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Streaming Stimulates the Live Concert Industry: Evidence from YouTube

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Streaming Stimulates the Live Concert Industry: Evidence from YouTube

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Abstract

I exploit the removal of Warner Music content from YouTube in the first three quarters of 2009 as a plausible natural experiment to investigate the impact of streaming on live concert sales. I find that this Warner-YouTube blackout had statistically and economically negative effects on Warner artists relative to non-Warner artists. Specifically, relative revenues and prices were lower and relative attendance was not higher. These effects were stronger among artists who recently had a song in the *Billboard* Hot 100 and among those who were more frequently searched on YouTube. These findings suggest that the diffusion of streaming has stimulated the demand for live concerts. The evidence is also consistent with a differentiated Bertrand model of ticket pricing in which prices are strategic complements and prices and streaming penetration gives rise to increasing differences in the artist profit function. More broadly, the paper is an example of how the results from the monotone comparative statics literature can be adapted for use with difference-in-differences estimation.

Keywords: live music, streaming, digitization, monotone comparative statics, refutability

JEL Codes: D2, L2, L8, Z11

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1 Introduction

In terms of both relative and absolute revenue, live performance is becoming increasingly important in the music industry. As illustrated in Figure 1.1a, since 2000 real US recorded music revenues have largely declined, although they have rebounded recently due to the widespread uptake in streaming. Over the same time period, real revenues from live performance in North America (NA) have risen and converged with recorded music revenues in the United States.[1] And as illustrated in Figure 1.1b, which is based on my calculations from Pollstar's Top 200 NA Tours charts, the increase in live performance revenue has been driven by both real prices (right axis) and ticket sales (left axis).[2]

While live performance is important to the music industry as a whole, it is absolutely vital for artists as it generates the majority of their revenue (Krueger, 2019). Among the 2018 Billboard Top 50 Money Makers, an average of 80 percent of revenue was generated from touring, 8 percent from streaming, and the rest from sales and publishing. Only two artists—Drake and Taylor Swift—made the list without touring.

The rise in live performance coincides with the digitization of music and the market penetration rate of streaming. From the launch of Napster in 1999, iTunes in 2003, Pandora in 2005, YouTube in 2006, Spotify in 2008 and its subsequent competitors, digital music and the streaming industry in particular have been growing rapidly. In broad terms, this paper attempts to understand whether and how the increased market penetration rate of streaming can explain the rise of the live music industry.

In particular, I exploit a licensing dispute between Warner Music and YouTube in 2009 as a natural quasi-experiment to identify the causal effect of recorded video streaming on live music revenue and related outcomes. As a result of this dispute, all Warner and subsidiary label content was removed from YouTube from January 2009 to October 2009. YouTube had resolved similar disputes with other labels, so this outcome was unexpected. At the time, record labels and YouTube had little stake in the live concert industry, so the dispute and resulting blackout were unrelated to events in the live music business. Thus, the blackout was a plausibly unanticipated exogenous shock to the live music industry.

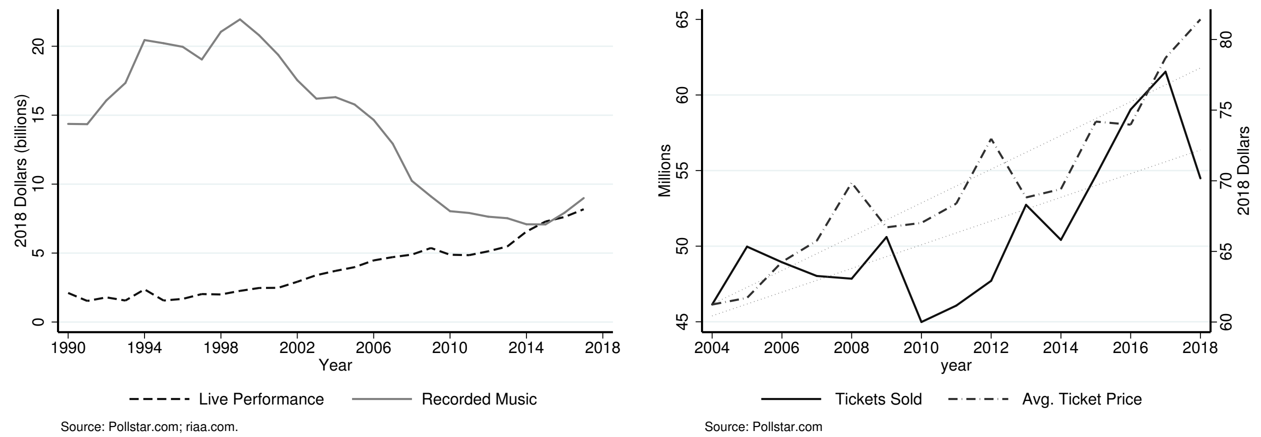
Hiller (2016) uses the Warner-YouTube blackout to identify the causal effect of legal streaming on recorded music sales. He finds that the blackout increased the difference in album sales between Warner artists and non-Warner artists. In contrast, I find that the

[1] Live performance data includes some non-musical acts like magicians. Non-musical acts cannot be filtered out since these data are provided in aggregate form in Pollstar's annual report, "Year End Business Analysis."

[2] Pollstar is an industry magazine which collects box office data from venues, artists, and promoters. I have excluded non-musical acts from the Top 200 chart. See the data description in Section 5 for more detail.

Figure 1.1: Music Industry Trends

(a) Live Performance and Recorded Music Revenue (b) Concert Ticket Prices and Tickets Sold, Top 200



blackout decreased the difference in live concert revenue and prices, and weakly decreased the difference in quantity, especially among "hot" artists. Note that since Hiller (2016) finds that the blackout increased album sales, it is unlikely that the results in this paper could be interpreted as listeners "punishing" Warner artists.

In more detail, the empirical analysis is based on a repeated cross-sectional data set compiled from Pollstar's 2006-2012 Top 200 NA Tours charts, together with discography data from allmusic.com and historical weekly *Billboard* Hot 100 charts.[3] Compared to non-Warner artists, the removal of Warner content from YouTube in 2009 caused Warner artists to earn on average 18 percentage points less annual concert revenue. The difference in ticket prices decreased 11.8 percentage points. I do not pick up a statistically significant effect on annual total ticket sales, tickets per performance, or the number of performances.

These effects are amplified among "hot" artists, defined as those who had a *Billboard* Hot 100 single in the year of or year before making the Top 200 NA Tours. For this group, revenue, price, and measures of quantity were negative and statistically significant. Moreover, artists who were more frequently searched for on YouTube just prior to the blackout had worse outcomes during the blackout. These findings further support the conclusion that YouTube stimulated concert demand.

I develop a theoretical model to help interpret these results. The model builds off of Krueger (2005) which argues that concerts were traditionally used to generate album sales, so tickets were priced below what would maximize concert profits alone. Digitization weakened

[3]The *Billboard* Hot 100 is a weekly ranking of songs based off of physical sales, paid downloads, terrestrial radio play, and streams.

the complementarity between concerts and album sales by allowing consumers to obtain recorded music without purchasing an album. This caused ticket prices and revenue to increase.

The monopoly model in this paper enriches the analysis by accounting for complementarity in both directions. Digitization, and streaming in particular, increases access to recorded music. This has two effects on ticket prices. First, it increases demand for concerts and therefore (likely) puts upward pressure on price. But it also increases the return to lowering ticket prices because larger crowds will return even more streams. Ticket prices increase if the upward pressure from converting streamers into concert-goers is stronger than the downward pressure from converting concert-goers into more streams.[4] Evidence from Papies and van Heerde (2017) is suggestive that the upward pressure dominates.

In a differentiated Bertrand duopoly setting in which concerts are substitutes, strategic effects may overturn the monopoly result an exogenous shock raises the streaming rates for one artist while decreasing it for the other. However, I show that *difference* in prices increases unambiguously. In the present context, the blackout decreases streaming rates for Warner artists and may boost streaming rates for non-Warner artists through substitution effects. So the prediction is that Warner artists' price does not increase relative to non-Warner artists' prices. This is the key prediction that I take to the data using a difference-in-differences (DD) estimation strategy.

This approach is novel for two reasons. First, it is an example of how the insights from the monotone comparative statics literature can be adapted for reduced form empirical analysis (e.g. Topkis, 2011; Milgrom and Roberts, 1990; Vives, 1990, 1999). The predictions in this literature are generally not DD predictions and are thus not directly testable with the widely-used DD estimation strategy. But using concepts such as strategic complements, increasing differences, and decreasing differences I am able to make a DD prediction.

Second, the Bertrand model allows one to infer more from the data by employing contrapositive logic, specifically the identity "if $A \Rightarrow B$ then $\neg B \Rightarrow \neg A$." In this context, A is the set of assumptions of the model, and B is the unambiguous prediction that Warner's relative price does not increase as a result of the blackout. Since the data do not reject B, the assumption set A is not refuted. The economic assumptions in A are that concert ticket prices are strategic complements between artists and that the artist profit function has increasing (nonincreasing) differences in own ticket prices and the own (rival's) penetration rate of streaming. The former assumption is natural if concerts are substitutes between artists (Vives, 1999). The latter is natural if live and recorded music are complements in demand within artists and the streams-to-concerts path is stronger than the concerts-to-

[4]The model accounts for substitution between streaming and sold music.

streams path. I emphasize that the empirical results do not prove that A is valid, but rather that A={strategic complements $\cap$ increasing/nonincreasing differences} as a model of concert pricing is not rejected by the data.

In the next section I provide a more detailed discussion of the mechanisms through which digitization could affect live music, as well as the contributions of this paper to that literature. Section 3 give background on the music industry. The theoretical model is developed in Section 4. In Section 5 I discuss the data and provide summary and descriptive statistics. The estimation strategy is described in Section 6. Section 7 reports the empirical results and the final section concludes. The Appendix provides a proof and additional empirical results and robustness analysis.

2 Related Literature on the Music Industry

There is a significant body of scholarship which investigates the role that digitization has played in the decline of the recorded music industry.[5] Less work has investigated its connection to the live music industry, a gap to which this paper contributes. Digitization could plausibly affect live music through "long tail" mechanisms or by stimulating demand.

Long tails in production and consumption may be at play. On the production side, Aguiar and Waldfogel (2018b) argue that the reduced costs of production due to digitization stimulate experimentation which leads to new formulas for commercial success, thus raising quality. A reasonable corollary would be that the demand for live (and recorded) music increases. On the consumption side, artists may leverage user location and listening data from streaming services to plan tour stops more profitably. Consistent with this hypothesis, Cho, Smith and Telang (2017) document that in the years 2000-2011 artists performed more shows with increasing geographical dispersion.[6]

Increased access to recorded music due to digitization could depress or stimulate the demand for live music if live and recorded music are substitutes or complements, respectively. They could be substitutes if listeners are driven to consume music privately instead of paying increasingly high concert ticket prices. However, the standard modeling approach treats live and recorded music as complements.[7] This assumption is supported by evidence from

[5]See, for example, Aguiar (2017), Aguiar and Martens (2016), Waldfogel (2010), Aguiar and Waldfogel (2018a), Hiller (2016), Oberholzer-Gee and Strumpf (2007) and Liebowitz (2006), among others.

[6]Alternatively, the rise of social media could be a way for artists to identify fan clusters (Cho, Hwang and Park, 2018).

[7]See Gayer and Shy (2006), Dewenter et al. (2012), Piolatto and Schuett (2012), and Curien and Moreau (2009), among others.

consumer and artist surveys as well as evidence from consumer behavior and sales data.[8]

I argue that streaming services, especially interactive ones like YouTube, have stimulated demand for live music beyond the stimulus provided by terrestrial radio and sales of physical media. The key mechanisms are a *discovery and exploration effect*, a *preparation effect,* and a *souvenir effect*.

By providing personalized and more varied music recommendations, streaming services can help listeners *discover* new songs and artists more frequently than through terrestrial radio. Bandwagon effects can be generated through collaborative filtering recommendation systems and playlist shares. Collaborative filtering recommends songs from users with a similar taste profile, so popular songs are recommended more often. Additionally, users can follow other users' pages or playlists, including those created by the platform. Songs appearing on popular playlists are more likely to be discovered.

No matter how a person discovers a song, interactive streaming services allow the individual to listen to a song as much as he or she likes, to explore other songs by the artist, and perhaps to follow a link to the artist's website.[9] This ability to *explore* can turn a listener into a fan by engaging him or her more deeply with an artist, thereby making it more likely that the listener will attend a concert.

Similarly, concerts are more fun if you know the music and can sing along. Interactive streaming services allow potential concert-goers to *prepare* more easily for the concert.

Finally, the *souvenir effect* refers to the fact that listening to a recording is enhanced if one can reminisce about the time at the concert, and knowing this in advance can make attending the concert more attractive. The on-demand and interactive nature of many streaming services have made this nostalgic listening easier.

Mortimer, Nosko and Sorensen (2012) provide some evidence that digitization stimulated demand for concerts. They find that the growth rate in US concert revenue for a given rank is higher after the 1999 launch of Napster, a file sharing service.[10] Moreover, the growth rate gradient is increasing in the broadband penetration and download activity of a major market area (DMA), both of which serve as proxies for file-sharing.

Empirically, this paper updates the environment in Mortimer et al. (2012) from illegal file

[8]For consumer surveys see Nguyen, Dejean and Moreau (2014); Jin and Oh (2019); Montoro-Pons and Cuadrado-García (2011); for artist surveys see Bacache-Beauvallet, Bourreau and Moreau (2015); Aly-Tovar, Bacache-Beauvallet, Bourreau and Moreau (2019); for consumer behavior and sales data see Mortimer, Nosko and Sorensen (2012); Papies and van Heerde (2017).

[9]The importance of linking is captured in the following line from the CEO of Warner Music Group, Edgar Bronfman, Jr., in the opening letter of the 2009 Warner Annual Report. "We have established a platform on YouTube that provides us with greater monetization opportunities with premium brand advertisers and drives commerce through links to artist websites."

[10]They also find that the growth rate of album sales is lower, but I concentrate on their findings for concerts.

sharing around 1999 to legal streaming around 2009. The fact that the results are broadly consistent lends additional credence to the claim that digitization has stimulated the demand for live concerts. Moreover, the quasi experimental design pioneered in Hiller (2016) gets closer to the experimental ideal as there is a treatment group (Warner artists) and a control group (non-Warner artists) as opposed to the event study analysis in Mortimer et al. (2012) where all artists are simultaneously exposed to the Napster launch. The experimental design enables me to more plausibly claim that demand effects rather than other changes in the treatment year, such as changes in production technology, are driving the results. In my view, these improvements amount to cleaner identification and a more plausible estimation of the causal effect of streaming on live concerts.

3 Background on the Concert and Recording Industries

This section provides some background on the music industry. I focus on the years 2006-2012 in North America (defined here as Canada, the United States, and Mexico) since this is the period and place of the data.

Artists and their managers work with record labels to produce, distribute and market recorded music.[11] Record labels are primarily responsible for setting or negotiating the price of recorded music.

The industry structure remained largely stable in the years 2006-2012 with four major labels: Warner Music Group, Sony Music Entertainment, Universal Music Group, and EMI. BMG joined with Sony in 2004 and EMI was sold off piecemeal over the years 2012-2013.[12] According to the industry publication Music & Copyright, the market share of the major labels hovered around 75 percent throughout the 2006-2012 period. For comparison, in 2019 Music & Copyright reports that the big 3 labels (Warner, Sony, and Universal) accounted for 68 percent of the market.

The key players in organizing a concert are the artist and her agent, the promoter, the venue, and the ticket seller. A single company may play multiple roles. For example, Live Nation is a promoter which owns the ticket seller Ticketmaster and several venues.

The artist's agent and concert promoter connect, possibly via an independent booking agent, to produce either an individual show or a multi-performance tour for the artist. The artist and promoter jointly determine ticket prices and share the revenue. The artist usually

[11] Online music and reduced production and distribution costs have helped to break this model, but most major artists like the ones that are the focus of this article adhere to it.

[12] BMG formed a joint venture with Sony in 2004 to form Sony BMG, but Sony bought out BMG's remaining stake in 2008 and renamed itself to Sony Music. Parts of EMI were sold to the three remaining major labels but the majority was sold to Universal.

receives a guaranteed minimum payout plus a share of ticket revenue above a predetermined split point. The concert promoter assumes the financial risk and is responsible for obtaining the performance space and marketing the event.

Venues make money by renting the space, selling concessions, and collecting parking fees. The ticket seller collects a service fee. During the study's time period the record labels may have received some concert revenue, but not a large share of it. While Warner and other labels were aggressively pursuing "360-degree" or "expanded-rights" deals with artists to entitle them to some touring revenue, Warner stated in its 2009 Annual Report that this was less than 10 percent of its overall revenue.

The two major national concert promoters are currently AEG and Live Nation Entertainment. Live Nation was spun off of Clear Channel Communications in 2005. In 2006 it acquired the House of Blues chain and in 2010 it completed a merger with the ticketing company Ticketmaster to become Live Nation Entertainment. While AEG and Live Nation are the dominant national concert promoters, local and regional promoters still play an important role in the concert industry.

4 A Model of Ticket Pricing

A simple model of concert ticket pricing in the shadow of the recorded music industry will help interpret the findings. Following Krueger (2005), I begin by focusing on the artist decision problem since they are the primary decision makers regarding concert ticket prices. I then embed this into a differentiated Bertrand duopoly framework.

Artists produce live and recorded music which can be streamed or sold (e.g., downloads and CDs). Assume artists have market power in the live music industry but are price-takers in streaming and sales. The fact that artists and promoters jointly decide on ticket prices justifies the market power assumption in the live music industry. For recorded music, prices are determined by the label for sold music and through negotiations between the label and streaming service for streams. With few exceptions, artists have little say over the price of recorded music (Krueger, 2019).

Artist revenue from streaming depends on the platform. To simplify a bit, ad-based platforms like YouTube share some of the ad revenue with the rights-holder (typically record labels). Subscription-based platforms like Spotify Premium split a share of the subscription revenue with the rights-holders according their stream share–the fraction of the total streams belonging to the rights-holder. The rights-holder, in turn, pays the artist according to their contract. For modeling purposes, I abstract away from the label-artist contracting problem and assume that a single streaming platform pays the artist directly.[13] This is without loss of generality since the key assumption is that artist's marginal revenue from an additional stream is nonnegative.

4.1 Monopoly-Competitive Model

Let $p = (p_1, p_2, p_3)$ prices paid by consumers for concert tickets (p_1), streaming (p_2), and sold music markets. For an ad-based platform p_2 should be thought of as the ad-load and for a subscription-based platform it should be thought of as the subscription price.

The number of streams is $q_2 = D_2(p;\lambda) = \lambda s(p)$, where $s(p)$ is potential demand and λ is the streaming *penetration rate.*[14] Let $R_2(D_2, p; \lambda)$ be streaming revenue, which depends on the number of streams and the prices paid by users. The demand for live music and sold music is $q_1 = D_1(p;\lambda)$ and $q_3 = D_3(p;\lambda)$, respectively. Finally, live music has constant marginal cost $c \geq 0$; recorded music has zero marginal cost.

Artists choose the ticket price p_1 to maximize

$$\max_{p_1} \pi(p;\lambda) = p_1 D_1(p;\lambda) + R_2(D_2, p;\lambda) + p_3 D_3(p;\lambda) - c D_1(p;\lambda).$$

The YouTube blackout is represented as an exogenous decrease in the penetration rate λ among Warner artists. Thus, the main concern is to determine conditions under which the price of concert tickets increases with streaming market penetration.

Assume $\pi(p;\lambda)$ is Morse.[15] Then p_1^* maximizes profit only if

$$\frac{\partial \pi(p;\lambda)}{\partial p_1}|_{p_1=p_1^*} = 0 \text{ and } \frac{\partial^2 \pi(p;\lambda)}{\partial p_1^2}|_{p_1=p_1^*} < 0. \tag{4.1}$$

Suppose that the optimal price, if it exists, is contained in the nonempty interval $[0, \bar{p}]$, $\frac{\partial \pi(p;\lambda)}{\partial p_1}|_{p_1=0} > 0$, and $\frac{\partial \pi(p;\lambda)}{\partial p_1}|_{p_1=\bar{p}} < 0$. Then following Christensen (2017), p_1^* exists and is unique if and only if $\frac{\partial \pi(p;\lambda)}{\partial p_1}|_{p_1=p_1^*} = 0$ implies $\frac{\partial^2 \pi(p;\lambda)}{\partial p_1^2}|_{p_1=p_1^*} < 0$.

By the Implicit Function Theorem, ticket prices weakly increase as the market penetration

[13] Alternatively we could assume that the terms of the contract between the label and artist are proportional to the terms between the platform and label.

[14] An alternative interpretation is that λ is the number of users and $s(p)$ is each user's demand.

[15] A Morse function is a smooth function whose critical points are non-degenerate, meaning $\frac{\partial^2 (p;\lambda)}{\partial p_1^2}|_{p_1=p_1^*} \neq 0$ whenever $\frac{\partial \pi(p;\lambda)}{\partial p_1}|_{p_1=p_1^*} = 0$. This class of functions is generic.

of streaming increases if and only if

$$\frac{dp_1}{d\lambda} = -\frac{\frac{\partial^2 \pi(p;\lambda)}{\partial p_1 \partial \lambda}}{\frac{\partial^2 \pi(p;\lambda)}{\partial p_1^2}} \geq 0 \tag{4.2}$$

at the maximizer p_1^*. In other words, the price of live music increases with the penetration rate if and only if there the profit function has (strictly) *increasing differences* in (p_1, λ) at p_1^*, that is, $\frac{\partial^2 \pi(p;\lambda)}{\partial p_1 \partial \lambda} \geq 0$ at p_1^*.

Increasing differences requires

$$\frac{\partial^2 \pi(p;\lambda)}{\partial p_1 \partial \lambda} = \frac{\partial D_1}{\partial \lambda} + (p_1 - c)\frac{\partial^2 D_1}{\partial p_1 \partial \lambda} + \frac{\partial R_2}{\partial D_2}\frac{\partial s}{\partial p_1} + p_3 \frac{\partial^2 D_3}{\partial p_1 \partial \lambda} \geq 0. \tag{4.3}$$

To interpret this condition, assume streaming revenue is non-decreasing in the number of streams, $\frac{\partial R_2}{\partial D_2} \geq 0$ and $\frac{\partial R_2}{\partial \lambda} \geq 0$, and that streaming and live music (sold music) are complements (substitutes) which implies $\frac{\partial D_1}{\partial \lambda} \geq 0$, $\frac{\partial D_3}{\partial \lambda} \leq 0$, and $\frac{\partial s}{\partial p_1} \leq 0$.

An increase in the the streaming penetration rate affects the concert pricing decision in three ways. By complementarity it increases the demand for live music which creates upward pressure on price as long as the live music demand curve is not flattened too much.[16] This effect is captured in the first two terms of equation (4.3). But there is downward pressure on ticket prices arising from the fact that higher ticket prices could lower the demand for streams. This effect is captured in the third term. Finally, the fourth term will be positive if an increase in streaming penetration causes the demand for sold music to be less elastic with respect to concert ticket prices (cross-price elasticity increases).[17] This is plausible if people substitute sold music with streaming, which the makes sold music demand less responsive to changes in ticket prices. The magnitude of these terms will differ by artist depending on the relevance of the markets to the artist's revenue model.

In any case, setting aside the impact on the sold music market, the main insight of the model is that complementarity between live music and streaming gives rise to a tension on ticket prices when streaming penetration increases exogenously. One the one hand, more streaming stimulates concert demand which (probably) puts upward pressure on price; on the other hand artists may want to lower ticket prices to leverage the increased streaming demand into even more streams. Evidence from Papies and van Heerde (2017) is suggestive that the upward pressure dominates.[18] Hence, given a nonnegative fourth term in equation

[16] Specifically, as long as $\frac{\partial D_1}{\partial \lambda} \geq -(p_1 - c)\frac{\partial^2 D_1}{\partial p_1 \partial \lambda}$.

[17] $\frac{\partial \varepsilon_{31}}{\partial \lambda} = \frac{p_1}{D_3}\frac{\partial^2 D_3}{\partial p_1 \partial \lambda} - \frac{p_1}{D_3^2}\frac{\partial q_3}{\partial p_1}\frac{\partial D_3}{\partial \lambda} > 0$ whenever $\frac{\partial D_3}{\partial \lambda} < 0$ if and only if $\frac{\partial^2 D_3}{\partial p_1 \partial \lambda} > 0$.

[18] They find that the elasticity of concert revenue with respect to lagged sold music revenue is seven times more than the elasticity of sold music revenue with respect to lagged concert revenue.

(4.3), increasing differences appears to be a reasonable assumption.

The following simple linear example helps to illustrate the tension on ticket prices.

Example 1. For simplicity, suppose that an artist does not sell music.[19] The artist streams music on an ad-based platform such as YouTube. The streaming platform's ad revenue A is linear in the number of streams, $A = \phi D_2$ for $\phi > 0$, and it pays the artist, who is assumed to be the rights-holder for simplicity, a fraction $\theta \in [0, 1]$ of the revenue. Let. $\gamma \equiv \theta\phi$. Then the artist's revenue from streaming is $R_2(D_2, p; \lambda) = \gamma D_2(p; \lambda) = \gamma\lambda s(p)$.

If demands are linear and λ acts as a shift parameter (no rotation) in the live music demand function, then the demand for live music and the revenue from streaming is, respectively,

$$D_1(p; \lambda) = a_1\lambda - \frac{b_{11}}{2}p_1 - b_{12}p_2 \text{ and}$$
$$R_2(D_2, p, \lambda) = \gamma\lambda(a_2 - b_{21}p_1 - b_{21}p_2),$$

where $b_{ij} > 0$ for all $i, j = \{1, 2\}$. Demand complementarity follows from $\partial D_i/\partial p_j = b_{ij} > 0$ for $i \neq j$ and $\partial D_1/\partial\lambda = a_1 > 0$. By inequality (4.3), ticket prices increase with the streaming penetration rate if and only if the increase in demand for concerts is greater than the change in the rate at which ticket price increases lower the demand for streams, or $a_1 > \gamma b_{21}$.

4.2 Differentiated Bertrand-Competitive Model

While the monopoly-competitve model yields valuable insights, the estimation strategy in this paper relies on a DD estimator which measures the effect of the blackout on the difference in outcomes between Warner and non-Warner artists. Fortunately, the Bertrand duopoly setting provides a clear prediction on relative prices under weak assumptions.

To see this, suppose two firms, Warner (w) and Non-Warner (nw) compete in a differentiated Bertrand duopoly. To ease notation, drop the numerical subscripts denoting the market and let p_w be the ticket price chosen by Warner and p_{nw} the price chosen by Non-Warner. Let λ_w be the streaming penetration rate for Warner.

Assume that ticket prices are *strategic complements*, $\frac{\partial^2\pi_i}{\partial p_i\partial p_j} \geq 0$ for $i \neq j \in \{w, nw\}$, which implies that own optimal price is increasing in the rival's price. I illustrate in the example below that this is a natural assumption when concerts are substitutes. Further assume increasing differences between live music and streaming within Warner, $\frac{\partial^2\pi_w}{\partial p_w\partial\lambda_w} \geq 0$, but that $\frac{\partial^2\pi_{nw}}{\partial p_{nw}\partial\lambda_w} \leq 0$. The latter *decreasing differences* assumption and strategic complementarity in prices are consistent since both capture the idea that Non-Warner benefits—in the sense

[19] Alternatively and equivalently for the purpose of signing comparative statics, assume $\frac{\partial^2 D_3}{\partial p_1\partial\lambda} = 0$.

that marginal profit of raising own ticket prices increases—if either Warner's price increases or Warner's streaming penetration decreases.

If $\frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial \lambda_w} = 0$ and equilibrium is unique, then Warner's and Non-Warner's ticket prices are non-decreasing with Warner's streaming penetration since this is a game of strategic complements.[20] More generally, $\frac{dp_w}{d\lambda}, \frac{dp_{nw}}{d\lambda} \geq 0$ if and only if equilibrium is stable, and under reasonable dynamic adjustment processes equilibrium prices increase with λ even at unstable equilibria (Echenique, 2002; Christensen and Cornwell, 2018).

On the other hand, if $\frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial \lambda_w} < 0$ the effect on prices is ambiguous. However, subject to some regularity conditions, the change in the *price difference* is nonnegative, that is, $\frac{dp_w}{d\lambda_w} - \frac{dp_{nw}}{d\lambda_w} \geq 0$.

The *regularity conditions* are that (i) π_i for $i \in \{w, nw\}$ are Morse, (ii) for each artist $i = \{w, nw\}$ and for any rival's price p_j, each artist's optimal price is contained in the nonempty interval $[0, \bar{p}_i]$ with $\frac{\partial \pi_i}{\partial p_i}|_{p_i=0} < 0$ and $\frac{\partial \pi_i}{\partial p_i}|_{p_i=\bar{p}_i} < 0$; and (iii) $\frac{\partial^2 \pi_i}{\partial p_i^2} \leq -\frac{\partial^2 \pi_i}{\partial p_i \partial p_j}$ for $i \neq j \in \{w, nw\}$. The first two conditions are similar to the regularity conditions for the monopoly-competitive model and ensure that an equilibrium exists in $(0, \bar{p}_w) \times (0, \bar{p}_{nw})$. The third condition means that for each firm marginal profit is affected more by changes in own price than by changes in the rival's price.

I summarize the results in the following proposition. A proof is in the appendix.

Proposition 2. *Suppose that the regularity conditions are satisfied, ticket prices are strategic complements, and, as motivated in the above text* $\frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w} \geq 0$ *while* $\frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial \lambda_w} \leq 0$*. Then there is a unique non-zero and finite equilibrium, and*

1. $\frac{dp_w}{d\lambda_w} \geq 0$ *if and only if* $\frac{\partial^2 \pi_{nw}}{\partial p_{nw}^2} \frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w} \leq \frac{\partial^2 \pi_w}{\partial p_w \partial p_{nw}} \frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial \lambda_w}$,
2. $\frac{dp_{nw}}{d\lambda_w} \geq 0$ *if and only if* $\frac{\partial^2 \pi_w}{\partial p_w^2} \frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial \lambda_w} \leq \frac{\partial^2 \pi_{nw}}{\partial p_{nw} \partial p_w} \frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w}$, *and*
3. $\frac{dp_w}{d\lambda_w} - \frac{dp_{nw}}{d\lambda_w} \geq 0$.

To think through the intuition of Proposition 2, it is helpful to imagine a dynamic price response to an increase in λ_w, where prices initially react to the increase in λ_w without regard to strategic interaction (the partial effect), and then to adjust the response taking into account strategic price responses (the interactions effect).

Notice that $\frac{dp_w}{d\lambda_w} \geq 0$ and $\frac{dp_{nw}}{d\lambda_w} \geq 0$ if $\frac{\partial \pi_{nw}}{\partial p_{nw} \partial \lambda_w} = 0$. In this case, the partial effect of an increase in λ_w is to raise Warner's price. Due to strategic complementarity the partial effect is reinforced by the interactions effect so prices climb and converge to a higher equilibrium.[21] But if $\frac{\partial \pi_{nw}}{\partial p_{nw} \partial \lambda_w} < 0$, then initially Warner raises its price while Non-Warner decreases its

[20] As is well-known, smoothness assumptions are not required to reach this conclusion. See, for example, Amir (2005).

[21] Convergence is guaranteed by the regularity condition.

price. The strategic price response oscillates until it settles at a new equilibrium. The qualitative effect on individual prices is unclear, but part 3 of the Proposition says that the price difference will unambiguously increase.

This is the key prediction of the model. The YouTube blackout represents a decrease in Warner's streaming market penetration, so the DD estimator is estimating the difference $-\left(\frac{dp_w}{d\lambda_w} - \frac{dp_{nw}}{d\lambda_w}\right)$.[22] The model predicts that this difference will be negative. In the empirical section below I find that the DD estimate is statistically significant and negative, that is, *the blackout lowered Warner artists' relative ticket prices.* Thus, the model is not refuted. Hence, the evidence is consistent with a framework in which the ticket pricing game is one of strategic complements in prices, and that the artist's profit function has increasing (decreasing) differences in ticket prices and own (rival's) streaming market penetration.

Example 3. As in Example 1, assume neither firm sells music and that the revenue from streaming on an ad-based service takes an analogous linear form. The demand for live music and the revenue from streaming is, respectively, for $i \neq j \in \{w, nw\}$

$$\begin{aligned} D_1^i(p;\lambda) &= a_{11}^i\lambda_i - \mathbf{a_{12}^i}\lambda_\mathbf{j} - \frac{b_{11}^i}{2}p_i - b_{12}^i p_2 + \mathbf{d^i p_j} \text{ and} \\ R_2^i(D_2^i, p, \lambda) &= \gamma_i\lambda_i(a_{21}^i - \mathbf{a_{22}^i}\lambda_\mathbf{j} - b_{21}^i p_i - b_{22}^i p_2), \end{aligned}$$

where all coefficients are nonnegative, $d^i \geq 0, a_{ij} \geq 0,$ and $b_{ij} \geq 0$ for all $i, j = \{1, 2\}$. The variables typeset in bold represent those which differ from Example 1 due to the strategic setting. The assumption $d^i \geq 0, a_{12}^i \geq 0$, and $a_{22}^i \geq 0$ imply that concerts and streams by different artists are substitutes in terms of demand.

Assuming zero costs, artists select p_i to maximize $\pi_i(p;\lambda) = p_i D_1^i(p;\lambda) + R_2^i(D_2, p, \lambda)$. Let $t^i = (a_{11}^i - \gamma_i b_{21}^i)\,\lambda_i - a_{12}^i\lambda_j - b_{12}^i p_2$. Then

$$\frac{\partial \pi_i}{\partial p_i} = t^i - b_{11}^i p_i + d^i p_j.$$

Substitutes give rise to strategic complements since $\frac{\partial^2\pi_i}{\partial p_i \partial p_j} = d^i \geq 0$, and the third regularity condition of Proposition 2 requires $b_{11}^i > d^i$. Profit functions exhibit increasing differences in (p_i, λ_i) if $\frac{\partial^2\pi_i}{\partial p_i \partial \lambda_i} = a_{11}^i - \gamma_i b_{21}^i > 0$, which is the same condition in the monopoly-competitive example under which increased streaming penetration leads to higher optimal pricing.

The best response functions are $BR_i(p_j) = \frac{t^i}{b_{11}^i} + \frac{d^i}{b_{11}^i}p_j$ for $i \neq j$. Solving this system gives the Nash equilibrium prices $p_i^* = \frac{b_{11}^j t^i + d^i t^j}{b_{11}^i b_{11}^j - d^i d^j}$ for $i = \{w, nw\}$ and the equilibrium price

[22] Strictly speaking, I use a log transformation, so I am estimating the change in the difference in logged prices.

difference $p_w^* - p_{nw}^* = \frac{t^w(b_{11}^{nw}-d^{nw})-t^{nw}(b_{11}^w-d^w)}{b_{11}^i b_{11}^j - d^i d^j}$. The regularity condition ensures a positive denominator.

Since $\frac{\partial t^w}{\partial \lambda_w} = a_{11}^w - \gamma_w b_{21}^w > 0$ and $\frac{\partial t^{nw}}{\partial \lambda_w} = -a_{12}^{nw} \leq 0$, it follows that the sign of $\frac{dp_i^*}{d\lambda_w}$ for $i = \{w, nw\}$ is ambiguous. The term $-a_{12}^{nw} = \frac{\partial \pi_{nw}}{\partial p_{nw} \partial \lambda_w}$ represents the direct effect of an increase of Warner streaming penetration on nonWarner's live music demand. If there is no direct effect, $a_{12}^{nw} = 0$, then prices increase: $\frac{dp_i^*}{d\lambda_w}{>}0$ for $i = \{w, nw\}$. However, the price difference increases whether or not there is a direct effect: $\frac{d(p_w^* - p_{nw}^*)}{d\lambda_w} > 0$ for $a_{12}^{nw} \geq 0$.

5 Data and Sample Selection

The data for this paper come from several sources. The main source is Pollstar's annual Year End Top 200 North American Tours charts from 2006 to 2012.[23] The tours are ranked by total revenue from shows performed in North America. The data also contain average ticket price, average tickets per show, and average gross. From these data I infer the total tickets sold and number of shows performed in North America.[24]

The Top 200 NA Tours chart is comprised of musical acts, comedy shows, and theatrical acts like Cirque du Soleil or magicians. I restrict data to musical acts as the emphasis in this paper is on the interaction between concerts and online streaming. I exclude festivals since the headliner is not necessarily the main factor driving ticket sales. I also drop tribute acts such as "Rain – A Tribute to the Beatles" since these acts are fundamentally different from original artists. These choices reduce the number of observations from 1,400 to 1,167.

With respect to data quality, Pollstar's Top 200 NA Tours chart is based on data reported to Pollstar by venue operators, artists or their managers, or promoters. While the data do not capture everything, independent audits by Mortimer et al. (2012) and Krueger (2019, Appendix) suggest that these data are reasonably accurate. Importantly, there is no reason to believe that the data quality varies with the artist's label, the variable which determines treatment status.

I combine the Pollstar data with artist discographies collected from allmusic.com. These data list the album name, release year, and record label for albums an artist (or band) has recorded throughout her career. Typically the parent label is not listed, so these were assigned by me using various sources. Artist genres were assigned according to Pollstar's classification.

[23] I requested data for lower ranked tours from Pollstar but this was cost prohibitive.

[24] For the top 100 tours we also have the number of cities and shows. However, there appears to be an inconsistency in the way this data is recorded. In most cases the number of cities equals the total gross divided by the average gross, but in some cases this calculation equals the number of shows. To maintain consistency I create a new variable "performances" which is total gross divided by average gross.

I also compiled data from Google Trends on the number of YouTube searches of an artist. These data are available beginning in 2008. Google normalizes to 100 the number of searches for the most searched artist in a specified time period. A small but significant set of artists were not included since they did not appear as a musician in the autocomplete predictions drop down list. This issue arose mostly among artists with generic names like Chicago, Journey, or Heart.

Finally, I assembled artists' *Billboard* Hot 100 history. The *Billboard* Hot 100 is a weekly ranking of songs based off of physical sales, paid downloads, terrestrial radio play, and streams. *Billboard*'s formula has changed as music production and consumption has changed. Streaming was incorporated beginning in 2007 but in a limited capacity, constituting only 5 percent of the chart's total points.[25] Streaming weighed more heavily in the Hot 100 beginning in 2012, and included streams on YouTube beginning in 2013.[26,27] The key point for this paper is that the Hot 100 did not account for streaming in a significant way until the final year of the data set, and YouTube is not incorporated throughout. This is important because the Hot 100 is a key interaction variable which determines which artists are affected most by the Warner-YouTube blackout.

5.1 Summary and Descriptive Statistics

Note that an artist can appear in more than one observation if they make the top 200 in different years. I return to this point when discussing the estimation strategy, but the reader should keep this in mind when evaluating the summary statistics. For the sake of readability I refer to observations as artists, but a better term might be artist-years.

Summary statistics by rank cohort are provided in Table 1. The top ranks take a disproportionate share of revenues, charge higher prices, play larger shows, and give more performances. Figure 5.1 plots revenue by rank for 2009. The other years are not shown but they all follow the same power law distribution. The same pattern holds for average tickets per show, total tickets sold, YouTube searches and, to a lesser extent, average ticket price when these variables are placed in rank order.[28] This suggests that it will be important to take the log of these variables when using a linear model for estimation.

The top 50 tend to have had a song appear in the *Billboard* Hot 100 more recently, but on average it has been 8.6 years since the last Hot 100 song. In this case averages are deceptive. As illustrated in Figure 5.2, 26 percent of artists in the Top 200 have never had a song in

[25] https://www.billboard.com/articles/news/1050326/billboard-hot-100-to-include-digital-streams

[26] https://www.billboard.com/articles/news/502020/hot-100-impacted-by-new-on-demand-songs-chart

[27] https://www.billboard.com/articles/news/1549399/hot-100-news-billboard-and-nielsen-add-youtube-video-streaming-to-platforms

[28] The number of performances does not follow this pattern.

Table 1: Summary Statistics by Rank Cohort (means)

Rank	Revenue (millions)	Avg. Ticket Price[a]	Avg. Tickets/ Performance	Perfor-mances[b]	Yrs. Since Debut Album	Yrs. Since Last Hot 100 (if any)
1-50	$43.9	$88.85	15,117	42.5	22.3	5.6
51-100	$12.9	$71.38	7,963	36.9	23.1	9.0
101-150	$6.8	$60.69	5,979	35.0	21.7	10.7
150-200	$4.2	$56.05	4,513	31.1	18.7	10.0
Top 200	$17.1	$69.32	8,432	36.4	21.4	8.6

Notes: The source is Pollstar's Year End Top 200 North American Tours chart. Festivals, tribute bands, and non-musical acts are excluded as described in the text. [a]Normalized to 2018 dollars. [b]No. of performances is the total gross divided by average gross.

the *Billboard* Hot 100. Examples include Mannheim Steamroller, The Wiggles, Iron Maiden, Juan Gabriel, Andrea Bocelli, Yanni, Diana Krall, and Casting Crowns. Thirty-two percent of artists had a Hot 100 in the year of or year before they made the Top 200, 16 percent had their last Hot 100 song 2-10 years before making the Top 200.

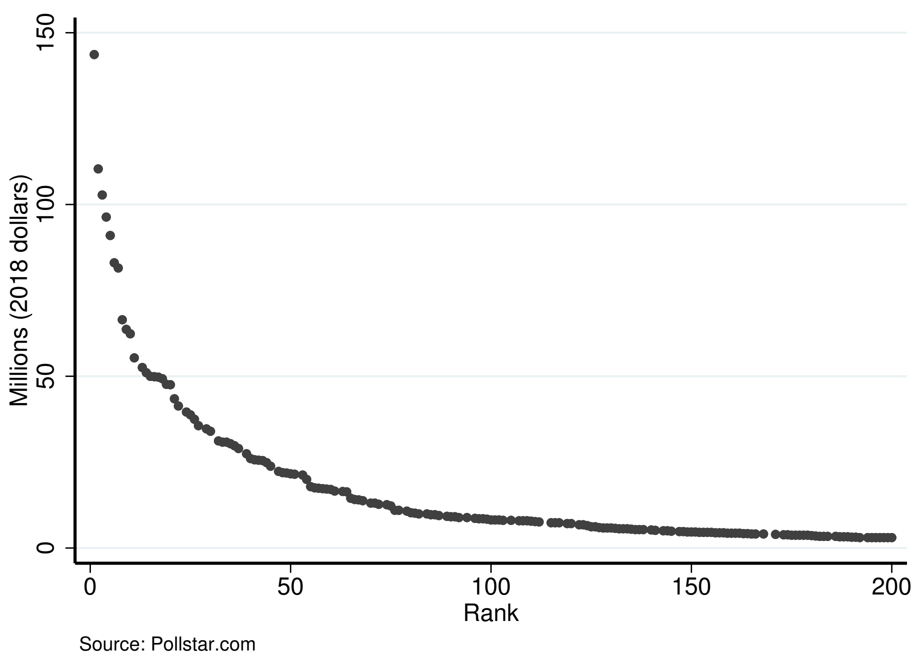


Figure 5.1: Revenue by Rank in 2009

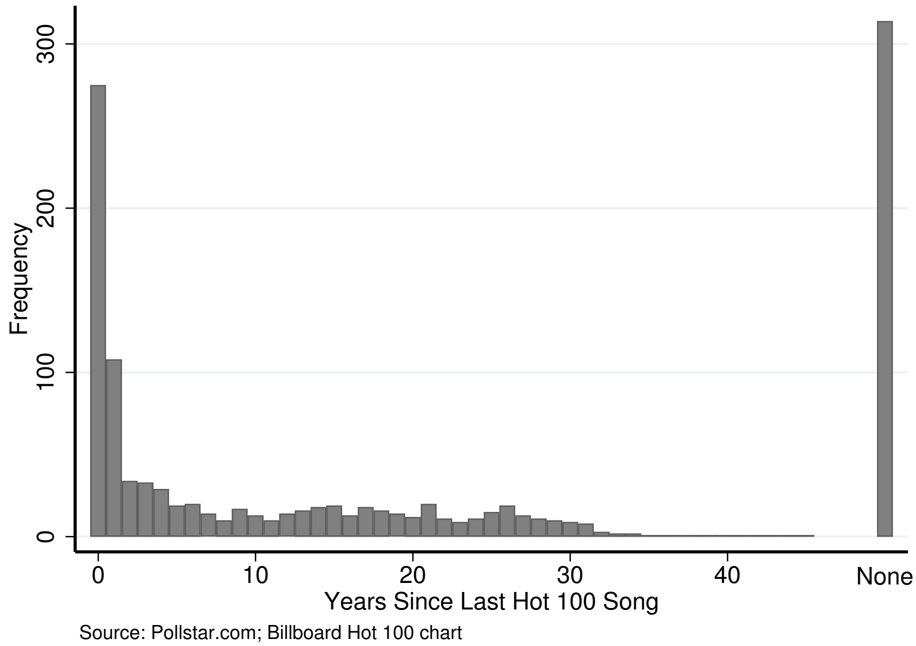


Figure 5.2: Years Since Last Hot 100 Song Among Top 200

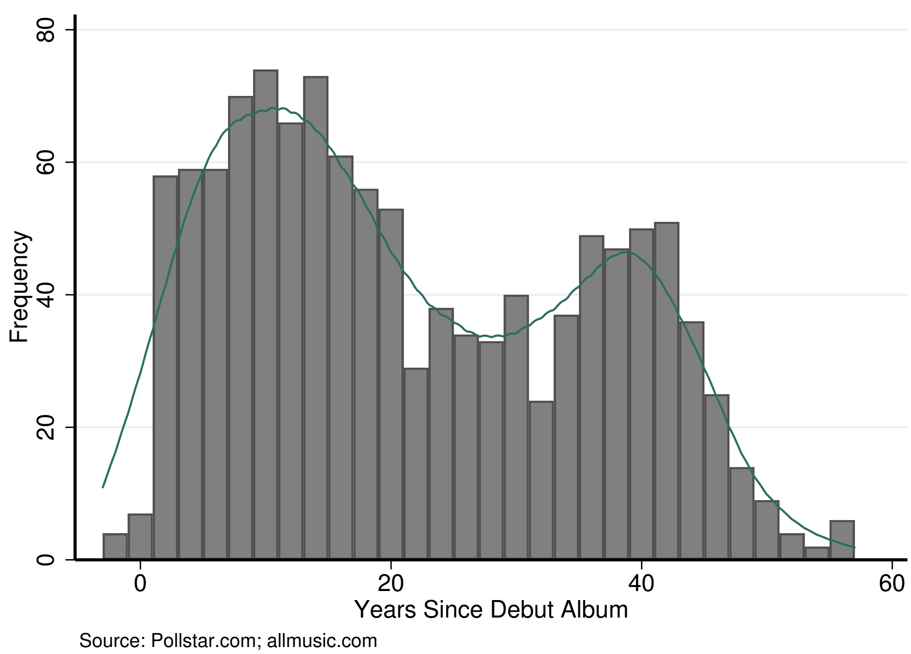


Figure 5.3: Years Since Debut Album Among Top 200

On average, artists in the Top 200 debuted their first album 21.4 years before appearing in the Top 200. But again, averages are deceptive. The distribution of years since debut is

Table 2: Summary Statistics by Year (means)

Year	Revenue[a] (millions)	Avg. Ticket Price[a]	Avg. Tickets/ Performance	Perfor- mances[b]	Yrs. Since Debut Album	Yrs. Since Last Hot 100 (if any)
2006	$17.8	$65.25	7,719	39.2	19.4	8.0
2007	$17.2	$66.62	9,290	36.0	19.3	7.0
2008	$18.5	$72.25	8,707	33.0	22.4	8.2
2009	$18.0	$68.25	8,923	34.5	21.6	8.9
2010	$15.8	$68.55	7,772	35.3	22.1	8.9
2011	$16.2	$69.81	8,416	37.3	22.4	9.8
2012	$16.5	$74.83	8,268	39.3	22.9	9.5

Notes: The source is Pollstar's Year End Top 200 North American Tours chart. [a]Dollars are normalized to 2018 dollars. Festivals, tribute bands, and non-musical acts are excluded as described in the text. [b]No. of performances is the total gross divided by average gross.

bimodal. Figure 5.3 is a histogram of the years between the time that an artist released his or her debut album and when he or she made the Top 200. The primary peak occurs around 10 years since their debut, and a secondary peak occurs around 40 years. The latter group includes Aretha Franklin, Dolly Parton, Neil Young, Bob Dylan, Journey, Willie Nelson, and The Rolling Stones.

Summary statistics over time are reported in Table 2. The recovery from the 2008 financial crisis is apparent in the 2009 and 2010 numbers. This issue is addressed in the estimation using time fixed effects.

5.2 The Warner-YouTube Blackout as a Natural Experiment

In a December 19, 2008 blog post, YouTube explained that it was beginning to remove Warner content from its site due to a licensing dispute.[29] On September 29, 2009, YouTube announced on its blog that Warner content was returning.[30] This period is termed the Warner-YouTube blackout, or simply the blackout. In order for the blackout to serve as a good natural experiment it must be relevant and valid.

YouTube launched in November 2005 and was acquired by Google in 2006. Other online streaming services were available but YouTube was dominant, and until Vevo emerged in December 2009, it was the only major online service to offer music videos. Most notably, Pandora launched in 2005, but this service is not nearly as interactive as YouTube and does

[29]https://youtube.googleblog.com/2008/12/ups-and-downs-of-music-licensing-for.html
[30]https://youtube.googleblog.com/2009/09/warner-music-comes-back-to-youtube.html

not allow consumers to explore and discover music as freely. Spotify launched in the United States in 2011 and later still in Canada and Mexico. Spotify is not a major factor in the current study.

According to comScore's "The 2009 U.S. Digital Year in Review", in 2009 YouTube accounted for 26 percent of total time viewing online videos, more than the sites ranked 2 to 25 combined. By June 2009, over 112 million viewers watched 7.6 billion videos.[31] Clearly, the absence of Warner music from YouTube could have a significant effect on these artists. In other words, the blackout is relevant.

The blackout was the result of a dispute between Warner and YouTube, rather than between artists and YouTube. This distinction is important because Warner was concerned about recorded music sales—not live music sales—and the source of the dispute appears entirely due to the terms of compensation for Warner recorded music on the site.[32] For its part, YouTube stated at the beginning of the blackout that "Sometimes, if we can't reach acceptable business terms, we must part ways with successful partners." On the other side Warner issued the following statement: "We are working actively to find a resolution with YouTube that would enable the return of our artists' content to the site. Until then, we simply cannot accept terms that fail to appropriately and fairly compensate recording artists, songwriters, labels and publishers for the value they provide."

Thus, the dispute was orthogonal to trends in the concert industry. In fact, it appears the idea that streaming could stimulate the live music industry was not widely circulated at the time; I could not find any contemporary reporting or evidence which connected the blackout to artists' live music revenues. In addition, the blackout was a surprise. The other major labels were able to strike a deal with YouTube, and reporting on the Warner-YouTube negotiations indicated that a deal was close but ultimately could not be reached.[33] In other words, the blackout was a plausibly exogenous and unanticipated shock to the live concert industry.

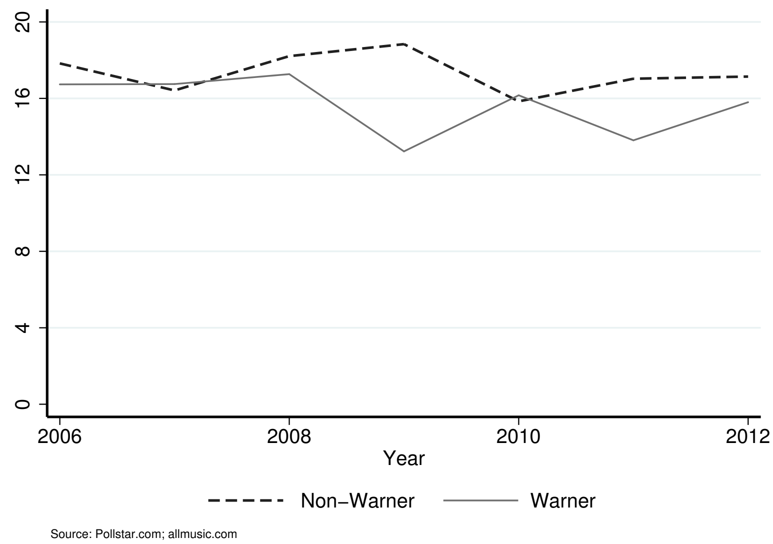
The data largely appear to support this conclusion. Figure 5.4 graphs the log of revenue in 2018 dollars by year and Warner status. There is no discernible trend in the years leading up to 2009, a large dip of Warner revenue in 2009 relative to non-Warner artists, and a secondary dip in 2011. There is no clear pattern of divergent trends, but the relative dip in 2011 in Warner artists' concert revenue warrants further investigation. In the robustness

[31] https://www.comscore.com/Insights/Press-Releases/2009/8/Major-News-Stories-Drive-June-Surge-in-U.S.-Online-Video-Viewing-to-Record-157-Million-Viewers

[32] As noted earlier, at the time Warner was beginning to pursue expanded-rights deals where they were beginning to share in live music revenue, but this was a very small part of their business at the time.

[33] http://allthingsd.com/20081220/warner-music-group-disappearing-from-youtube-both-sides-take-credit/

Figure 5.4: Parallel Trends Analysis (Log of gross millions, 2018 dollars)



analysis I run the regression model as if the blackout occurred in 2011 to see if the analysis picks up a statistically significant difference. It does not.

A valid natural experimental design will also have similar environments in the treatment year compared to the control years, conditional on time fixed effects. While I have data for 2006-2012 to help control for time trends, the environment in 2010 onward is different in important ways. First, the largest concert promoter (Live Nation) merged with the largest ticket seller (Ticketmaster) in 2010. Second, Vevo launched in December 2009. At the outset, the company published videos of Universal and Sony artists, as well as several major independent labels such as Concord and Disney and distributed them through its own website and YouTube. In the first month of operation it had over 35 million unique visitors to its web network.[34] Importantly, Warner did not participate in this venture until 2016.[35] This put Warner at a streaming disadvantage for reasons unrelated to the blackout. Consequently, estimates using the sample years 2010-2012 may be biased.

Another concern for the experimental design surfaces from the fact that the data only include the Top 200 tours. OLS estimation gives a conditional expectation, so it may be that the dip in, say, average revenue among Warner artists is due to a larger number of artists making the Top 200 but at the lower end of the ranking. This would pull down the average but may nevertheless indicate a good outcome for Warner artists. As shown in Table 3, between the years 2006 to 2012 the largest number of Warner artists made the Top 200 in

[34]https://www.prnewswire.com/news-releases/vevo-was-most-trafficked-us-entertainment-music-web-network-in-december-2009-81347087.html

[35]http://routenote.com/blog/after-7-years-major-label-warner-music-signs-a-deal-with-vevo/

Table 3: Number of artists in the Top 200 by label

Year	Warner	Sony	Universal	EMI	Independent	Non-Music
2006	25	54	46	13	33	28
2007	21	44	41	15	41	38
2008	35	42	42	10	38	33
2009	37	42	35	13	41	32
2010	26	45	40	8	48	33
2011	25	42	41	8	51	33
2012	24	41	46	4	45	40

Source: Pollstar, allmusic.com

2009 with 37, but 2008 was close behind with 35.

To address these concerns my preferred sample year span is 2008-2009.

Finally, we want to ensure that the treatment is "randomly" assigned. In this setting the treatment is clustered on Warner rather than random, so the central identifying assumption is that blackout status is assigned randomly *conditional* on label status. To evaluate this I run an OLS regression of blackout status against artist characteristics which may cause concern for omitted variable bias while controlling for Warner status. If treatment is conditionally random then the coefficients on these characteristics should be jointly zero. The characteristics I use in the test are limited by the data, but they include whether the artist had a song in the *Billboard* Hot 100 in the year of or year before the year they made the Top 200, the years since their debut album, years since the last album, an indicator for whether the genre is pop/rock, and an indicator for whether they co-headline their tour. Coefficient estimates with associated robust standard errors are reported in Table 4 for different year ranges corresponding to the main estimation samples. F-statistics and associated p-values are provided for joint significance tests of categorical variables with more than two categories. The F-tests on the "Hot 100" and "Years Since Debut" categories do not reject the null that these variables have no effect on blackout status. The coefficient estimates on the remaining variables are not individually statistically significant and an F-test, reported in the final row of the table for each model with p-values in parentheses, does not reject the null hypothesis that all coefficients are jointly zero. All told, it seems to fair to conclude that blackout is assigned "randomly" conditional on Warner status.

6 Estimation Strategy

The structure of the data gives rise to two selection issues.

The top 200 is not a representative sample, so results apply only to this selected group. I

Table 4: The correlation between artist characteristics and blackout status

Dependent Variable: 1 = Artist was subject to YouTube blackout			
	Year Range		
	2006-2012	2006-2009	2008-2009
Billboard Hot 100 status[a]			
0-1 years	-.002 (.012)	-.002 (.020)	.006 (.050)
2-10 years	-.008 (.014)	-.003 (.024)	-.023 (.040)
>10 years	-.007 (.013)	-.006 (.022)	.023 (.039)
F-stat (p-value)	.14 (.93)	.02 (.99)	.44 (73)
Years since debut album[b]			
0-10 years	-.007 (.014)	-.008 (.023)	.003 (.042)
11-20 years	.002 (.013)	.001 (.020)	.007 (.036)
21-30 years	-.024 (.014)	-.040 (.022)	-.053 (.038)
F-stat (p-value)	1.17 (.32)	1.42 (.24)	.96 (.41)
Years since last album	.001 (.001)	.001 (.002)	.001 (.002)
Pop/rock artist	-.004 (.009)	.036 (.017)	-.013 (.025)
Solo show[c]	-.014 (.018)	-.018 (.032)	-.018 (.044)
Warner[d]	.182 (.022)	.305 (.034)	.512 (.047)
Year fixed effects	Y	Y	Y
Observations	1,132	650	326
R^2	.35	.43	.58
F stat (p-value)[e]	.59 (.80)	.75 (.66)	.54 (.85)

Notes: Robust standard errors are reported in parentheses except in the last row where a *p*value of the associated F-test is reported. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours, allmusic.com, and Billboard Hot 100. [a]An indicator equal to one if the artist had a song in the Billboard Hot 100 the year of or year before he or she made the Top 200. The reference group is artists who never had a Hot 100 song. The F stat is from a test of the joint significance of the Hot 100 categories. [b]The reference group is artists whose first album was released 31 years or more before they made the Top 200. The F stat is from a test of the joint significance of the categories for years since debut. [c]An indicator equal to one if the artist did not co-headline a tour. [d]An indicator equal to one if in the year of observation the artist's last album was released under the Warner label. [e]This F stat is from a test of the joint significance of all variables except the Warner identifier and time fixed effects. *Significant at the 10 percent level, **Significant and the 5 percent level, *** Significant at the 1 percent level.

will refer to this as *selection at the aggregate level.* This issue is endemic to studies involving music industry sales since observations are usually restricted to top performers. But the top 200 represent a little over 70 percent of the revenue industry-wide during 2006-2012.[36] Thus, the top 200 captures a large and significant portion of the industry.

There is also *selection at the observation level.* Some artists make the top 200 in all years but most only make it sometimes. An artist who makes the top 200 in one year will not do so in another if either they were not on tour or they were on tour but did not gross enough. Consequently, artists who appear more frequently probably have higher revenue, sell more tickets and/or charge a higher price.

If one were to construct a panel from these data using the artist as the unit, the result would be a balanced panel with many non-randomly missing outcome variables. For example, in the 2008-2009 sample 82 artists appear in both years, 79 appear only in 2008, and 83 appear only in 2009. A panel constructed from these data would have 244 artists and 162 missing outcome variables. The missing values problem would be severe.

Rather than trying to address the missing values problem with imputation or selection methods, my approach instead is to treat the data as repeated cross sections and cluster error terms at the artist level.[37] This approach mitigates the selection at the observation level since the blackout effect is being estimated off of variation within Warner status rather than variation within artist. Consequently, the interpretation of the estimates will be for Warner artists as a group rather than for the typical Warner artist.[38]

To be explicit, the repeated cross-sectional model I estimate with OLS is

$$y_{it\ell} = \beta_1 warner_{it\ell} * D_t + \beta_2 warner_{it\ell} + X'_{it\ell}\gamma + \alpha_t + \underbrace{\theta_i + \mu_{it\ell}}_{=\varepsilon_{it\ell}}, \tag{6.1}$$

[36]North American revenues for the concert industry as a whole are from Pollstar's annual report, "Year End Business Analysis."

[37]Nonrandomly missing outcome variables lead to bias (Baltagi and Song, 2006). In principle, a selection model for panel data such as Wooldridge (1995) could work. But to identify such a model I would need a variable which determines selection into the top 200 of revenues but is independent of the outcome variable, all of which are closely related to revenue (e.g., log of revenues, price, quantity). No such variable comes to mind. Imputation of missing values using past or future outcomes is dubious at best since in some years artists don't even tour. If they do tour and don't appear in the top 200, an imputed value based off of averaging from observable years would yield imputed values that suggest a higher level of sucess than they actually enjoyed, distorting results.

[38]This disctinction is important. For example, Krueger (2005) observes that the total number of tickets sold among a fixed set of artists (p. 12) "fluctuated around 30 million per year from the late 1980s and has dropped since 2000." The last year for which he presents data is 2003. In contrast, Mortimer et al. (2012) fix the rank but not the set of artists and document that ticket sales fluctuated from 1996-2000 and *rose* significantly in 2001 and 2002. In my view, the second approach better reflects industry trends since the fate and fame of individual artists fluctuates, often rapidly. Similarly, we would expect the data in this application to be less subject to hard-to-model popularity swings when analyzing them at the label level.

where $y_{it\ell}$ is the outcome variable of interest for artist i on label ℓ in year t. $warner_{it\ell}$ is an indicator that equals 1 if, as of year t, artist i's last album was released with Warner. D_t is an indicator which equals one in the year of the blackout, $t = 2009$. $X_{it\ell}$ is a vector of artist-time-label level characteristics. α_t is a vector of time fixed effects, and $\varepsilon_{it\ell}$ is the error term. The estimated impact of the blackout is then the OLS estimate $\hat{\beta}_1$, the DD estimator.

The error term $\varepsilon_{it\ell} = \theta_i + \mu_{it\ell}$ decomposes into an artist-specific effect θ_i and an idionsyncratic component $\mu_{it\ell}$. The term θ_i gives rise to serial correlation in the error terms. For example, the error Elton John in 2008 is likely to be correlated with the error for Elton John in 2009. I correct for this by clustering at the artist level. At the same time, the experimental design has clustered treatment so error terms should be clustered at the recording label level (Abadie, Athey, Imbens and Wooldridge, 2017). Since neither cluster nests the other, I implement the two-way cluster procedure described in Cameron and Miller (2015).

7 Empirical Results

I begin by estimating model (6.1) with log revenues as the outcome variable. I exclude artist characteristics given the analyis in Section 5.2. The OLS estimators of the key parameters in equation (6.1) are displayed in Table 5. Results are reported across columns for the 2006-2012 sample, 2006-2009 sample, and for the 2008-2009 sample, respectively. In all regressions the DD estimator is negative and statistically significant, implying that the blackout lowered Warner artists' relative revenue. As a robustness check, I illustrate in the Appendix in Table 10 that when artist characteristics are included the DD estimate barely changes but the noise increases, as expected.

The magnitude of these effects and the sample size are smaller with shorter time spans. Nevertheless, my preferred time span is the two-year span 2008-2009 because, apart from the YouTube blackout, the environment in the concert and related industries is very similar as described in Section 5.2. The similarity between 2008 and 2009 may be the reason that the precision of the DD estimate is the greatest in the 2008-2009 sample even though the sample size is the smallest.

Longer time spans offer the ability to perforam a variety of robustness checks. First, the results from the other samples show that the negative and statistically significant DD estimate is not and artefact of the sample years. The longer time spans also better account for other time trends and have a larger sample size. Also recall that the parallel trends analysis revealed a dip in Warner revenue in 2011. I ran the model on the 2006-2012 sample as if the blackout occurred in 2011 and did not find a statistically significant DD estimator.

Thus, focusing on the 2008-2009 sample and granting a causal interpretation, the estimate

Table 5: DD estimation of YouTube blackout on log revenues

Dependent Variable: Log of Revenues in 2018 dollars			
	Year Range		
	2006-2012	2006-2009	2008-2009
Warner*Year 2009	-.234*** (.059)	-.224*** (.059)	-.180*** (.035)
Warner[a]	-.042 (.091)	-.052 (.107)	-.096 (.072)
Year 2009[b]	.037 (.107)	.037 (.106)	-.130*** (.019)
Year FE	Y	Y	Y
Observations	1,137	652	328

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts, excluding festivals and tribute bands, for the years indicated in column headings. *Sources*: Pollstar Top 200 North American Tours and allmusic.com.[a]An indicator equal to one if, in the year the artists made the Top 200, his or her album was released on a Warner label.[a]An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

says that the blackout caused the change in Warner artist revenues from 2008 to 2009 to be 18 percentage points lower compared to non-Warner artists. Since the blackout lasted 9 months and the data are annual, this is likely a conservative estimate. A simple adjustment to approximate what the effect would have been if the blackout had lasted the full year would be to multiply this by 4/3. Doing so suggests that Warner revenues during a yearlong blackout would have been 4/3*18=24 percentage points lower.

Revenues can be calculated as the product of ticket price, tickets sold per performance, and the number of performances. Revenues decrease only if one or more of these variables decreases. I estimate via OLS equation (6.1) using the log of price, log of average tickets, log of total tickets, and performances as the dependent variable in the 2008-2009 sample. When I use measures of number of tickets sold, I restrict the sample to artists whose average concert size is 50,000 or less. This eliminates three outliers whose inclusion skewed results.[39] Results are reported in Table 6.

The average ticket price among Warner artists is 11.8 percentage points lower compared to other artists.[40] This estimate is significant at the one percent level. This finding aligns with the key prediction of Proposition 2. Therefore, we cannot reject the Bertrand ticket pricing model in Section 4.

The blackout had statistically zero effect on the typical show size, total tickets sold, or

[39]The outliers were Juan Gabriel in 2008 (51,620), Radiohead in 2009 (109,480) and U2 in 2009 (82,004).

[40]When the average ticket price is used as the dependent variable, the change in price in 2018 dollars is estimated to be $9.43 lower among blacked out artists. This estimate is statistically significant at the one percent level.

Table 6: DD estimation of YouTube blackout on various outcomes, 2008-2009

Dependent variable	Log of Avg. Ticket Price	Log of Tickets/Performance	Log of Total Tickets	Performances
Warner*Year 2009	-.118*** (.010)	-.071 (.044)	.038 (.107)	1.51 (2.59)
Warner[a]	.007 (.036)	-.129 (.103)	-.191*** (.069)	-.148 (2.79)
Year 2009[b]	-.034*** (.010)	-.071*** (.044)	.002 (.100)	1.16 (2.46)
Year FE	Y	Y	Y	Y
Observations	328	325	325	328

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts in 2008 or 2009, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com. [a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label. [b]An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

the number of performances changed. Combined with higher prices, this is consistent with the conclusion that the blackout caused equilibrium relative demand for concerts to fall.

I also ran the same regressions on the 2006-2009 and 2006-2012 samples. Results are reported in Tables 11 and 12 in the Appendix. Results are qualitatively similar except I wish to point out that the estimates for tickets per performance are negative and statistically significant in both samples. This further supports the conclusion that the blackout caused equilibrium relative demand for concerts to fall.

These findings provide evidence that the blackout negatively affected Warner artists' live performance business. However, recall from Table 3 that in 2009 the greatest number of Warner artists made the Top 200 list. So the empirical results could be due to additional Warner artists making the Top 200 near the bottom of the list and therefore pulling down the average. If this is what is driving the results then we might conclude that the blackout helped Warner artists, supportive of the idea that YouTube streaming depresses the demand for live concerts. I explore this concern further in the Appendix and find that the data do not support this conlusion.

7.1 Heterogeneous Treatment Effects

The blackout may not have affected all artists the same way. To explore whether there is a difference for artists at the top, in Table 7 I present estimates for the 2008-2009 sample separately for the top 100 and then for ranks 101-200. For both groups the impact on revenue is negative and statistically significant. The DD estimate on price is negative and significant for the top 100 but statistcally zero for 101-200. The reverse is true for the typical show

Table 7: DD Estimation of YouTube blackout on various outcomes, 2008-2009, by rank cohort

Dep. var	Log of Rev.	Log Avg. Ticket Price	Log Tickets/Perf.	Log Total Tickets	Perfor-mances
Panel A: Ranks 1-100					
Warner* Year 2009	-.255** (.118)	-.314*** (.015)	.026 (.081)	.087 (.119)	3.23 (4.41)
Warner[a]	.050 (.058)	.182*** (.029)	-.194*** (.06)	-.139** (.063)	1.82 (3.35)
Year 2009[b]	.008 (.131)	.036*** (.007)	-.079 (.080)	-.058 (.108)	1.87 (4.18)
Year FE	Y	Y	Y	Y	Y
Obs.	163	163	161	161	163
Panel B: Ranks 101-200					
Warner* Year 2009	-.237*** (.017)	.023 (.027)	-.211** (.091)	-.139 (.200)	-.725 (2.47)
Warner[a]	.018 (.029)	-.092** (.044)	.051 (.099)	-.009 (.226)	-.431 (2.88)
Year 2009[b]	-.204*** (.018)	-.096*** (.027)	-.157 (.091)	.116 (.199)	.775 (.248)
Year FE	Y	Y	Y	Y	Y
Obs.	165	165	164	164	165

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts in 2008 or 2009, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com.[a] An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label.[b] An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

size. It appears the blackout affected both groups but that artists in the top 100 had more of a strategic price response than the next 100.

Heterogeneous treatment effects may be due to charateristics of an artists' fan base. For example, Willie Nelson and Diana Krall's concert audiences were probably less influenced by YouTube in 2008-2009 compared to those of Taylor Swift or the Spice Girls. The former group of artists is likely less affected by the blackout than the latter. To capture this idea, I run the model on the subsample of artists who had a song in the weekly *Billboard* Hot 100 chart in the year or year before the artist made the Top 200.[41] The hypothesis is that "hot" songs drive traffic to YouTube for those songs and artists (the exploration effect), and this in turn helps promote the artists' tours as discussed in Section 2. Thirty-three percent of artists in the Top 200 in this sample had a recent Hot 100 song. Results are presented in Panel A of Table 8.

The estimated impact of the blackout on this subsample is more negative on every out-

[41] I have also run a model on the full sample where Hot 100 status is interacted with the treatment variable. The results are similar, if not larger in magnitude, to those reported here.

come variable compared to the full sample with the exception of performances, in which case we again observe no statistically significant effect. The change in revenues were down 47.6 percentage points, and ticket prices were 16.8 points lower. Average tickets sold were 16.6 points lower and statistically significant at the one percent level. Total tickets sold were down 30.2 points. Thus, for this subsample the evidence provides stronger support for the conclusion that the blackout caused relative demand to fall. The number of performances does not seem to have changed for this group, either. It appears "hot" artists were affected by the blackout more than other artists.[42]

Even though the Hot 100 formula did not weigh streaming heavily at the time of the data, it is possible that the blackout reduced the chances a song would make it to this list. This fact may be driving the results in panel A of Table 8. To capture this effect I ran the model again on the recent Hot 100 subsample while controling for the log of the number of normalized YouTube searches. Since the YouTube search data exists for less than 90 percent of the original sample, I also reran the original model on the subset of recent Hot 100 artists for whom search data exists. This facilitates a more direct comparison. The results for the model without search data are presented in panel B of Table 8; the results with the search data are presented in panel C. Comparing the panels we can see that the magnitude of the estimates is smaller when the search data are included, but remain larger compared to the original estimates using the top 200.

Finally, using the top 200 sample for 2008-2009, I interact the DD term with the number of YouTube searches for an artist in 2008.[43] To be precise, I estimate the equation

$$\begin{aligned} y_{it\ell} =& \beta_0 + \beta_1 warner_{it\ell} + \beta_2 lnYT_i + \beta_3 D_t + \beta_4 warner_{it\ell} * D_t \\ &+ \beta_5 warner_{it\ell} * lnYT_i + \beta_6 lnYT_i * D_t + \beta_7 warner_{it\ell} * D_t * lnYT_i + \varepsilon_{it\ell}, \end{aligned} \tag{7.1}$$

where $lnYT_i$ is the log of the normalized number of YouTube searches for artist i in 2008. The other variables have the same interpretation as in equation 6.1. In this set-up the DD estimate is a linear function of YouTube searches: $\hat{\beta}_4 + \hat{\beta}_7 lnYT_i$. The parameter $\hat{\beta}_7$ is the marginal effect of searches on the DD estimate.

The estimated parameters of equation (7.1) are presented in Table 9 for various outcomes. The number of YouTube searches has a negative an significant impact on revenues. This

[42]To be clear, artists without a recent Hot 100 song were also affected by the blackout. Running the model on this subsample gives statistically and economically significant estimates for log revenues (b=-.107, $s.e.$=.052) and log average ticket price (b=-.099, $s.e.$=.004). The estimates for log average tickets sold (b=-.084, $s.e.$=.127), log total tickets (b=-.176, $s.e.$=.152), and performances (b=-1.08, $s.e.$=3.68) were not statistically significant, however.

[43]In this exercise we do not want to use search data for 2009 since the blackout likely affected the number of searches of a Warner artist.

Table 8: DD Estimation of YouTube blackout on Hot 100 subsample, 2008-2009

Dep. var	Log of Rev.	Log Avg. Ticket Price	Log Tickets/Perf.	Log Total Tickets	Perfor-mances
Panel A: No YouTube search data					
Warner* Year 2009	-.476*** (.131)	-.168*** (.030)	-.166*** (.058)	-.302*** (.111)	-1.29 (3.03)
Warner[a]	-.317*** (.066)	-.098*** (.030)	-.208*** (.067)	-.219** (.087)	1.43 (2.30)
Year 2009[b]	.151 (.131)	-.078*** (.030)	-.074 (.058)	.219** (.111)	6.10** (3.04)
Obs.	108	108	106	106	108
Panel B: No YouTube search data; Using only obs. for which YT data exist					
Warner* Year 2009	-.463*** (.145)	-.193*** (.043)	-.082 (.056)	-.262** (.113)	–3.18 (3.34)
Warner[a]	-.250*** (.072)	-.077** (.031)	-.192** (.087)	-.174* (.101)	2.48 (2.32)
Year 2009[b]	.167 (.145)	-.078* (.043)	-.040 (.056)	.234** (.113)	5.78* (3.34)
Obs.	95	95	93	93	95
Panel C: With YT search data					
Warner* Year 2009	-.341*** (.084)	-.157*** (.056)	.007 (.053)	-.176* (.089)	-2.96 (3.51)
Warner[a]	-.351*** (.042)	-.107** (.051)	-.266*** (.030)	-.244*** (.048)	2.31 (2.46)
Year 2009[b]	-.341*** (.113)	-.115** (.056)	-.131** (.054)	.146* (.088)	5.56 (3.52)
Log YouTube Searches[c]	.221*** (.084)	.064** (.026)	.160** (.081)	.154** (.069)	.394 (1.19)
Obs.	95	95	93	93	95

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. Year fixed effects are included in all regressions. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts in 2008 or 2009, excluding festivals and tribute bands, and who also hat a song in the Hot 100 either the year of observation or the year before. *Sources*: Pollstar Top 200 North American Tours and allmusic.com. [a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label. [b]An indicator equal to one if the year of observation is 2009. [c]A normalized measure of the number of searches on YouTube for a given artist in 2008. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

Table 9: Linear-in-YouTube-searches DD estimation of the blackout with comparisons, 2008-2009

Dep. var	Log of Rev.	Log Avg. Ticket Price	Log Tickets/Perf.	Log Total Tickets	Perfor-mances
$\hat{\beta}_1$	-.023 (.092)	.088** (.039)	-.177* (.101)	-.405*** (.068)	.087 (.086)
$\hat{\beta}_2$	-.185*** (.041)	-.029 (.023)	-.134*** (.049)	-.074 (.118)	-.052 (.077)
$\hat{\beta}_3$	.203*** (.044)	.008 (.019)	.269*** (.044)	.293*** (.100)	-.066** (.026)
$\hat{\beta}_4$	-.114** (.056)	-.195*** (.023)	.102* (.056)	.384*** (.127)	-.001 (.081)
$\hat{\beta}_5$	.002 (.044)	-.028 (.019)	.086* (.044)	.261*** (.101)	-.064** (.026)
$\hat{\beta}_6$	.080* (.044)	-.005 (.033)	-.026 (.046)	-.016 (.096)	.082 (.065)
$\hat{\beta}_7$	-.088** (.045)	.037 (.032)	-.132*** (.046)	-.352*** (.096)	.037 (.065)
Obs.	286	286	283	283	286

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. Year fixed effects are included in all regressions. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts in 2008 or 2009, excluding festivals and tribute bands, and who also hat a song in the Hot 100 either the year of observation or the year before. *Sources*: Pollstar Top 200 North American Tours and allmusic.com.[a] An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label.[b] An indicator equal to one if the year of observation is 2009. See equation (7.1) and the text for in interpretation of the beta hats in Panel B. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

means that Warner artists who were searched more on YouTube in 2008 were more affected in 2009 by the blackout. This finding is consistent with the Hot 100 analysis and suggests that concert success rises with streaming volume. The marginal search effect is statistically zero for price and performances, but negative and significant for both measures of quantity.

8 Discussion and Conclusion

This paper has found evidence that removing Warner content from YouTube lowered relative revenue, prices and tickets sold for live concerts among Warner artists. These findings were more pronounced among artists with a recent Hot 100 song and those who were searched more often on YouTube just prior to the blackout. The plausibly causal estimates were based on the unexpected removal of Warner content from YouTube in the first three quarters of 2009 and its effect on Warner artists who made the annual Pollstar Top 200 North American Tours. The licensing dispute between YouTube and Warner was likely orthogonal to events in the live concert industry since neither Warner nor YouTube had a significant stake in the industry at the time.

More broadly, this paper demonstrates with sales data that streaming has a stimulative effect on live music, bolstering research based on consumer surveys (see Nguyen et al., 2014; Jin and Oh, 2019; Montoro-Pons and Cuadrado-García, 2011). It also updates the environment in Mortimer et al. (2012) and features heterogeneous treatment (only Warner artists were subject to treatment) compared to uniform treatment (all artists were exposed to the Napster launch simultaneously). While both studies find evidence that digitization primarily affected demand, with uniform treatment it is difficult to separate out demand shocks from supply shocks. However, with heterogeneous treatment any supply shock in 2009 that affected artists in the same way would be canceled out in the DD estimate, thus plausibly isolating a demand shock.

The empirical analysis is also consistent with a Bertrand model of concert pricing in which prices are strategic complements and profit functions have increasing (decreasing) differences in ticket prices and own (rival's) streaming penetration rates. This model allows quantity and price to move in the same direction (down) with the blackout, whereas Krueger (2005) builds the model to explain an increase in price with a decrease in quantity. More broadly, the model is an example of how the monotone comparative statics literature can be adapted for use with reduced form DD estimation. The clear comparative statics prediction that relative prices do not increase with the blackout, coupled with widely-used empirical techniques, are what allows the model to be refuted not just in theory, but in practice.[44]

The main limitation to this research is that the concert revenue data are restricted to annual data on the top 200 concerts. I have addressed the implications for estimation in the paper, but it also means we have to take care in thinking about how broadly these results apply. Many artists in the top 200 have recently had a Hot 100 song, but at the same time there are many artists with a Hot 100 song that do not make rank in the top 200 concerts. It is quite likely that the *discovery and exploration effect* described in Section 2 applies to the latter group of artists as well. In fact, artists outside of the top 200 are likely to benefit more from the *discovery effect* since they are less likely to be broadly known. For these reasons I suspect that streaming stimulates the demand for live concerts for artists outside of the top 200 as well, but the magnitude of the effect is probably different.

Moreover, the experiment in this paper relates to streaming of recorded videos, so do the results generalize to audio streaming? I think the qualitative results in the paper generalize to audio streaming. Without the video component there is less of an emotional connection to the artist, so audio streaming is a worse substitute for live music than video streaming. At the same time, the discovery and exploration effect, the preparation effect, and the souvenir effect apply to audio streaming, so one could argue that the audio streaming is

[44] Samuelson (1948) and Silberberg (1978) emphasize the need for theory to make refutable predictions, but do not provide guidance on how to take their predictions to the data.

more stimulative of live music than video streaming.

Finally, the music industry has evolved since 2012. According to Music & Copyright the major labels retain 69 percent of market share as of 2019. But streaming subscription rates have risen considerably, perhaps due in part to new technology such as smart speakers and apps like CarPlay and Anroid Auto which make these services more convenient to use. Labels are also pursuing more 360 deals and are integrating more with streaming services. I suspect that these developments have strengthened the complementarity between streaming and live music. This suspicion is at least plausible given the continued rise of the live music industry documented in Figure 1.1a since 2012.

9 Appendix

This Appendix provides a proof, additional results tables, and additional robustness analysis.

9.1 Proof

The following is a proof of Proposition 2.

The regularity conditions satisfy the conditions of Part 4 of Proposition 5 in Christensen (2019). Hence, there is a unique, non-zero equilibrium.

The profit maximizing condition analoguous to condition (4.1) applies to both firms. The only differences are that the price vector now includes competitor prices and that the streaming penetration rate $\lambda = (\lambda_w, \lambda_{nw})$ is now a 2-vector. Collect the first order derivatives into a vector $\nabla\Pi(p,\lambda) = \left(\frac{\partial \pi_w(p;\lambda)}{\partial p_w}, \frac{\partial \pi_{nw}(p;\lambda)}{\partial p_{nw}}\right)^T$. As usual, the Nash equilibrium $p_1^* \equiv (p_w^*, p_{nw}^*)$ is the price vector which satisfies $\nabla\Pi(p,\lambda)|_{p_1=p_1^*} = 0$. By the Implicit Function Theorem the equilibrium effect of an increase in Warner's streaming market penentration is $Dp_1(\lambda) = -\left[D_{p_1}\nabla\Pi(p,\lambda)\right]^{-1} D_\lambda \nabla\Pi(p,\lambda)$, evaluated at equilibrium. Letting $D \equiv \det\left(D_{p_1}\nabla\Pi(p,\lambda)\right)$, we have

$$\begin{bmatrix} \frac{dp_w}{d\lambda_w} \\ \frac{dp_{nw}}{d\lambda_w} \end{bmatrix} = -\frac{1}{D}\begin{bmatrix} \frac{\partial^2 \pi_{nw}}{\partial p_{nw}^2} & -\frac{\partial^2 \pi_w}{\partial p_w \partial p_{nw}} \\ -\frac{\partial^2 \pi_{nw}}{\partial p_{nw}\partial p_w} & \frac{\partial^2 \pi_w}{\partial p_w^2} \end{bmatrix}\begin{bmatrix} \frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w} \\ \frac{\partial \pi_{nw}}{\partial p_{nw}\partial \lambda_w} \end{bmatrix}.$$

Thus,

$$\begin{aligned} \frac{dp_w}{d\lambda_w} &= -\frac{1}{D}\left[\frac{\partial^2 \pi_{nw}}{\partial p_{nw}^2}\frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w} - \frac{\partial^2 \pi_w}{\partial p_w \partial p_{nw}}\frac{\partial^2 \pi_{nw}}{\partial p_{nw}\partial \lambda_w}\right], \text{ and} \\ \frac{dp_{nw}}{d\lambda_w} &= -\frac{1}{D}\left[\frac{\partial^2 \pi_w}{\partial p_w^2}\frac{\partial^2 \pi_{nw}}{\partial p_{nw}\partial \lambda_w} - \frac{\partial^2 \pi_{nw}}{\partial p_{nw}\partial p_w}\frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w}\right]. \end{aligned}$$

It follows that

$$\frac{dp_w}{d\lambda_w} - \frac{dp_{nw}}{d\lambda_w} = -\frac{1}{D}\left[\frac{\partial^2 \pi_{nw}}{\partial p_{nw}^2} + \frac{\partial^2 \pi_{nw}}{\partial p_{nw}\partial p_w}\right]\frac{\partial^2 \pi_w}{\partial p_w \partial \lambda_w} + \frac{1}{D}\left[\frac{\partial^2 \pi_w}{\partial p_w^2} + \frac{\partial^2 \pi_w}{\partial p_w \partial p_{nw}}\right]\frac{\partial \pi_{nw}}{\partial p_{nw}\partial \lambda_w}.$$

The regularity condition implies $D > 0$. The results follow immediately.

9.2 Additional Empirical Results

Table 10: Log of Revenues in 2018 dollars, with artist characteristics

Dependent Variable: Log of Revenues in 2018 dollars			
	Year Range		
	2006-2012	2006-2009	2008-2009
Warner*Year 2009	-.235*** (.033)	-.197*** (.068)	-.185*** (.071)
Warner[a]	-.050 (.521)	-0.89 (.113)	-.096 (.089)
Year 2009[b]	.070 (.090)	.060 (.096)	-.045 (.051)
Billboard Hot 100 status[c]			
0-1 years	.800*** (.127)	.726*** (.152)	.854*** (.171)
2-10 years	-.113 (.079)	.142 (.124)	.195 (.143)
Years since debut album[d]			
0-10 years	-.630*** (.098)	-.644*** (.156)	-.596*** (.109)
11-20 years	-.289*** (.078)	-.375** (.171)	-.457*** (.010)
21-30 years	-.122 (.104)	-.181 (.173)	−.104 (.123)
Years since last album	.000 (.009)	-.001 (.015)	.001 (.002)
Pop/rock artist	.099 (.111)	.159 (.129)	.175 (.145)
Solo show[e]	.053 (.769)	.078 (.250)	.162 (.318)
Year fixed effects	Y	Y	Y
Observations	1,132	650	326

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts, excluding festivals and tribute bands, for the years indicated in column headings. *Sources*: Pollstar Top 200 North American Tours and allmusic.com. [a]An indicator equal to one if, in the year the artists made the Top 200, his or her album was released on a Warner label. [b]An indicator equal to one if the year of observation is 2009. [c]Years since an artist had a song in the Hot 100. The reference group is artists who never had a Hot 100 song. [d]The reference group is artists whose first album was released 31 years or more before they made the Top 200. [e]An indicator equal to one if the artist did not co-headline a tour. [d]An indicator equal to one if in the year of observation the artist's last album was released under the Warner label. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

Table 11: DD estimation of YouTube blackout on various outcomes, 2006-2009

Dependent variable	Log of Avg. Ticket Price	Log of Tickets/Performance	Log of Total Tickets	Performances
Warner*Year 2009	-.108*** (.013)	- .203***(.059)	-.077 (.071)	4.37*** (1.57)
Warner[a]	-.003 (.051)	.003 (.072)	-.077** (.030)	-3.01*** (.838)
Year 2009[b]	.101*** (.023)	.110 (.101)	-.062 (.105)	-5.44*** (1.96)
Year FE	Y	Y	Y	Y
Observations	652	645	645	652

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts 2006-2009, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com.[a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label.[b]An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

Table 12: DD estimation of YouTube blackout on various outcomes, 2006-2012

Dependent variable	Log of Avg. Ticket Price	Log of Tickets/Performance	Log of Total Tickets	Performances
Warner*Year 2009	-.070*** (.016)	- .199***(.061)	-.136** (.065)	1.58 (1.09)
Warner[a]	-.042 (.045)	-.001 (.069)	-.028 (.030)	-.199 (.894)
Year 2009[b]	.096*** (.030)	.109 (.281)	-.053 (.104)	-5.02** (2.10)
Year FE	Y	Y	Y	Y
Observations	1137	1125	1125	1137

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts 2006-2012, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com.[a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label.[b]An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

Table 13: DD estimation of YouTube blackout on various outcomes with artist characteristics, 2008-2009

Dependent variable	Log of Avg. Ticket Price	Log of Tickets/Performance	Log of Total Tickets	Performances
Warner*Year 2009	-.118*** (.027)	-9.67*** (1.74)	-.036 (.137)	1.21 (.276)
Warner[a]	.048 (.056)	4.32 (4.11)	-.204** (.097)	-.215 (3.08)
Year 2009[b]	-.002 (.023)	.174 (1.72)	.082 (.090)	1.01 (2.70)
Billboard Hot 100 status[c]				
0-1 years	.141*** (.051)	8.43*** (2.74)	.769*** (.086)	2.01 (3.24)
>2 years	.095*** (.037)	4.94 (3.32)	.062 (.236)	.995 (2.64)
Years since debut album[d]				
0-10 years	-.457*** (.058)	-44.7*** (4.68)	-.114 (.105)	5.42* (3.23)
11-20 years	-.368*** (.046)	-27.4*** (4.03)	-.049 (.096)	3.16 (3.14)
21-30 years	-.127** (.061)	-12.7*** (4.63)	-.238 (.320)	-2.26 (3.64)
Years since last album	-.002 (.003)	-.222 (.247)	.010** (.005)	-.097 (.222)
Pop/rock artist	-.057* (.031)	-.749 (2.15)	.249 (.219)	2.14 (3.19)
Solo show[e]	.098 (.072)	5.86 (5.19)	.012 (.236)	12.5*** (3.30)
Year FE	Y	Y	Y	Y
Observations	326	326	323	326

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts 2006-2012, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com. [a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label. [b]An indicator equal to one if the year of observation is 2009. [c]Years since an artist had a song in the Hot 100. The reference group is artists who never had a Hot 100 song. [d]The reference group is artists whose first album was released 31 years or more before they made the Top 200. [e]An indicator equal to one if the artist did not co-headline a tour. [d]An indicator equal to one if in the year of observation the artist's last album was released under the Warner label. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

Table 14: DD estimation of YouTube blackout on various outcomes, 2008-2009, for artists with more than 12 shows

Dependent variable	Log of Rev.	Log of Avg. Ticket Price	Log of Tickets/Performance	Log of Total Tickets	Performances
Warner*Year 2009	-.145*** (.038)	-.090*** (.018)	- .199***(.061)	-.037 (.052)	.050 (.110)
Warner[a]	-.120 (.073)	-.014 (.036)	-.001 (.069)	-.148 (.096)	-.198*** (.071)
Year 2009[b]	-.141*** (.024)	-.041** (.017)	.109 (.281)	-.141*** (.048)	-.003 (.103)
Year FE	Y	Y	Y	Y	Y
Observations	325	325	325	322	322

Notes: Robust standard errors are reported in parentheses and corrected for two-way clustering on artist and label. *Sample*: Artist-years that made the Pollstar Top 200 North American Tours as musical acts 2006-2012, excluding festivals and tribute bands. *Sources*: Pollstar Top 200 North American Tours and allmusic.com. [a]An indicator equal to one if, in the year the artist made the Top 200, his or her album was released on a Warner label. [b]An indicator equal to one if the year of observation is 2009. *Significant at the 10 percent level, **Significant at the 5 percent level, ***Significant at the 1 percent level.

9.3 Additional Robustness Analysis

These findings provide evidence that the blackout negatively affected Warner artists' live performance business. However, recall from Table 3 that in 2009 the greatest number of Warner artists made the Top 200 list. So the empirical results could be due to additional Warner artists making the Top 200 near the bottom of the list and therefore pulling down the average. If this is what is driving the results then we might conclude that the blackout helped Warner artists, supportive of the idea that YouTube streaming depresses the demand for live concerts. This would be an interesting finding, but I do not believe the data support it for the following reasons.

First, I restricted the sample for the main analysis to 2008 and 2009. In 2009 Warner had only 2 more artists make the Top 200 compared to 2008. The fact that 2008 and 2009 were strong years for Warner may simply reflect a good couple of years in "Artists and Repertoire."

Second, looking at the distribution of ranks among Warner artists in Figure 9.1, it appears that 2009 is more heavily weighted to the bottom compared to 2008. The artists at the bottom of the distribution would most significantly contribute to the demand depression hypothesis, but the distribution in 2009 would still be bottom heavy compared to 2008 even if one were to reduce the last bar in 2009 from 9 to 7.

Third, as a more formal check, I reran the regressions for the 2008-2009 sample after removing the two lowest ranking Warner artists of 2009, Seal (rank 195) and Dream Theater (rank 197). For this sample the DiD estimate for log revenues is -.123 (s.e. = .035); for log of average ticket price it is -.124 (s.e. = .010); for log of average tickets sold it is -.023 (s.e.

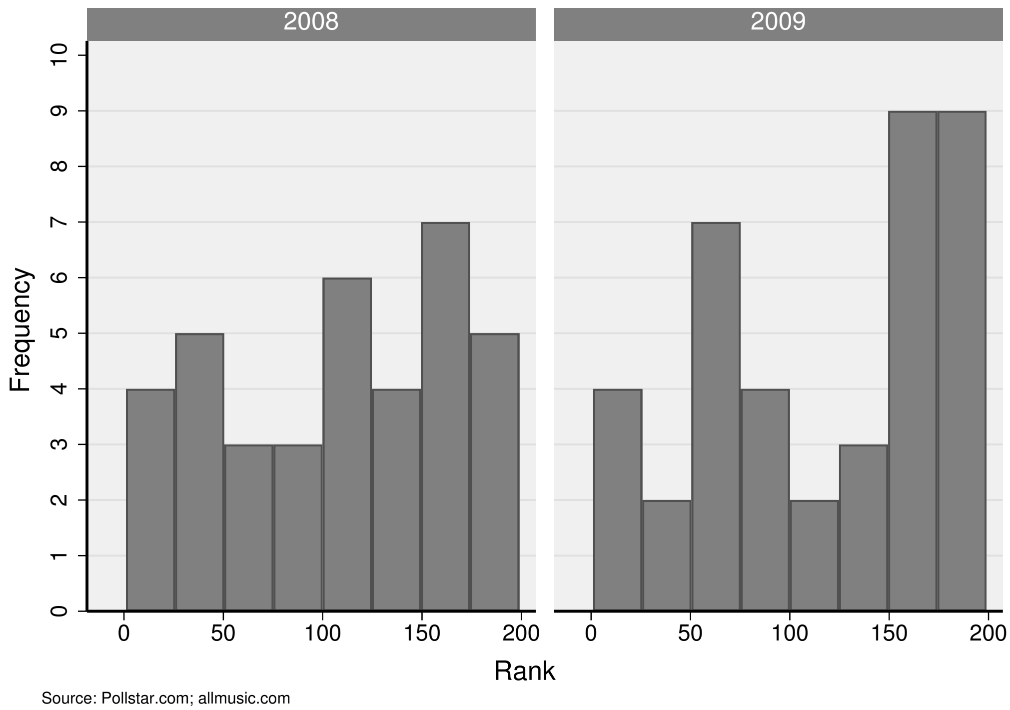


Figure 9.1: Histogram of Warner Ranks by Year

= .044); for log of total tickets it is .100 (s.e. = .107); and for the number of performances it is 2.04 (s.e. = 2.40). These findings are broadly consistent with the original estimates reported in Table 5 (column 3) and Table 6. Thus, additional artists at the bottom of the ranking are not driving the results.

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