically, I impose random recommendations, as a proxy for no recommendations. I find that in the absence of recommender systems, songs are on average 50 seconds longer, more heterogeneous, and less profitable. As a result, fewer songs are released, and consumer welfare is 13% lower than in the status quo. This suggests that Spotify's recommender system has indeed changed the sound of music, and that while these changes have reduced the variety of music available to consumers, they have also increased both the quantity of songs and consumer welfare.

This research has significant managerial and policy implications. The results from this model suggest that digital platforms can use their recommender systems strategically to affect both the demand for and supply of products on their platform. It also shows that consumers care more about the quantity of available products, even if they are more homogeneous, than the variety of products available, and that recommender systems can help improve consumer welfare. Additionally, it suggests that firms need to consider both the consumer and the platform when designing their products, and that they should be aware of the strategic implications of their decisions. Moreover, this research also has implications for antitrust authorities, who should consider the effects of these systems on competition and consumer welfare when evaluating mergers and acquisitions in the digital space.

This paper proceeds as follows. Subsection 1.1 places this paper in the context of the literature and identifies the contribution. Section 2 provides the background for the recorded music industry, describes the industry structure, including music characteristics, and provides reduced-form analysis of how technological changes have affected song characteristics, in order to motivate the structural model. Section 3 describes the data I use in this paper, including the Music Streaming Session Dataset and Spotify Charts. Section 4 details the structural model of music streaming, and describes the oblivious equilibrium in which rightsholders release music. Section 5 explains the estimation strategy. Section 6 provides and discusses the estimates of demand parameters, recommender system parameters, and fixed costs. Section 7 conducts several counterfactual analyses, modifying the recommender system to observe how equilibrium song releases change. Section 8 concludes.

1.1 Literature Review

This paper contributes to several strands of the economics literature. First, it contributes to the literature on the economics of music, by developing a structural model of the music streaming industry. Other works have analyzed the impact of Spotify on the industry. Aguiar, Waldfogel, and Waldfogel 2021 uses reduced-form analysis to identify bias in the rankings of songs on Spotify's New Music Friday playlist. They find that higher-ranked songs tend to perform better after placement on the playlist, suggesting that the curators are looking to maximize ex-post streams. They also find that the curators of this playlist tend to favor songs by women and from independent labels, because they rank higher than their ex-post performance would suggest. Benner and Waldfogel 2016 use a difference-in-difference design to estimate how digitization of recorded music has affected the release strategy of record labels. They find that, after digitization, major labels both release fewer albums and become more reliant on previously successful artists; conversely, independent labels release more albums. I extend these papers by taking these insights into Spotify playlists and digitization and embedding them in a structural model of the industry. It also builds on Aguiar and Waldfogel 2018, which developed a structural model of the digital music industry. They model consumer demand for digital music across countries, and estimate the fixed cost of entry under three different scenarios: perfect quality foresight, no quality foresight, and imperfect quality foresight. They estimate this fixed cost as the expected revenue of the worst-performing song, and find that the fixed cost is higher when rightsholders have no quality foresight. Their counterfactual analysis find that tripling the choice set under imperfect foresight adds nearly 20 times as much consumer surplus as tripling the choice set under perfect foresight. I extend this model into the music streaming industry, by modifying the choice structure to reflect the streaming industry, incorporating a recommender system into the model, and introducing forward-looking rightsholders. I apply their entry condition to estimate the fixed cost of entry on Spotify.

Second, I contribute to a growing literature on recommender systems in economics. Many recent papers have focused on the effect of recommender systems on pricing. Calvano et al. 2020 embeds learning algorithms in a repeated Bertrand oligopoly setting, and they find that these algorithms result in supracompetitive prices. This outcome is a result of collusive strategies that the algorithms adapt without explicitly communicating with each other. I extend this paper's insight into equilibrium effects of algorithms into product characteristics. Other papers have studied the effects of recommender systems through theoretical models or through reduced-form analysis. Bourreau and Gaudin 2022 uses a Hotelling model of music listening with a recommender system and a digital platform hosting both songs. They find that the platform uses the recommender system to drive consumers to cheaper songs, even if they are further away from the consumer's ideal song. Aridor and Gonçalves 2022 similarly embeds recommender systems in a theoretical model of digital platforms. They focus on the effect of these systems when the platform competes with its sellers (i.e., acts as a hybrid). They find that the platform uses the recommender system to steer consumers towards its own products, and that this can reduce consumer welfare through foreclosure of third-party sellers. They also find that policy remedies are ambiguous in their effects, and that they can reduce consumer welfare if they are not carefully designed. I extend these analyses to an empirical model of the music industry, focusing on how these systems affect producer product decisions. Melchiorre et al. 2021 introduces a large-scale dataset of music listening from Last.FM, a scrobbling service, and they use these data to investigate how several algorithms may exhibit gender bias. They find that significant disparities exist in the recommendations towards certain gender groups. Aridor et al. 2023 conducts a field experiment to determine whether recommender systems affect consumption, using the recommendation service MovieLens. They find that recommender systems increase consumption beyond just the exposure provided by the recommendation. They also induce consumers to acquire additional information beyond what the recommendation provides. I apply their experiments to a structural model of the music industry.

Finally, I contribute to the literature on digital platforms and intermediation. Recent work in this area has focused on the role of platform exclusives, and the possibility that these platforms can bias search and recommendation results towards certain profit-maximizing products, at the expense of consumer welfare. Lee 2013 constructs an empirical model of the video games industry, focusing on the role of exclusive games on console platforms. He finds that in the absence of exclusivity agreements, console sales and consumer welfare would both be higher, but that only the incumbent console manufacturer would benefit from the removal of such agreements. I extend his model of games production to the music industry, and I build on his use of first-order Markov processes to model firm dynamics. Reimers and Waldfogel 2023 develop an equilibrium framework to develop a workable definition of platform bias. Their model establishes a welfare frontier for platforms, which is a weighted sum of consumer and producer surplus. They then test for biased rankings (recommendations) on the platform by evaluating whether the platform is on the frontier. They illustrate the approach by estimating the amount of bias in a structural model of Amazon and Expedia, finding that both platforms are off the frontier. Aguiar and Waldfogel 2021 estimate the effect of including a song on a Spotify playlist using a discontinuity and instrumental variable design. They find that being included on a playlist significantly increases a song's eventual streams. I build on this work by incorporating algorithmic playlists into my model of the music industry.

2 Background and Industry Structure

2.1 Background

Technological changes have revolutionized the music industry over the last thirty years, as evinced by their fall and rise in real revenue in figure 1.

Figure 1 about here

Growing access to the internet in the 1990s made it easier for consumers to digitally copy and share music, which led to the creation of illicit file-sharing services, such as Napster and Limewire, in the late 1990s. The creation of these services was concurrent with a marked decline in revenues for the industry, which industry participants attributed to these illegal file-sharing services, and legal challenges brought by the Recording Industry Association of America resulted in their closure in the 2000s.

To take advantage of the market for digital music and to support its iPod music players, Apple launched the iTunes store in 2003. iTunes made it easy for consumers to legally purchase digital music at low prices (99 cents per song). To address concerns about piracy, Apple made it difficult to share music sold on its platform, and designed its files such that they could only be played through iTunes or listened to on iPods.[5] Additionally, Apple negotiated a revenue-sharing deal with labels, giving them 30 percent of the revenue of every sale on iTunes, setting a precedent for revenue-sharing arrangements on digital platforms for the next two decades. While other digital companies attempted to launch their own

5. https://www.engadget.com/2013-04-29-the-itunes-influence-part-one.html

music platforms (e.g., Google, Microsoft), none of them reached the level of financial success or cultural impact as iTunes. iTunes also broke up the album format, allowing consumers to purchase individual songs, rather than entire albums, another important precedent for streaming services.

In the late 2000s, some companies (e.g., Yahoo, Microsoft) began to experiment with streaming services, which provided consumers with on-demand access to an entire library of music for a subscription fee.[6] Such services did not see widespread acceptance until the early 2010s, when Spotify launched in the U.S. Spotify combined an expansive library and an accessible two-tiered plan that included a free, ad-supported tier, and a paid, ad-free subscription tier. The subscription fee was waived for the first six months after launch.[7] Streaming made piracy much more difficult than copying digital downloads from iTunes or other digital platforms, because the service relied on streaming music from a centralized server.[8]

Spotify and similar streaming services (e.g., Apple Music, YouTube Music) proved incredibly popular, and helped to reverse the decline in the recorded music industry. Today, these services have become the primary way that consumers access music, with streaming accounting for 84 percent of the industry's revenue in 2023 (Figure 1).

2.1.1 Music and its Characteristics

Recorded music is the uniquely arranged combinations of sounds and vocals typically recorded in a studio. As a product, recorded music exists along numerous dimensions: length, chords, pitch, beats per minute, vocals, choices of instruments, etc. This results in infinitely many possible forms of music, many of which can be esoteric (e.g. John Cage's 4'33"). Many of these dimensions are continuous, making it possible to use them as characteristics in a model

6. https://www.thurrott.com/music-videos/groove-music/6033/microsoft-is-finally-retiring-zune-zune-music-pass

7. https://www.theverge.com/2012/1/6/2688250/spotify-free-account-restriction-10-hours-per-month

8. Amusingly, Spotify initially used pirated music before its agreements with record labels (Eriksson et al. 2019)

of consumer preferences. (Lancaster 1966). In addition to the classical characteristics from music theory (e.g, key, tempo, time signature), I include characteristics from machine learning models (e.g., danceability, energy, valence) in my model. I discuss these characteristics in more detail in section 3.

Recently, analysts have observed a decrease in pop song length over the last twenty years, alongside a decrease in title length and an increase in lyric density.[9] To augment this, I conduct a reduced-form analysis of songs on Billboard's Hot 100 to confirm these trends. Specifically, I estimate the correlation between the introduction of new music formats and song duration. My regression equation is the following:

$$\begin{aligned} Duration_j &= \beta_0 + \beta_1 \mathbb{1}\{Vinyl\}_t + \beta_2 \mathbb{1}\{Cassette\}_t + \beta_3 \mathbb{1}\{CD\}_t \\ &= \beta_4 \mathbb{1}\{Digital\}_t + \beta_5 \mathbb{1}\{Streaming\}_t + \beta_6 \mathbb{1}\{RecSys\}_t + \epsilon_j \end{aligned} \tag{1}$$

Each independent variable is an indicator variable for whether the particular format or technology was available at the time of the song's release. Table 1 reports the results of this regression.

Table 1 about here

These results are all statistically significant at the 1 percent level, and are negative for both the introduction of streaming services in the US in 2011 (as exemplified by Spotify), and the deployment of recommender systems on Spotify in 2015 (after their acquisition of Echo Nest). Combined, the introduction of these technologies are correlated with a 40-second decrease of average song length for songs that make it to Billboard's Hot 100, when comparing songs released in 2018 to songs released in 2010. This analysis is consistent with anecdotal evidence of changes in songs since the introduction of streaming services, but it does not establish a causal relationship, or the mechanism by which these changes occur.

9. https://michaeltauberg.medium.com/music-and-our-attention-spans-are-getting-shorter-8be37b5c2d67

For that I construct a structural model of the industry, whose agents and relationships I describe in the following subsection.

2.2 Industry Structure

I group the recorded music industry into four sets of agents: artists, rightsholders, streaming platforms, and consumers. Figure 2 maps out the relationships between these agents.

Figure 2 about here

Beginning on the left, artists create music, either by themselves or in contract with rightsholders. An artist on contract with a rightsholder (e.g., a record label) typically receives and advance and production assistance in exchange for ownership over the music they create. Artists also receive a share of the revenue (royalties) from the music they create, as negotiated with the rightsholders.[10] The market for artists is highly diffuse, with tens of thousands of artists working on music each day, competing not just with each other, but with the entire history of recorded music. The Bureau of Labor Statistics estimates that there are approximately 35,000 musicians and singers in the U.S., as of May 2023.[11]

Rightsholders, such as Sony, Warner, and Universal (the Big Three record labels), are responsible for distributing music to consumers, either through physical media (e.g., CDs) or through digital platforms (e.g., Spotify). They also search for new and upcoming artists to sign to contracts and promote their music. These labels also have a wide variety of subsidiary labels (or sublabels) to focus on particular types of music or audiences. These sublabels sometimes end up competing for artists. Rightsholders also negotiate with streaming platforms to distribute music, bargaining over the share of revenue they receive from the platform, and the terms of the contract. I discuss the bargaining between rightsholders and streaming platforms in more detail in the following subsection. Rightsholders are a highly

10. Song Royalties are an incredibly complex area of law, which I simplify for the purpose of this analysis by focusing on the payments between rightsholders and platforms. For a more detailed explanation, see https://www.royaltyexchange.com/blog/music-royalties-101-intro-to-royalties

11. https://www.bls.gov/oes/current/oes272042.htm

concentrated section of the industry, with the Big Three (WMG, Sony, and UMG, including their sublabels) capturing 77 percent of the market. Other independent labels comprise the remaining 23 percent of the market. Figure 3 shows the market share of rightsholders (and streaming services).

Figure 3 about here

Streaming platforms, such as Spotify, Apple Music, and Amazon Music, are responsible for distributing music to consumers, either through a subscription or ad-supported model. These platforms began to enter the U.S. market in the early 2010s, after starting in Europe in the late 2000s, and they have revolutionized the recorded music industry, allowing consumers to access a vast catalog of music for a fixed monthly fee. As with rightsholders, this section of the industry is highly concentrated, with five firms comprising approximately 80 percent of the market. Figure 3 shows the market share of streaming platforms (and rightsholders).

These platforms are relatively undifferentiated in their music offerings, differentiating instead on their recommendation engines, interface, and ancillary features (e.g., exclusive podcasts, integration with smart devices, etc.). I speculate that the presence of YouTube as a free, ad-supported platform for music and lyric videos made it difficult for these platforms to compete on exclusive content.[12] This is especially true because non-rightsholders can easily upload music to YouTube, creating a difficult cat-and-mouse game for uploaders, rightsholders and the platform. It is easier for rightsholders to upload their music to YouTube and gain ad revenue for it, thereby making YouTube a streamer of last resort for consumers.

Streaming platforms offer multiple services to consumers, which I group into two: ad-supported and premium subscriptions. Ad-supported subscriptions allows consumers to access music at no monetary cost, instead facing use restrictions and advertising. On Spotify, ad-supported consumers have total access to fifteen playlists, which are a mixture of editorial (human-curated) and alogrithmically-generated playlists. For any other playlist on the

12. While some music platforms (e.g., TIDAL) attempted to differentiate through exclusive music, they abandoned this strategy.

service, users can only shuffle songs (i.e., they cannot directly select a song). Additionally, ad-supported users can only skip up to six songs per hour, must listen to ad breaks during their streaming sessions, and stream at lower audio quality (bitrate). Premium subscribers pay a monthly fee ($11.99 a month at the time of writing, $9.99 at the time of analysis) to remove all of the aforementioned restrictions.[13]

2.2.1 Vertical Contracts between Rightsholders and Streaming Platforms

Spotify contracts with rightsholders to distribute music to consumers. These contracts set the terms under which Spotify can license music and how Spotify pays rightsholders.[14] Spotify pays rightsholders for royalty-bearing streams (RBS), defined as any play of a song that lasts more than 30 seconds.[15] Rightsholders earn income based on their song's streamshare, which is its number of royalty-bearing streams divided by the total number of royalty-bearing streams on the platform in a given month. I write the streamshare equation as follows:

$$\text{Streamshare}_j = \frac{\text{RBS}_j}{\sum_k \text{RBS}_k}$$

Spotify pays rightsholders separately for ad-supported and subscription consumers, and these two types of consumers have different payment structures. For premium subscribers, Spotify pays rightsholders the greater of a share of gross revenue or a per-subscriber fee, multiplied by a sharing parameter. For ad-supported subscribers, Spotify pays rightsholders the greater of a share of ad revenue of a per-stream fee. Figure 4 shows the payoff structure for rightsholders.

Figure 4 about here

At the time Spotify entered the market in 2011, its contract with Sony stated that the revenue share was 60%, the per-subscriber fee was $6, and the per-stream fee was $0.0225.

13. Spotify also offers a variety of group and student subscriptions which reduce the cost per user.
14. (Singleton 2015)
15. Spotify has begun to deploy longer cutoffs for certain types of songs to qualify for RBS. https://artists.spotify.com/en/blog/modernizing-our-royalty-system

The contract also had a most-favored nation clause, suggesting that these rates prevailed for all three of the major labels. Spotify has since renegotiated these rates, but the exact terms are not public.

At launch, Spotify charged $9.99 for a premium subscription, so the revenue share and per-subscriber fee were equivalent at that time. Since Spotify has gone public in 2017, its premium average revenue per user has been well below the the standard per-subscriber fee, primarily because of family and student plans, which reduce the cost per user. Assuming that Spotify has not renegotiated the per-subscriber fee with rightsholders, this would suggest that this fee (times the number of subscribers) is greater than the revenue share, and that Spotify is paying rightsholders the per-subscriber fee. Singer and Rosenblatt 2023 suggest, however, that the per-subscriber fee is a floor, and that Spotify pays rightsholders a revenue share of approximately 65 percent of gross revenue.[16]

The structure of this contract is vital for understanding the incentives of rightsholders to release different kinds of music on Spotify. The most apparent example is in the duration of a song: a shorter song can generate more RBS in a given period, thereby increasing the streamshare of the song and the revenue rightsholders receive from Spotify. Spotify, however, would pay more for ad-supported subscribers if more streams occurred, so they would prefer to have longer songs.

Spotify, in turn, responds to these incentives through its recommender system. (Singer and Rosenblatt 2023) report that Spotify's recommender system rewards songs that users complete, and penalize ones that consumer only partially listen to. This has driven rightsholders to adjust the structure and characteristics of their music to align with the priorities of Spotify's recommender system. I investigate how rightsholders have responded to the recommender systems, and whether these recommender systems are welfare-improving.

16. Specifically, labels receive 52 percent, and publishers receive another 10-12 percent.

3 Data

I leverage two sources of data in this project: the Music Streaming Sessions Dataset (MSSD, Brost, Mehrotra, and Jehan 2018), and data from Spotify Charts. The MSSD consists of 160mn consumer-level streaming sessions between July 15th and September 18th of 2018, with each session containing up to twenty songs a consumer interacted with on Spotify. The MSSD defines a streaming session as any listening session with less than 60 seconds between songs. The data also only contain streaming sessions with at least ten songs, and it truncates all streaming sessions after twenty songs.

The MSSD contains both song characteristics for the approximately 3 million songs in its data, as well as data for each of the approximately 2bn song-consumer interactions. The song characteristics include both musical characteristics and machine learning characteristics. Musical characteristics include tempo, duration, key, time signature, and mode. Machine learning characteristics are data generated by machine learning classification systems, and these characteristics include danceability, energy, valence, and acousticness. Machine learning characteristics are continuous on a $[0, 1]$ support, while musical characteristics may be continuous (e.g., tempo) or discrete (e.g., key).

Consumer-song interactions include a wide array of information about the consumer and how they interact with the song. The variable of interest is how long the consumer listens to the song, which is grouped into four bins (”skipped very early”,”skipped early”, ”listened to most of the song”, ”listened to the entire song”). I assume that consumers who do not skip a song very early (i.e., are not in the first bin) have listened to enough of the song for it as an RBS. I also observe details about the consumer's streaming session: the position of the song in the session, the date and hour when they listend to each song in the session, and whether the consumer was listening to a song they searched for, their own collection, an editorial playlist, or an algorithmic playlist or radio station. Additionally, I observe what the consumer did after each song, which I use to determine under what circumstances a consumer ended their streaming session. Moreover, I observe the consumer's subscription status at the time of listening. I use these choice-level data to estimate my model of consumer demand and the recommender system.

My second data source is Spotify Charts, a website that reports the top 200 songs on Spotify daily for each country Spotify operates in. For each of these top 200 songs, Spotify reports the number of streams, providing market-level consumption information for these top 200 songs. Spotify also provides the song's Spotify ID, which can be connected to Spotify's API to retrieve the song's characteristics. I rely on a Kaggle dataset that scraped Spotify Charts and Spotify's API to collect this data.[17] I use these data, in conjunction with the demand and recommender system estimates, to estimate the supply model of the industry and to conduct counterfactual analysis.

3.1 Descriptive Statistics

Table 2 reports the descriptive statistics for the Spotify Charts data.

Table 2 about here

I focus on the top 200 songs in the US between 2017 and 2021. In this period, $9,244$ unique songs entered Spotify's top 200. The average song length is 3 minutes and 24 seconds, with a standard deviation of 54 seconds. However, the range of length is very wide, with songs as short as 30 seconds and as long as 15 minutes and 45 seconds making it to the top 200. The average song tempo is 122 beats per minute (BPM), with a low of 40 BPM and a high of 212 BPM. All of the machine learning characteristics are bounded between 0 and 1, but their averages vary widely: the average song has an average danceability of 0.67, but an average acousticness of 0.23. The average song is an uptepmo, energetic, and danceable track, unlikely to be a live recording or acoustic performance. It's also unlikely to be a spoken word song, but it could convey either positive or negative emotion (the valence is 0.46). Some examples of songs that fit this description are...

17. https://www.kaggle.com/edumucelli/spotifys-worldwide-daily-song-ranking

The Spotify Charts data also provides information about the lifecycle of songs. Figure 6 reports the number of streams of a song by day afer release:

Figure 6 about here

This figure shows the average number of streams each song that made it on Spotify's Top 200 received in the days since its release. Unsurprisingly, songs get a significant number of their streams in the first 100 days after release, with the average number of streams above $400,000$ for the first 100 days. After that, the number of streams decreases, with a small uptick around the one and two-year marks, but continuing to fall off over time. The number of streams becomes more volatile after the three-year mark, because fewer songs have been out for that long in my data.

4 Model

To model the effect of recommender systems on the music industry, I develop a structural model of the industry, with three sets of agents: consumers, a recommender system, and rightsholders. Consumers (the demand side) receive songs from the platform (and its recommender system) and choose whether to listen to them. I capture this choice using a random utility model, which generates a probability of listening to a song based on its characteristics and the consumer's characteristics. The recommender system, which I treat as an exogenous technology, computes the probability consumers receive particular songs based on their characteristics and the consumer's characteristics. The recommender system surfaces songs in proportion to their probability of being listened, and the joint probability of being surfaced and the probability of being heard is the choice probability rightsholders face. On the supply side, rightsholders choose whether to release songs provided to them by artists, paying a fixed cost to releasing them. Rightsholders (the supply side) choose whether to release the song they have in their inventory, based on its expected profit, which is a function of the choice probabilities at the time of release and in the future. These rightsholders are forward looking, anticipating the evolution of the market and the recommender system through first-order Markov processes. My solution concept is an oblivious equilibrium, where each firm considers only the long-run average choice of the industry, rather than each rival's choice. Figure 7 describes the timing of the model each period.

Figure 7 About Here

4.1 Demand

Consumers in my demand model are subscribers to a streaming platform offering them a catalog of songs.[18] Each day, these consumers open the streaming app and start receiving songs from the platform, as informed by the recommender system. For each song they receive, consumers make one of three possible choices: listen to the song (up to the amount necessary for a Royalty-Bearing Stream), skip the song, or stop listening to the platform, which I treat as an outside option. Figure 8 describes the decision tree for consumers in the demand model.

Figure 8 About Here

I make one key assumption about consumers in my model:

Assumption 1 *Consumers are **myopic**, thinking only about the song choice they currently face, not about future songs, or about how their choice affects future recommendations.*[19]

This assumption allows me to model consumers as static agents, simplifying the demand model and allowing me to focus on the supply-side effects more directly.

Consumers have random utility over the songs they receive and the outside option. Consumer i's utility of listening to a particular song j in session position s is given by:

18. I do not model the extensive decision to subscribe to Spotify (or join the ad-supported tier). While Spotify does report subscriber data, price variation is somewhat limited over time.

19. Anecdotal evidence suggests consumers do not extensively think about future songs when deciding whether to listen to a song, or how their choice affects future recommendations, especially when they are uninformed about the specific mechanisms of the recommender system.

$$U_{L,ijs} = \beta X_j + \gamma Y_i + \eta_s + \epsilon_{ijs}(\sigma) \tag{2}$$

In this utility function, X_j are a vector of song characteristics (alternative-specific variables), Y_i are a vector of consumer characteristics (case-specific variables), η_s are position-specific fixed-effects, and $\epsilon_{ij}(\sigma)$ is a generalized extreme value error term, with σ governing within-nest correlation. Intuitively, consumers prefer certain types of music, which I decompose in to quantitative characteristics, and their utility from a particular song may depend on when they are listening, both during the day, and where they are in their streaming session. Passive consumers may not skip songs often (if at all); active users are likely to skip songs often, finding one they like; and hybrid consumers may skip early in the streaming session before settling on a set of songs they enjoy, and listening to them.

I normalize the mean utility of the outside option to zero:

$$U_{i0s} = \epsilon_{i0s}(\sigma) \tag{3}$$

4.1.1 Utility of Skipping Songs

To capture the utility of skipping to the next song, consumers form expectations over the characteristics of the next song, based, generally, on the songs they have received in their streaming session so far. Their utility from skipping has the following equation:

$$U_{S,ijs} = \beta E_{is}[X_j | X_{j,s-1}] + \gamma Y_i + \eta_s + \epsilon_{ijs}(\sigma) \tag{4}$$

I refine these expectations using the listening context data from the MSSD. Specifically, I apply the following rules:

- If consumers are listening to an algorithmic playlist or radio station, then their expected utility of skipping comes from the average characteristics of the songs they have received in their streaming session so far.

- If consumers are listening to their own catalog or playlist, or a song they searched for, then their expected utility of skipping comes from the average characteristics of the songs in their entire streaming session.

- If consumers are listening to editorial playlists or top 200 playlists, then their expected utility of skipping depends on whether they shuffle the playlist: if they do, expected utility comes form the characteristics of songs received so far; if not, then the expected utility comes from the average characteristics of the songs in streaming session.

Intuitively, consumers know more about their own playlists, music catalog, or searches, so their expectations will be more refined than just discovering music on an algorithmic playlist. If they are listening to an editorial playlist or top 200 playlists, I use shuffling as a proxy for awareness of songs on the playlist: consumers who do not shuffle may be more aware of the tracks on the playlist, and therefore more aware of their characteristics, than those who do not.

4.1.2 Choice Probabilities

In this model, consumers choose whether to listen to the song they receive, to skip it, or to log off, ending their streaming session and taking an outside option.

The GEV error term in the utility function allows me to model the choice probabilities as a nested logit model. The probability that consumer i listens to song j in session position s, conditional on the song being recommended, is given by:

$$P(i \text{ listens to } j|\text{RS surfaces } j \text{ to } i) = \frac{\exp(\sigma V_{Spotify})}{\exp(\sigma V_{Spotify}) + 1} \frac{\exp\left(\frac{\beta X_j + \gamma Y_i}{\sigma}\right)}{V_{Spotify}} \tag{5}$$

Here, $V_{Spotify}$ is the inclusive value of staying on Spotify:

$$V_{Spotify} = log\left(\exp\left(\frac{\beta X_j + \gamma Y_i}{\sigma}\right) + \exp\left(\frac{\beta E_i[X_j|X_{j,s-1}] + \gamma Y_i}{\sigma}\right)\right)$$

The first term is the probability of a consumer choosing to stay on Spotify, rather than logging off. The second term is the probability of a consumer choosing to listen to the song, rather than skip it, conditional on staying on Spotify. I take equation 5 to the data.

4.2 Recommender System

Recommender systems are an integral component to music streaming, directing consumers towards songs the system thinks they will enjoy. These recommender systems are functionally trying to solve a multi-armed bandit problem: finding the best product (arm) to offer to consumers (slot machines), with success being a purchase or interaction with the product. To train the optimal recommender system, platforms must balance exploration (trying new products) and exploitation (recommending products that are likely to be successful). Firms typically rely on an ϵ-greedy algorithm, where the firm chooses the best product with probability $1 - \epsilon$, and a random product with probability ϵ.

I group these systems into three types: collaborative filtering recommender systems, content-based recommender systems, and hybrid recommender systems. Collaborative filtering recommender systems surface products based on products similar users like. For example, if person 1 likes songs, X, Y, and Z, and person 2 likes songs W, X, and Y, then the system may recommend song Z to person 2 and song W to person 1.[20] Content-based recommender systems decompose products into characteristics, and recommend products with similar characteristics to those the user has liked in the past. For example, if person 1 likes songs with a high tempo, the system may recommend songs with a high tempo to person 1.[21] Hybrid recommender systems combine aspects of both collaborative filtering and content based recommender systems. Most recommender systems are hybrid, albeit weighted towards one end or the other.

Spotify's recommender system is a hybrid system weighted heavily towards content-based

20. Amazon uses collaborative filtering when recommending products ”people like you also bought”.

21. Continuing the Amazon example, they use content-based recommendations when describing ”similar products”.

recommendations. They use a combination of user and song characteristics to recommend songs to users. While the recommender system itself is a black box, various research papers have discussed its mechanisms, and I use these papers for guidance in constructing my model of the recommender system, particularly McInerney et al. 2018.

McInerney et al. 2018 describes Spotify's recommender system as having an objective (or reward) function with the following form:

$$r_{ij} = \sigma(\iota_1 X_j + \iota_2 Y_i)$$

In this equation, r_{ij} is the binary outcome from recommending a song j to listener i. X_j are the song characteristics, and Y_i are the listener characteristics. ι_1 and ι_2 are the parameters to be trained. σ is a sigmoid loss, making this equation a logistic regression. McInerney et al. 2018 further augment this function with higher-order interactions between the user and consumer characteristics to obtain more personalized recommendations. To implement the recommender system, they use a standard ϵ-greedy algorithm.

I use a logistic regression to model Spotify's primarily content-based recommender system. I treat this recommender system as an exogenous technology to which Spotify has access, and I estimate the parameters of the recommender system using data from the MSSD. I assume for simplicity that, when Spotify is recommending songs, they are following a pure exploitation strategy, rather than an ϵ-greedy strategy.

My model's recommender system has the following objective function:

$$P(\text{RS surfaces } j \text{ to } i) = \frac{exp(\eta R_{ijt})}{1 + exp(\eta R_{ijt})} \tag{6}$$

Here, $P(\text{RS surfaces } j \text{ to } i)$ is estimated probability that Spotify recommends song j to consumer i, R_{ijt} is a vector of song and consumer characteristics, and η is a vector of parameters to be estimated. Unlike in my choice model, the outcome variable $P(\text{RS surfaces } j \text{ to } i)$ is a listen to completion, rather than just enough to qualify as an RBS. The recommender system also places no value on skipping a song, whereas consumers may have some expected utility for skipping a song (e.g., to find a song they like more). I take equation 6 to the MSSD data.

Having described the recommender system and the choice model, I turn to how to combine these probabilities into the demand that rightsholders face on Spotify. I define this unconditional demand as the joint probability Spotify recommends a song and a consumer listens to it:

$$
\begin{aligned}
P(i \text{ listens to } j) &= P(\text{RS surfaces } j \text{ to } i) \times P(i \text{ listens to } j|\text{RS surfaces } j \text{ to } i) \\
&= \frac{exp(\eta R_{ijt})}{1 + exp(\eta R_{ijt})} \frac{\exp(\sigma V_{Spotify})}{\exp(\sigma V_{Spotify}) + 1} \frac{\exp\left(\frac{\beta X_j + \gamma Y_i}{\sigma}\right)}{V_{Spotify}}
\end{aligned}
\tag{7}
$$

This approach builds on Goeree 2008, who using a joint probability to create a demand structure. She uses this structure to model the demand for computers when consumers have limited information. In place of a recommender system, she uses advertising to inform the consumers and construct consideration sets. I do not explicitly construct consideration sets, because my choice structure is a sequence of binomial listen/skip choices (with an outside option), rather than a single multinomial choice.

In constructing this joint probability, I assume that consumers only receive recommended songs, but this demand structure is effective for newly released songs, about whom consumers may not have ex-ante information. These are the songs whose cost I estimate in the supply side of my model.

4.3 Supply

Rightsholders are the supply side of the music industry, choosing whether to release songs to Spotify. They are forward-looking agents, considering both current and future profits when making their decision. Rightsholders face a fixed cost to release a song, and they receive revenue each period based on that song's streamshare.[22]

Each rightsholder receives a song from an artist, knowing its characteristics, and they decide whether to pay the fixed cost to release the song on Spotify. In making this decision, rightsholders consider both the probability the recommender system will amplify their song, and the probability consumers will listen to their song. I make one key assumption about rightsholders in my model:

Assumption 2 *Each song has an independent rightsholder (i.e., no multiproduct competition), and each song has an exogenous release date, so firms face a one-time binary release/no-release decision.*

Once a song is on Spotify, it remains on the platform in perpetuity, so rightsholders can earn revenue in future periods. To effectively make this decision, they must have some way to model future period profits. Specifically, rightsholders need to model two sets of evolutionary processes:

- The evolution of the recommender system (i.e., the probability her song is recommended to consumers)
- The evolution of rival songs, which affects the probability consumers listen to her song

I define $\mathcal{X}_t$ as the mean characteristics of all songs on a given day on Spotify Charts, and I define ϕ as the probability the recommender system recommends a song to a consumer in future periods. With these terms defined, I now define the following first-order Markov processes by which the recommender system and rival songs evolve:

$$\mathcal{X}_{t+1} = \nu_0 + \nu_1 \mathcal{X}_t + \epsilon_t^{\mathcal{X}} \tag{8}$$

$$\phi_{j,t+1} = \psi_0 + \psi_1 \phi_{jt} + \epsilon_{jt}^{\phi} \tag{9}$$

22. Because I have exogenized the consumer's subscription decision, I treat revenue from Spotify as exogenous

To motivate these processes, I use an oblivious equilibrium (Weintraub, Benkard, and Van Roy 2005) as my solution concept. This equilibrium is a typically used to analyze dynamic oligopoly models with a large number of firms. In an oblivious equilibrium, firms make decisions based only on their own state and average industry conditions, ignoring the specific states of their competitors. Weintraub, Benkard, and Van Roy 2005 show that, under certain conditions, the oblivious equilibrium is equivalent to the Markov Perfect Nash Equilibrium. This simplification allows me to tractably estimate my supply model while capturing the key dynamics in the industry.

As applied to my model, each firm is an oblivious agent, choosing whether to release its song based on those song's characteristics, the long-run average characteristics of all songs, and the probability the recommender system will recommend their songs. Recall that each song has its own rightsholder, so each song competes with every other song in the market, past, present, and future, so my model has a very large number of firms.

Having explained how rightsholders act in the model, as well as the motivating solution concept, I now define their expected profit function:

$$E[\pi_j(X_j)] = 0.6\left(\sum_{t=0}^{T}\delta^t R_t\left(\frac{P(i\text{ listens to }j\text{ with characteristics }X)}{\sum_K P(i\text{ listens to }k\text{ with characteristics }\mathcal{X})}\right)\right) - F_j \qquad (10)$$

Each period t, defined as a day, the rightsholder owning song j receive a share of Spotify's gross revenue R_t. I define this share as follows:

$$s_{jt} = \frac{R\hat{B}S_{jt}}{\sum_k R\hat{B}S_{kt}} = \frac{P(i\text{ listens to }j\text{ with characteristics }X)}{\sum_K P(i\text{ listens to }k\text{ with characteristics }\mathcal{X})}$$

This share is the streamshare of song j in period t. δ is the firm's discount factor. F_t is the onetime fixed cost to release song j on Spotify, which varies by period.

I further simplify the streamshare equation by cancelling terms:

$$
\begin{aligned}
s_{jt} &= \frac{R\hat{B}S_{jt}}{\sum_k R\hat{B}S_{kt}} \\
&= \frac{\frac{exp(\eta R_{ijt})}{1+exp(\eta R_{ijt})} \frac{\exp(\sigma V_{Spotify})}{\exp(\sigma V_{Spotify})+1} \frac{\exp\left(\frac{\beta X_j+\gamma Y_i}{\sigma}\right)}{V_{Spotify}}}{\sum_k \frac{exp(\eta R_{ikt})}{1+exp(\eta R_{ikt})} \frac{\exp(\sigma V_{Spotify})}{\exp(\sigma V_{Spotify})+1} \frac{\exp\left(\frac{\beta X_k+\gamma Y_i}{\sigma}\right)}{V_{Spotify}}} \\
&= \frac{\frac{exp(\eta R_{ijt})}{1+exp(\eta R_{ijt})} \times \exp\left(\sigma V_{Spotify}\right) \times \exp\left(\frac{\beta X_j+\gamma Y_i+\eta_s}{\sigma}\right)}{\sum_k \hat{\phi}_{kt} \times \exp\left(\sigma V_{Spotify}\right) \times \exp\left(\frac{\beta X_k+\gamma Y_i+\eta_s}{\sigma}\right)} \\
&= \frac{\frac{exp(\eta R_{ijt})}{1+exp(\eta R_{ijt})} \times \exp\left(\frac{\beta X_j+\gamma Y_i+\eta_s}{\sigma}\right)}{\sum_k \frac{exp(\eta R_{ikt})}{1+exp(\eta R_{ikt})} \times \exp\left(\frac{\beta X_k+\gamma Y_i+\eta_s}{\sigma}\right)}
\end{aligned}
$$

Having decomposed equation 10, we now turn to the entry condition. Because each rightsholder faces a oneshot binary decision to release or not release, they release as long as the following condition holds:

$$
0.6\left(\sum_{t=0}^{T} \delta^t R_t \left(\frac{P(i \text{ listens to } j \text{ with characteristics } X)}{\sum_K P(i \text{ listens to } k \text{ with characteristics } \mathcal{X})}\right)\right) \geq F(X_j) \tag{11}
$$

Specifically, their expected profit from releasing the song must be nonnegative. If the expected revenue exceeds fixed cost, the rightsholder releases the song; otherwise, it does not.

This entry condition is key to identifying the fixed cost of releasing a song. Because firms will enter up to the breakeven point, the marginal (or worst-performing) song will just break even. That is, its expected revenue will equal the fixed cost. Similar to Aguiar and Waldfogel 2018, I employ this condition to estimate the fixed cost of releasing a song on Spotify.

4.4 Equilibrium

My solution concept is an oblivious equilibrium (Weintraub, Benkard, and Van Roy 2005) where consumers optimally choose whether to listen or skip songs in their streaming session, or to log off; the recommender system optimally recommends songs to consumers, seeking to maximize the probability consumers listen to songs to completion; rightsholders, taking the above as given, choose whether to release songs based on the expected profit from releasing the song; songs enter the market up to the breakeven point, where the expected profit from releasing the song equals the fixed cost; and the fixed cost of releasing a song is equal to the expected revenue of the marginal (or worst-performing) song in each period

5 Estimation

My estimation strategy has several stages:

1. Demand and Recommender System estimation
2. Markov Process estimation
3. Expected revenue calculation
4. Fixed cost calculation

In the first stage, I estimate consumer preferences and recommender system preferences using the MSSD data. Specifically, I estimate $\theta_1 = (\beta, \gamma, \eta, \sigma)$ from equations 5 and 6 in this stage. For consumer preferences, I use a maximum likelihood estimator over choice probabilities, following Train 2009. As an initial simplification, I assume that consumer do not have an outside option (i.e., they always listen to a song or skip it), resulting in a binomial logit, rather than a nested logit. I identify my parameters through variation in the choice set for each consumer at each position in the streaming session. Similarly, I estimate the recommender system parameters using a maximum likelihood estimator over the probability a consumer completes a song.

In the second stage, I estimate the Markov processes governing the evolution of rightsholder perception of the recommender system and rival songs. Specifically, I estimate

$\theta_2 = (\nu_0, \nu_1, \psi_0, \psi_1)$ in this stage. To construct the Markov processes, I use the estimated θ_1 to construct the expected utility of all songs on Spotify's top 200 each day, and the probability the recommender system surfaces those songs to consumers.[23] I then take the daily average of these values to construct the Markov processes, and I estimate these θ_2 as AR(1) processes using conditional maximum likelihood.

In the third stage, I compute the expected revenue for each song released in 2018, and I apply my equilibrium condition to identify the fixed cost of releasing a song on Spotify. I limit my computation to songs released in 2018 to better match my demand and recommender system estimates. For each song, I compute the left hand term in equation 10, using the θ_1 and θ_2 estimates to predict future streamshare. To compute the rival songs in the streamshare measure, I take $\mathcal{X}$ for the songs available on the top 200 in the day the song has been released, and I input these characteristics to predict the probability the recommender system will surface the rival song. I then apply that predicted probability to the AR(1) process to estimate the probability the recommender system will surface the rival song in future periods. I also apply these characteristics to the AR(1) process to estimate the probability consumers will listen to the rival song. Because each song competes with every other song on the platform, I assume that the number of rival songs (each possessing the same characteristics) is equal to the number of songs on the platform, which is approximately 40mn in 2018.[24] This creates a lower bound for the amount of revenue any given song can generate.

6 Results

Table 3 reports the results for the consumer choice and the recommender system:

Table 3 about here

I find that consumers prefer songs that are more danceable, louder, and more uptempo.

23. As an initial matter, I drop the consumer-specific variables in constructing the utility and probability of being recommended for the Top 200 songs.

24. Cite Spotify 2018 Annual Report

They as less fond of high-energy songs, live recordings (rather than studio recordings), and older songs. Consumers also prefer longer songs, but it is a weak preference economically. I also find that premium subscribers are likelier to listen to songs than ad-supported subscribers. Given the restrictions on ad-supported subscribers (mandatory shuffling outside of a limited number of playlists), it makes intuitive sense that they would be likelier to skip songs. All coefficients are significant at the 1% level.

The recommender system exhibits somewhat different preferences to consumers: it recommends quieter songs, less danceable, and more energetic songs. Like consumers, it prefers to recommend newer music and recorded music. Notably, the recommender system strongly prefers to recommend shorter songs, which matches industry reports and trends in how music sounds. Interestingly, the time-of-day fixed effects are almost identical across the consumer and recommender system models, suggesting that song characteristics are the key differentiator in the two models.

Table 4 reports the results for the Markov processes:

Table 4 about here

Both AR processes are significant at the 1% level, and have coefficients less than 1, suggesting that they are both stationary.

Figure 9 plots the distribution of expected revenue for songs released in 2018 that entered Spotify's top 200 at least once:

Figure 9 about here

These songs have an expected revenue ranging from \$10 to \$50, with a mean at \$26. Applying my equilibrium condition this data, I estimate the fixed cost by taking the expected revenue of the marginal song on any given day. Figure 10 plots the distribution of fixed costs:

Figure 10 about here

The fixed cost of releasing a song on Spotify ranges from \$10 to \$40, with a mean of \$22. This distribution has a longer right-tail, with more songs clustered around the \$20-\$25 range.

Figure 11 plots the distribution of fixed costs by day in 2018. They represent the unique fixed costs estimated by the model:

Figure 11 about here

This distribution has the same support as the distribution of fixed costs, but is more normally distributed, with a mean of \$24.21.

This mean is close to the fixed cost estimate in Aguiar and Waldfogel 2018. They find that, in their imperfect foresight model, the fixed cost is \$18.97, approximately \$5 less than my estimate. Several factors explain this difference. First, their estimate is in 2011 dollars, whereas my estimate is in 2017 dollars. Adjusting for inflation, \$18.97 in 2017 dollars is \$20.92, based on the Bureau of Labor Statistic's CPI Inflation calculator.[25] This narrows the difference to approximately \$3. Second, their model only looks at the revenue generated by the song in 2011. I model songs more dynamically, looking at revenue generated in the first three years of release.

7 Counterfactual Analysis

Having estimated demand for song characteristics, the recommender system preferences, and the fixed cost to releasing a song onto Spotify, I now turn to the counterfactual analysis that can answer the question this paper poses: whether recommender systems have affected the kind of music record labels are releasing. To isolate the impact of recommender systems specifically, I conduct several counterfactuals. In the first, I construct a random recommender system, rather than one which relies on song and consumer characteristics.

25. https://data.bls.gov/cgi-bin/cpicalc.pl?cost1=18.97&year1=201101&year2=201701

7.1 Random Recommendations

Intuitively, this random recommender is akin to having no recommender system at all, insofar as the recommendations will be pure noise. I operationalize this counterfactual by constructing many consideration sets of songs, which the recommender system will recommend (randomly) to consumers. I will examine the profit and welfare generated by these consideration sets, in contrast with the profit and welfare generated by the data and model.

My counterfactual algorithm has the following steps:

1. Sample 200 of the approximately 1700 songs released on 2018 that made it onto Spotify's Top 200 at least once in 2018. These songs will be the consideration set. I choose 200 to match the market-level data I have (streams of the top 200 songs each day)

2. Assign each song has a $\frac{L}{N}$ chance of being recommended to consumers (where N is the number of songs in the consideration set). Recall that the demand a producer faces is the joint probability of being recommended and being listened to by a consumer. L is the number of songs in the consideration set that are recommended to consumers. For example, it represents the number of available slots on Spotify's New Music Friday playlist.

3. Given the sampled consideration set, assigned recommendation probability, and the estimated demand parameters, compute the expected revenue for each song.

4. Sample repeatedly to generate numerous consideration sets to evaluate the expected profit and welfare generated by the random recommender system.

I have conducted this counterfactual analysis for with $N = 200$, $L = 50$, and 100 iterations. As a benchmark, I compare the results of these consideration sets against the performance of the top 200 songs released in 2018 (as estimated by the model).

First, I compare average expected revenue for songs. Figure 12 reports the results of this comparison:

Figure 12 about here

Each observation in this figure represents the average revenue generated by the 200 songs in one of the 100 consideration sets, and the red line represents the average revenue generated by the top 200 songs in 2018, as estimated by the model. In the absence of recommender systems, I find that songs earn, on average, approximately $\frac{1}{3}$ less revenue than with functioning recommender systems. This occurs because the recommender system has a higher probability of recommending these hit songs, and at targeting consumers, than a random recommender system would in offering the same songs to each consumer.

Indeed, the reduction in revenue is so great that many songs in these consideration sets are unprofitable. Across the consideration sets, approximately $\frac{2}{3}$ of the songs are unprofitable, compared to the data. This does suggest that the presence of recommender systems is responsible for expanding the set of profitable songs, allowing for more entry into the music market. One caveat is that these counterfactual results with the fact that this outcome is not in equilibrium, as many of these songs will not enter, and the remaining songs will generate more revenue and be more profitable. A more relaistic approach, currently in progress, is to drop unprofitable songs one-by-one, recomputing the counterfactual revenue with each iteration, until all songs in the consideration set are profitable.

I now turn to the some song characteristic results and welfare implications of my counterfactual analysis. Figure 13 reports the average duration of songs in each consideration set.

Figure 13 about here

The average duration of songs in each consideration set is approximately 203 seconds (3 minutes, 23 seconds), with a range of 197 to 213 seconds. However, this duration is much higher than the average duration of the highest-grossing songs estimated by the model, which is approximately 150 seconds. This suggests that in the absennce of recommender systems, songs would be longer, on average, than they are with recommender systems, which also coheres with the recommender system estimates in Table 3.

Limiting each consideration set to just profitable songs (without recomputing the equilibrium outcome) Figure 14 presents the average duration of profitable songs in each consideration set:

Figure 14 about here

After removing the unprofitable songs, I find that random recommendations shifts the counterfactual distribution of song lengths even further to the right. The average duration of profitable songs is closer to 215 seconds, with the range shifted to 196 to 230 seconds. This counterfactual suggests that, in the absence of recommender systems, songs would be longer, on average, and that longer songs would be likelier to survive and profit.

I also examine the variance of duration; that is, whether random recommendations result in more or less homogenous songs. Figure 15 reports the variance of song duration in each consideration set:

Figure 15 about here

The standard deviation of song duration in consideration sets ranges from 39 seconds to 71 seconds, with a mean of 52 seconds. This distribution is right skewed, with an outlier around 71 seconds, but most consideration sets cluster around 50 seconds. However, all of these consideration sets exhibit a standard error greater than the top 200 songs, which have a standard error of 38 seconds. This suggests that, in the absence of recommender systems, songs are more heterogeneous. This matches the empirical regularities in the industry, that songs are becoming shorter and more homogenous, and this result attributes such homogenization to the recommender systems.

Finally, I turn to the welfare implications of my counterfactual analysis. Figure 16 reports the consumer surplus generated by each consideration set:

Figure 16 about here

I compute the consumer surplus generated by all of the songs in the consideration set by taking the log-sum of the exponentiated utility, following Anderson, Palma, and Thisse 1992. Formally, I define consumer surplus with the following equation:

$$CS = \log\left(\sum_{i=1}^{N} \exp\left(\frac{\beta X_j + \gamma Y_i + \eta_s}{\sigma}\right)\right) \tag{12}$$

Here, N represents the number of songs in the consideration set, rather than the binomial skip-listen decision. Additionally, to simplify the computation, I drop the consumer-specific variables and session fixed effects from the utility function, as I did in the Markov process estimation and computation of fixed costs. Note that this measure of consumer surplus is in utils, as there is no price coefficient against which to scale the results.

I find that, compared to the top 200 songs, random recommendations deliver a similar amount of consumer surplus as the top 200 songs overall. This suggests that the recommender system is not significantly affecting consumer surplus, but this does not account for the unprofitability of songs in the consideration set.

Figure 17 reports the consumer surplus generated by profitable songs in each consideration set:

Figure 17 about here

Because fewer songs are profitable in the consideration set, the consumer surplus is necessarily smaller, about 13% less than the consumer surplus generated by the top 200 songs in the model. This reduction, however, is disproportionate with the reduction in the number of songs, suggesting that those unprofitable are indeed marginal to the consumer's welfare.

Overall, this counterfactual analysis suggests that recommender systems do indeed affect the kind of music record labels are releasing. In the absence of any recommender systems, songs are less profitable, longer, and more heterogeneous. Consumers and firms are both worse off (firms especially), but the impact on consumer welfare is less pronounced than the impact on song variety.

7.2 Oracular Recommendations

The second counterfactual analysis I conduct is an oracular recommender system. I define an oracular recommender as one where the recommender is capable of giving the best possible song to each consumer, according to each consumer's preferences. Such a recommender system tends not to be feasible for several reasons: insufficient data, the cost of specifying such a granular model, and countervaling financial incentives. Bourreau and Gaudin 2022 and Reimers and Waldfogel 2023 both describe models in which platforms have incentives to bias recommender systems to maximize their own profit.

I operationalize this counterfactual in the following way:

1. Draw N consumers and give them preferences drawn from the estimated distribution of consumer preferences. Give each of them 20 slots in their streaming session.

2. Provide consumers with the songs that maximize their utility, given their preferences and the song characteristics, drawing from the songs released in 2018.

3. Compute the expected revenue generated by these streaming sessions, and compare it to the estimated revenue generated by the model.

This counterfactual analysis is in progress.

7.3 Popular Recommendations

The third counterfactual analysis I conduct is a popular recommender system. This recommender system is meant to replicate the market environment that existed prior to Spotify, when consumers would purchase singles on iTunes. At the time, the iTunes store did not have a recommender system; instead, it showed users what the top-selling singles and albums were. I replicate this by recommending songs that have higher popularity measures, as reported by Billboard.

I operationalize this counterfactual in the following way:

1. Create N consideration sets of 200 songs each, where each song is drawn from the top 200 songs on Spotify in 2018.

2. Using data from Billboard, create a popularity measure for each song, and scale it to a 0-1 scale.

3. Use the 0-1 scale to construct the probability that each song is recommended to consumers, and compute the expected revenue generated by these consideration sets.

This counterfactual analysis is in progress.

8 Conclusion

As recommender systems become more integrated into the US economy, it is paramount to understand the impact these systems have on both consumer demand and equilibrium supply decisions. This paper provides a structural model of the music streaming industry to estimate the impact these systems have had on music releases. Because the music industry is typically the vanguard for technology adoption, understanding the impact of recommender systems on music releases can provide insights into the impact of recommender systems on other industries, such as film, television, and shopping.

I find that recommender systems have indeed changed the sound of music, resulting in shorter, more homogeneous songs. These systems, however, allow for more songs to enter the market, earn more revenue, and increase consumer surplus approximately 15% compared to a random recommender system. I also find that the recommender system's preferences differ from consumer preferences, in part because the platform's incentives differ from rightsholders:

rightsholders want consumers to listen to at least 30 seconds of their songs to earn royalties, but Spotify's recommender system rewards complete listens, to reduce the amount of royalty payouts. In the absence of recommender systems, songs are more aligned with consumer preferences, though fewer of them are profitable.

Further avenues for research exist, particulary in applying this model to other industries. The skip/listen binary choice makes this model particularly applicable to short-form video services (e.g., TikTok, Instagram Reels, YouTube Shorts), whose content is almost entirely recommender-drivel. Additionally, random coefficients would particularly enrich the consumer demand structure, and better capture the variety of preferences consumers have for music. Moreover, this model excludes the extensive margin: whether to subscribe or not. Incorporating an endogenous platform decision would better capture Spotify's pricing incentives, and how much it can trade off pricing power with the music it provides. Such an analysis would also allow for a more nuanced antitrust analysis, seeing how much recommender systems can faciliate market power.

Tables

Table 1: Reduced Form Regression Results

Dep. Variable: Duration (minutes)		**No. Observations:** 6879
R-squared (Overall): 0.2370		**Estimator:** Panel OLS
Variable	**Coefficient**	**Clustered Std. Err.**
Intercept	3.0232***	(0.0202)
CD	0.8824***	(0.1413)
iTunes	-0.3431***	(0.0521)
Spotify	-0.2075***	(0.0468)
Echo Nest	-0.3935***	(0.0811)
Vinyl	-0.3486***	(0.0485)
Cassette	0.8241***	(0.1425)
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Table 2: Top 200 Song Characteristics

Variable	Mean	Std. Dev.	Min	Max
Duration (Minutes)	3.39	0.90	0.50	15.73
Release Date	2017-05-25	NA	1942-01-01	2021-12-31
Danceability	0.67	0.15	0.06	0.98
Energy	0.62	0.17	0.01	1.00
Loudness	-6.83	2.71	-38.86	0.35
Speechiness	0.15	0.13	0.02	0.97
Acousticness	0.23	0.25	0.00	0.99
Instrumentalness	0.01	0.09	0.00	0.96
Liveness	0.18	0.14	0.02	0.97
Valence	0.46	0.22	0.03	0.98
Tempo (BPM)	122.41	30.04	40.32	212.06
Time Signature	3.96	0.35	1.00	5.00

Table 3: Demand and Recommender System Parameter Estimates

Variable	RecSys (Std Err)	Demand (Std Err)
Constant	-0.752 (0.000)***	0.447 (0.001)***
Duration	-0.130 (0.000)***	0.003 (0.000)***
Danceability	-0.044 (0.000)***	0.032 (0.000)***
Energy	0.014 (0.000)***	-0.014 (0.000)***
Liveness	-0.011 (0.000)***	-0.006 (0.000)***
Loudness	-0.019 (0.000)***	0.027 (0.000)***
Tempo	-0.004 (0.000)***	0.010 (0.000)***
Age	-0.042 (0.000)***	-0.017 (0.000)***
Morning	0.147 (0.001)***	0.141 (0.001)***
Afternoon	0.086 (0.001)***	0.076 (0.001)***
Night	0.164 (0.001)***	0.119 (0.001)***
Premium		0.035 (0.001)***
N	97,931,008	97,931,008
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Table 4: AR(1) Model Results

	RecSys Model	Market Model
Dep. Variable:	κ_{t+1}	$\mathcal{X}_{t+1}$
No. Observations:	1821	1821
Log Likelihood	14305.562	6658.063
Constant	0.0002 (0.000)	0.0223*** (0.003)
AR	0.9994*** ($1.15e-18$)	0.9500*** (0.007)
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Figures

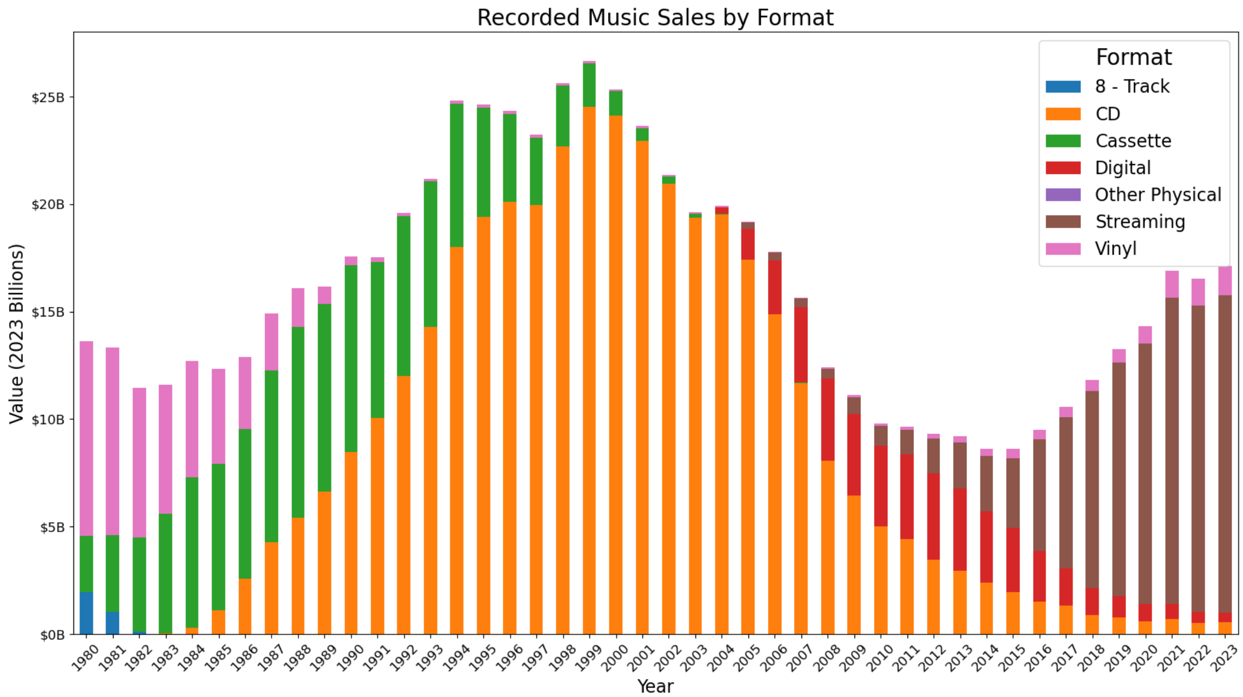

Figure 1: Real Revenue of the Recorded Music Industry, 1990-2023

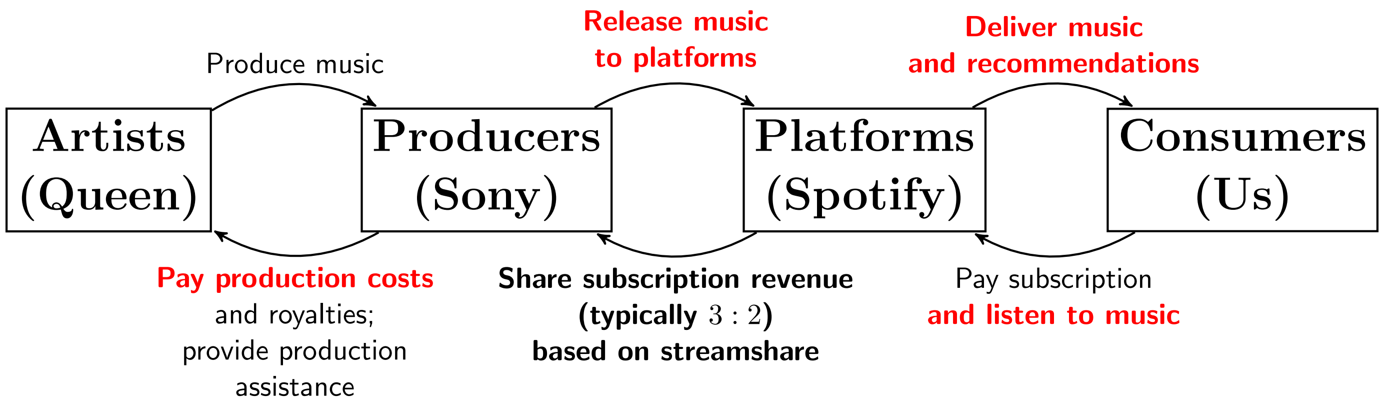

Figure 2: Vertical Structure in the Music Industry

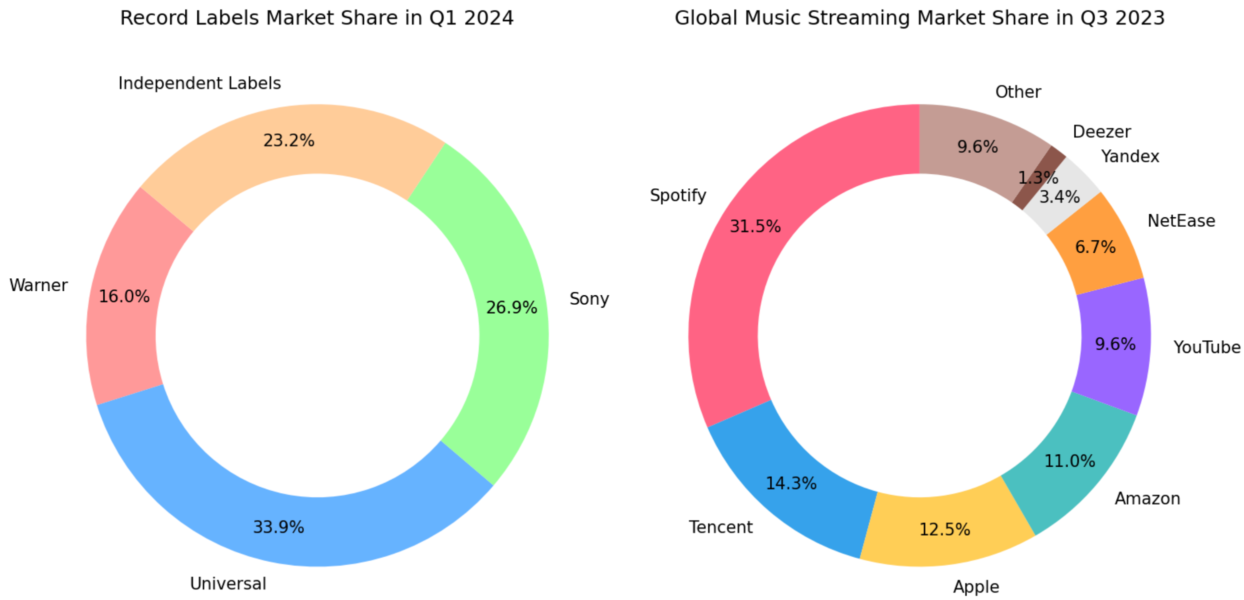

Figure 3: Concentration in the Recorded Music Industry, 2023

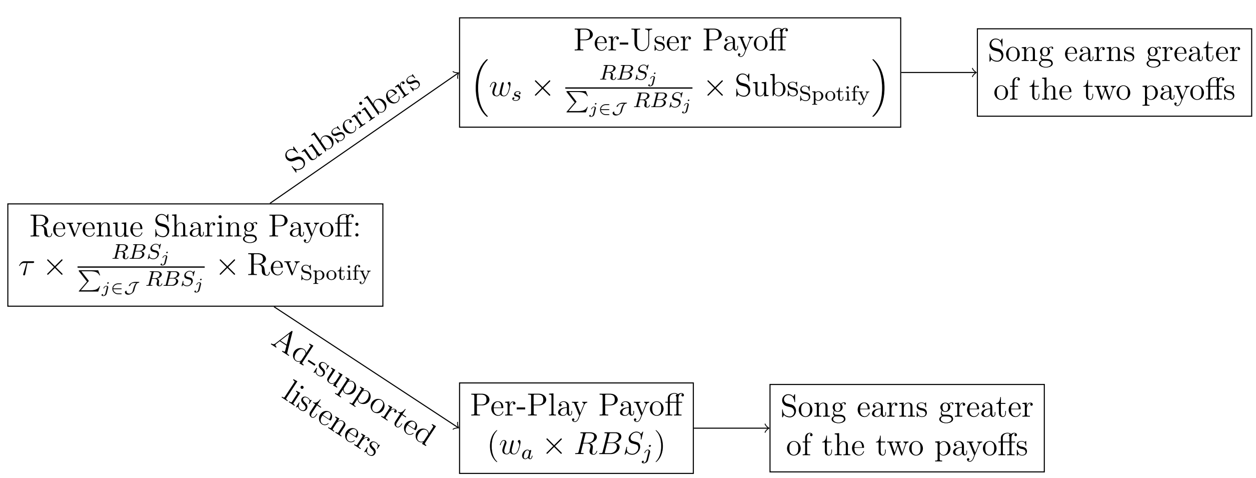

Figure 4: Revenue Sharing Payoff Structure

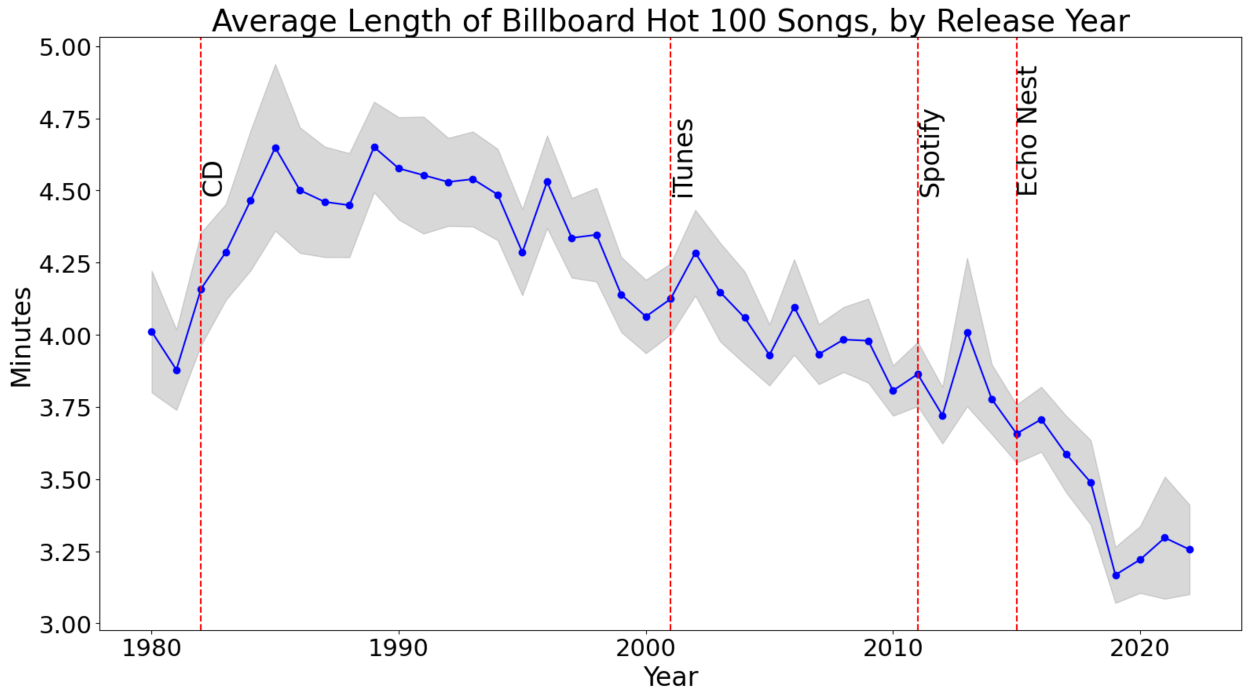

Figure 5: Average Song Duration on Billboard's Hot 100, 1990-2023

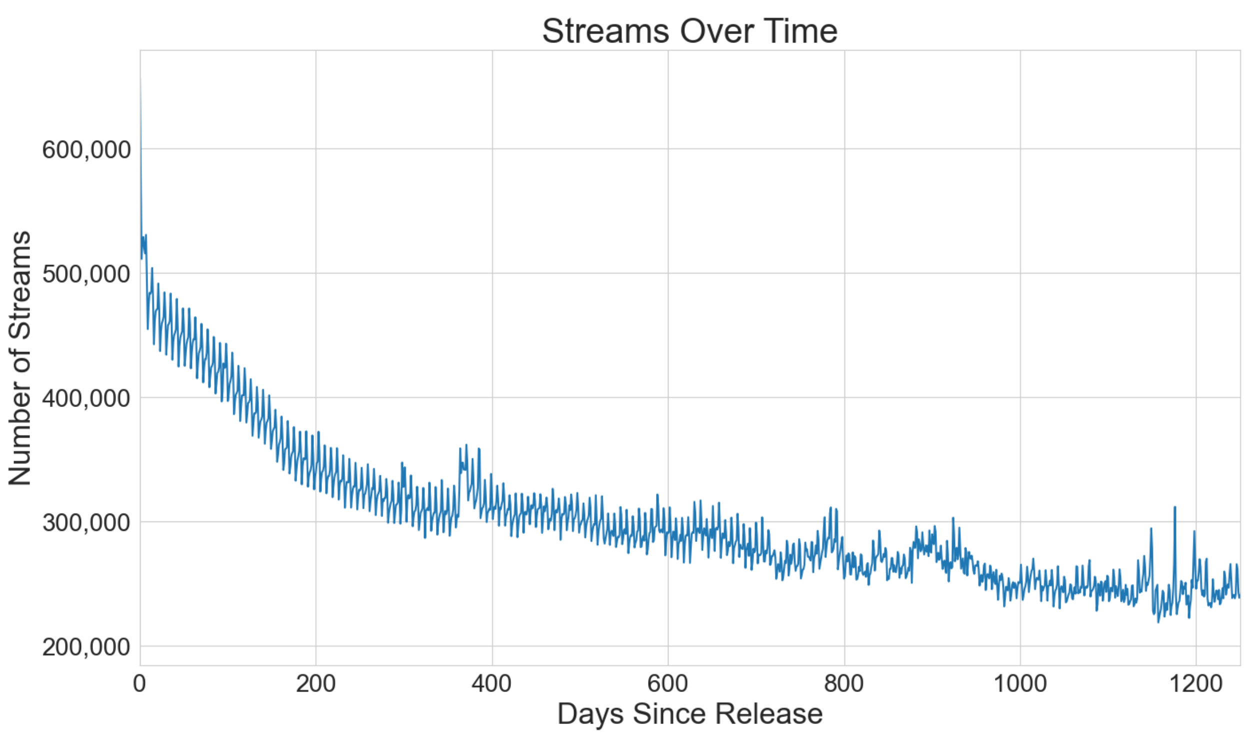

Figure 6: Number of Streams of Songs on Spotify's Top 200, by Days since Release

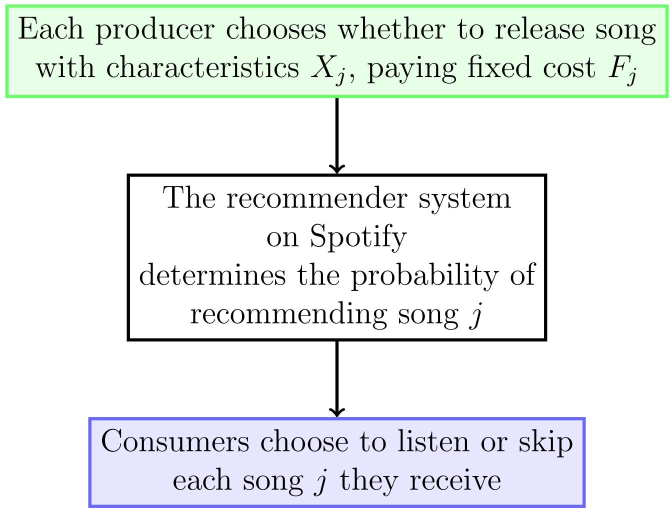

Figure 7: Timing of the Model in Each Period

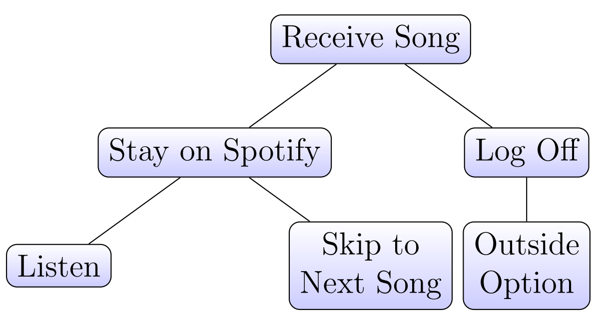

Figure 8: Consumer Decision Tree

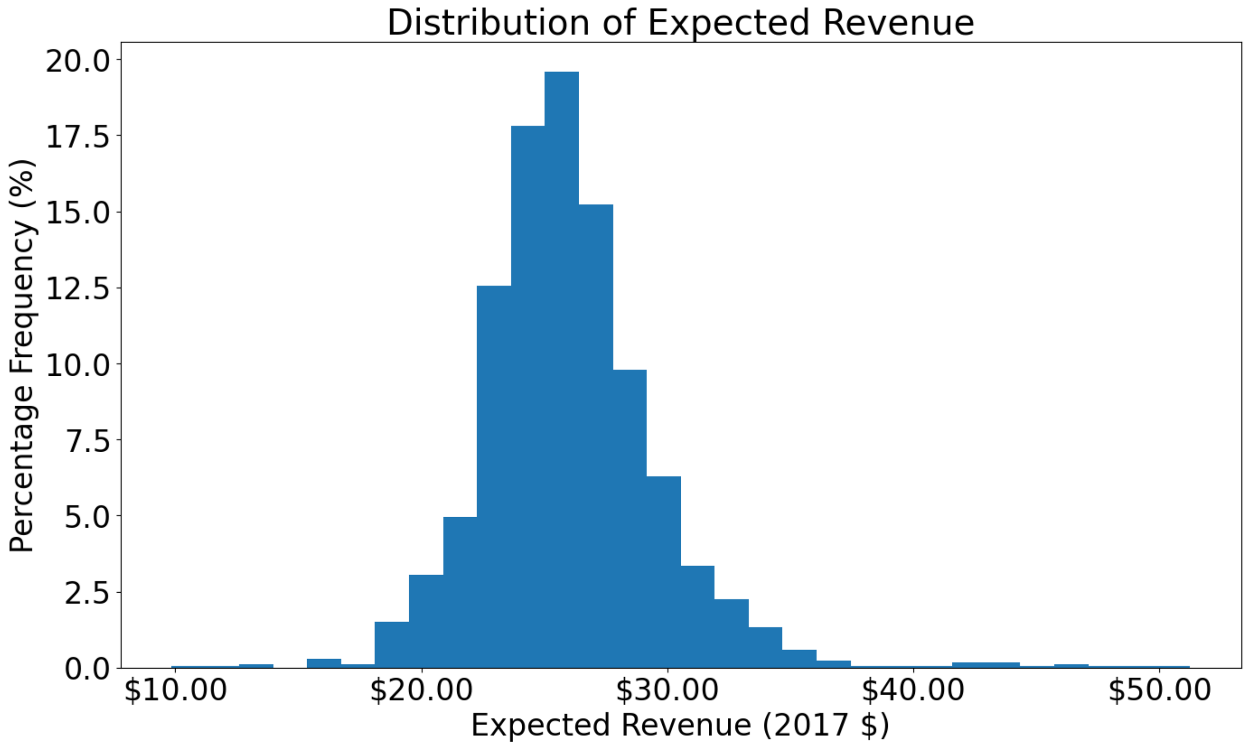

Figure 9: Expected Revenue of Songs Released in 2018 that Entered Spotify's Top 200

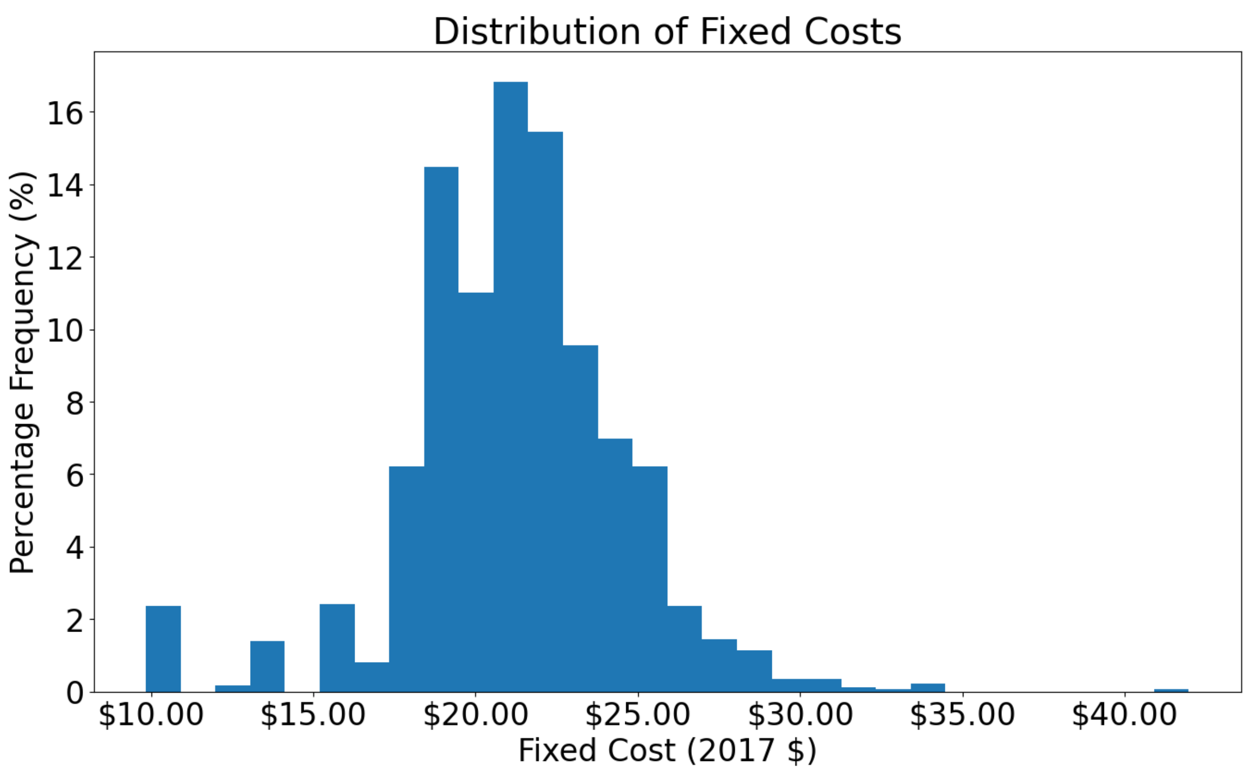

Figure 10: Fixed Costs of Songs Released in 2018 that Entered Spotify's Top 200

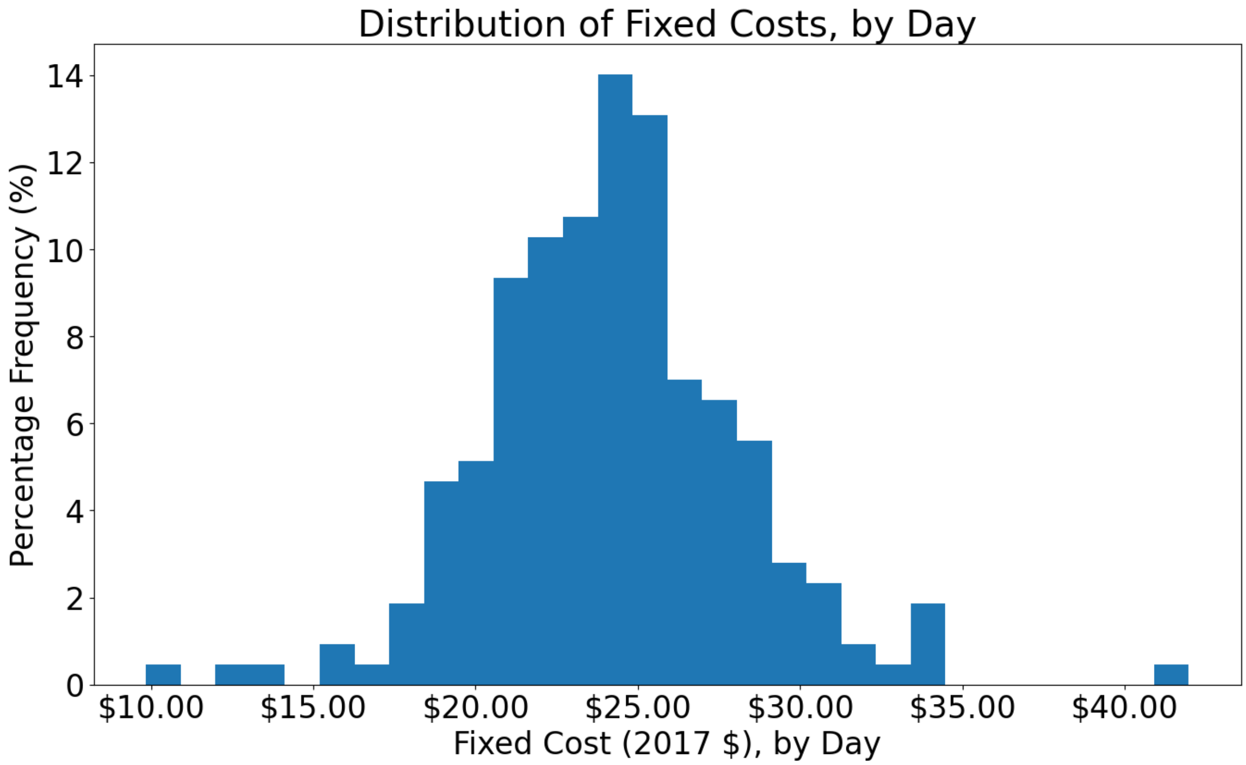

Figure 11: Distribution of Fixed Costs of Songs

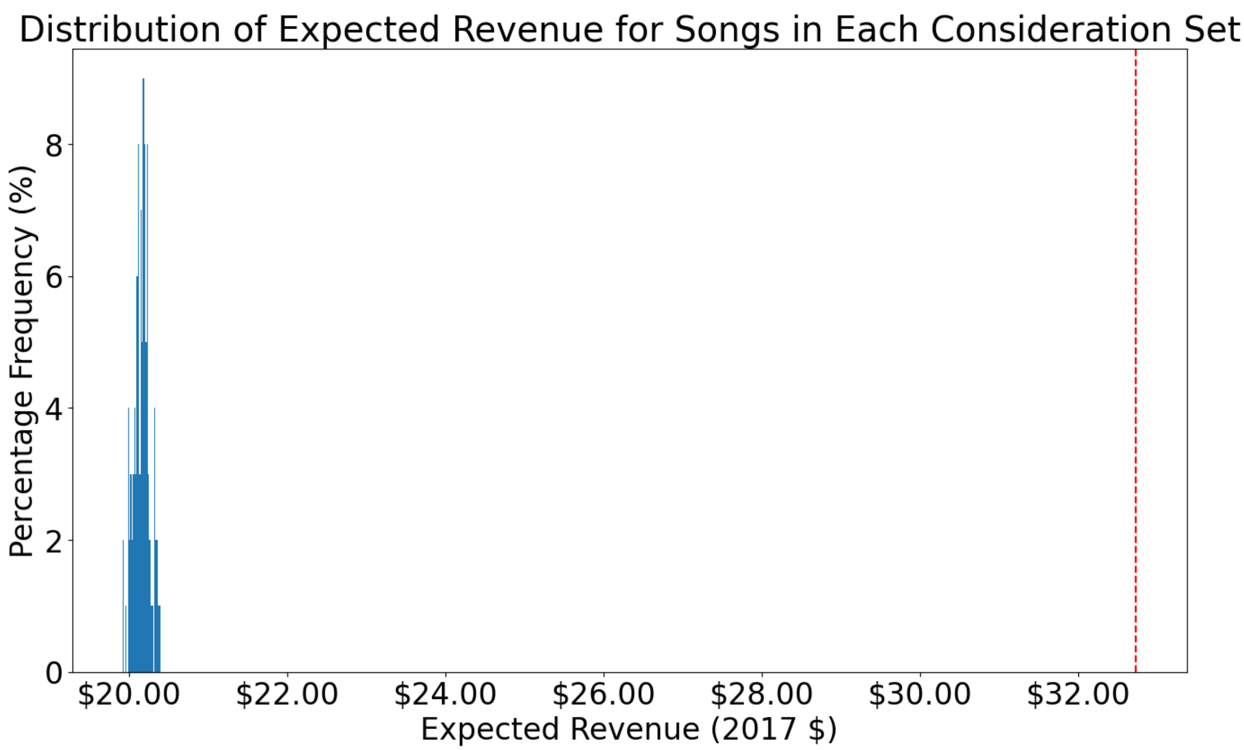

Figure 12: Distribution of Counterfactual Expected Revenue

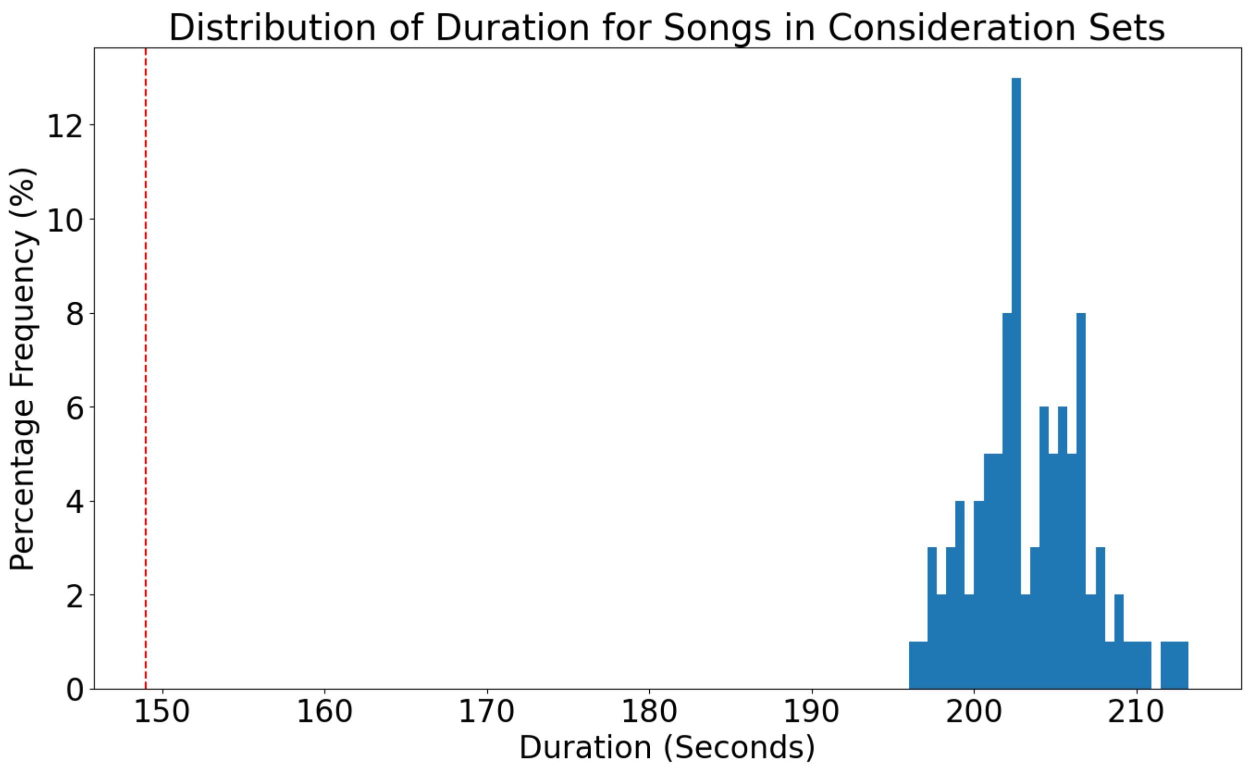

Figure 13: Distribution of Counterfactual Song Durations

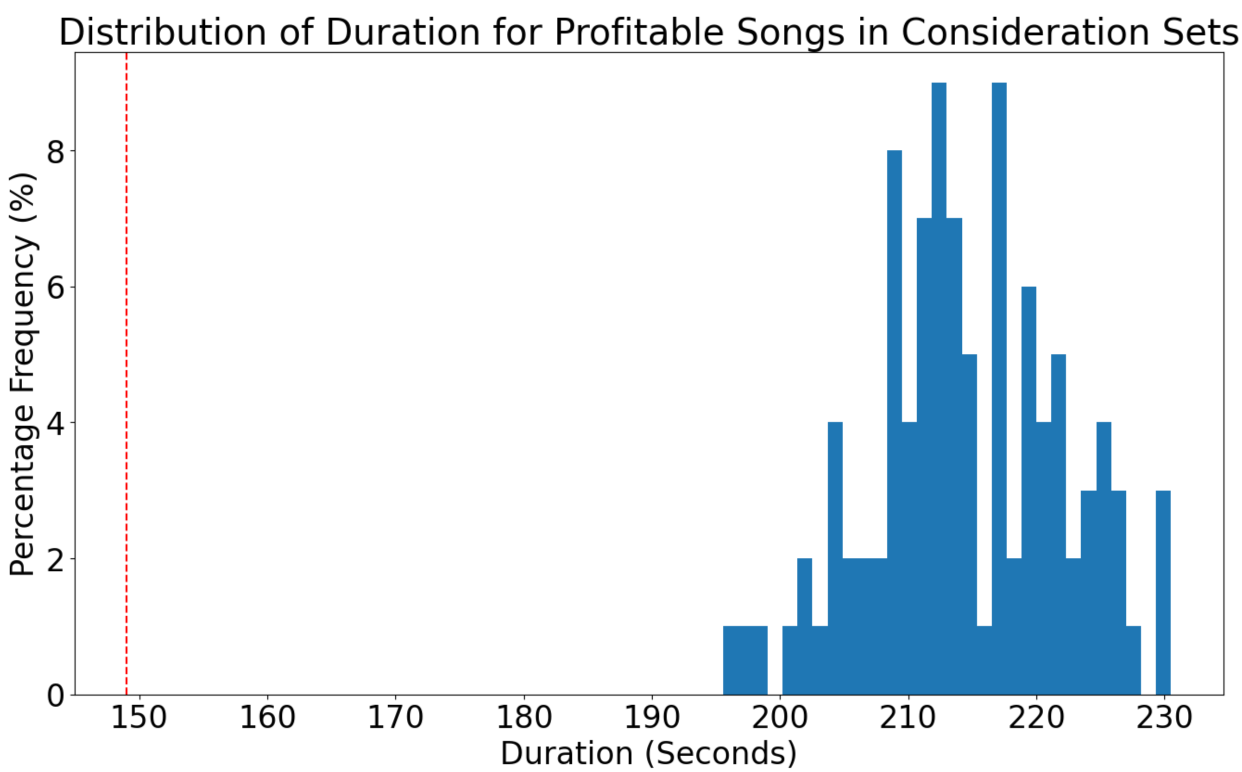

Figure 14: Distribution of Counterfactual Profitable Song Durations

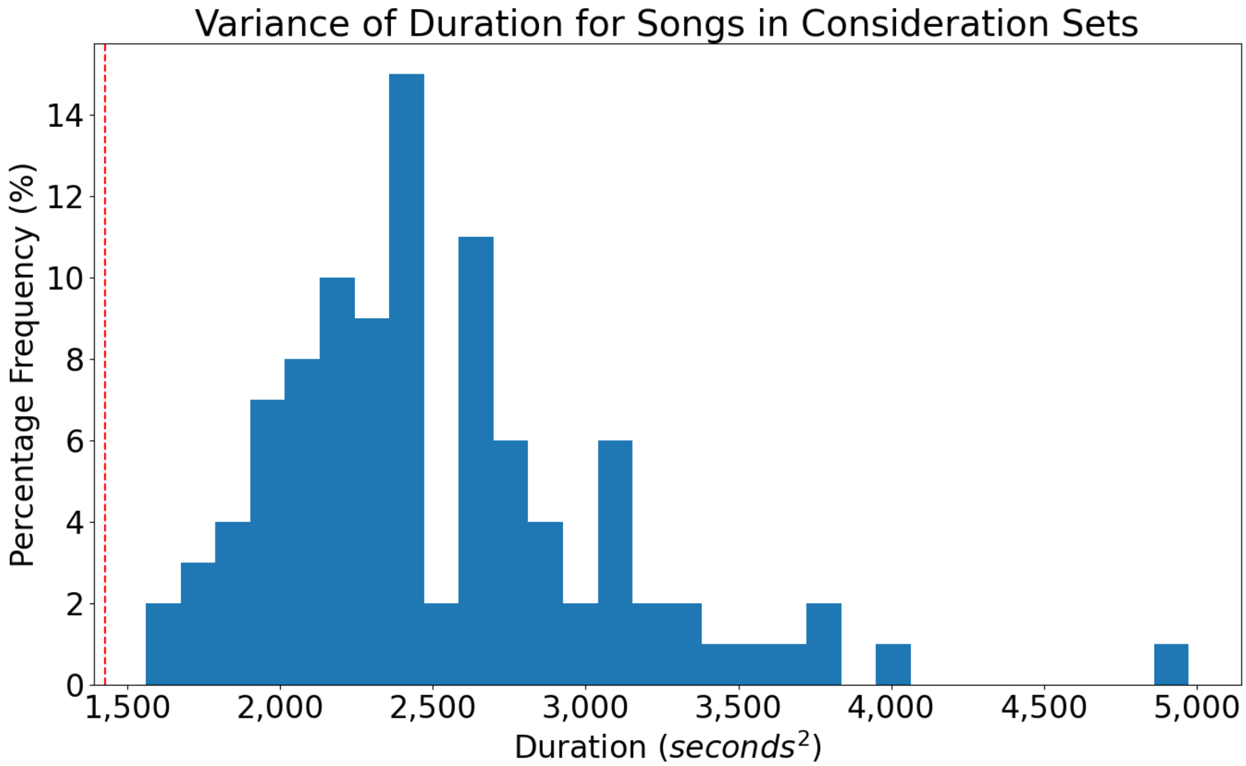

Figure 15: Distribution of Variance in Counterfactual Song Durations

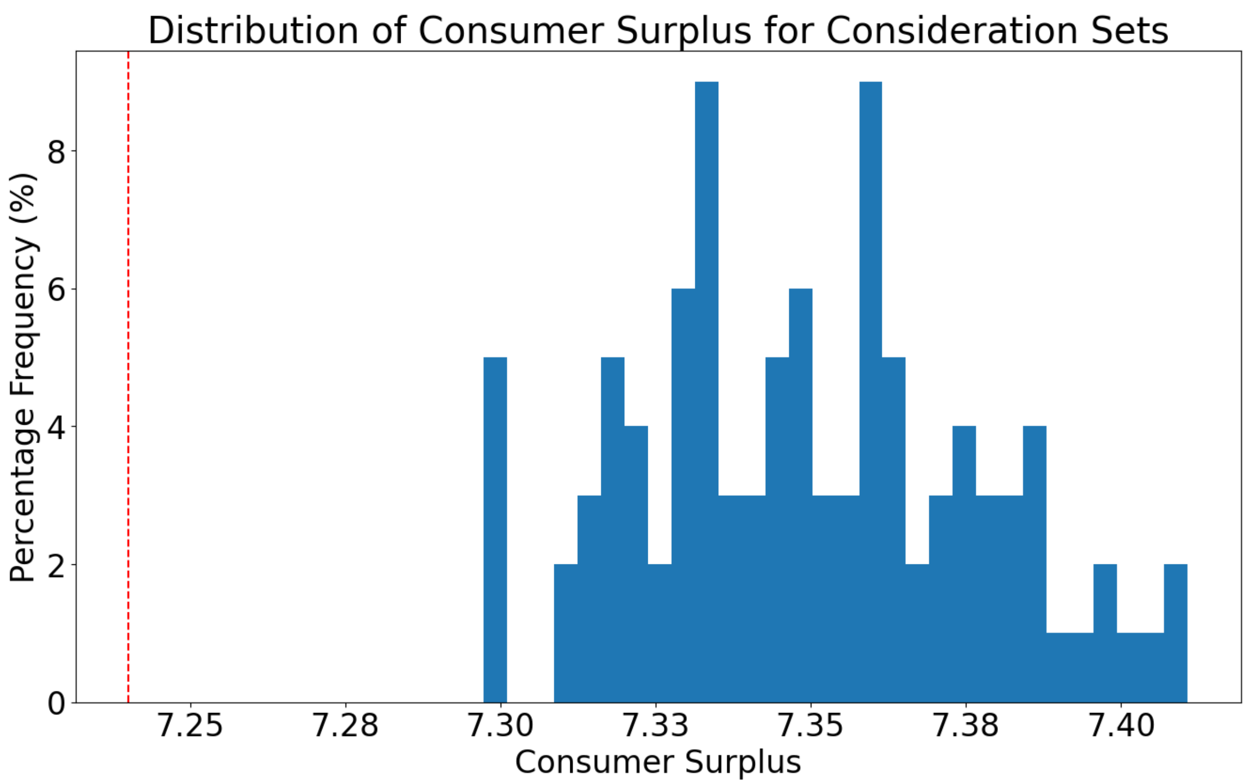

Figure 16: Distribution of Counterfactual Consumer Surplus

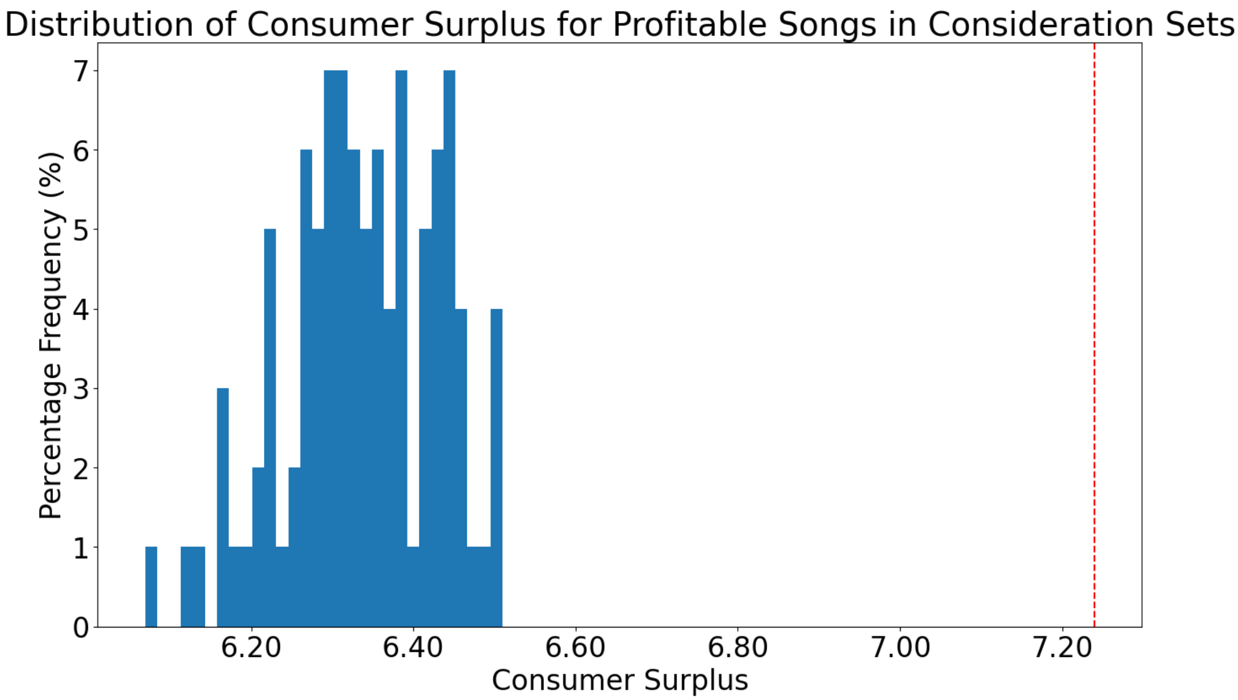

Figure 17: Distribution of Counterfactual Consumer Surplus for Profitable Songs

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