From Courtrooms to Charts: The Impact of Kavanaugh's Appointment on Music Consumption

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Abstract

This study provides evidence of increased music streams for female performers in the United States, particularly for songs with sexist and empowering lyrics. Using streaming data from Spotify's top 200 songs, a difference-in-differences analysis reveals a significant rise of at least 16% in streams of songs by female artists, underscoring shifts in consumer behaviour linked to gender representation in music. In particular, we explore the impact of Brett Kavanaugh's Supreme Court appointment, a socio-political event that intensified media focus on gender issues. The findings suggest that this heightened attention contributed to the observed changes in listening patterns post-appointment. The results are robust against potential confounders such as seasonal trends and Spotify's promotional activities. This research contributes to understanding political consumerism, showing how significant socio-political events can influence consumer preferences in seemingly unrelated sectors like the music industry. It underscores the importance of adaptive strategies in digital marketplaces in response to external socio-political changes, and highlights the broader societal implications of major events on consumer behaviour and attitudes, particularly concerning gender imbalances.

Keywords: Gender Equality, Music Industry, Social Movements, Political Consumerism

JEL codes: J16, L82

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1. Introduction

In recent years, gender inequality and sexual misconduct have come under increased public scrutiny, driven by social movements and high-profile events that have focused media attention on these issues. Despite their prominent exposure, the tangible impact of these events on everyday behaviour is still being actively studied (Castle, Jenkins, Ortbals, Poloni-Staudinger and Strachan, 2020; Lins, Roth, Servaes and Tamayo, 2022; Levy and Mattsson, 2023). Does the increased media emphasis on gender inequality and women's rights function primarily as an awareness-raising tool, or does it also have the potential to affect changes in everyday behaviour?

To explore, I focus on a pivotal event that sparked public discourse on sexual misconduct: Brett Kavanaugh's appointment to the Supreme Court in October 2018. In this paper, I analyse how the increased media coverage of this event affected music consumption patterns. Specifically, I examine the impact of Kavanaugh's appointment on the streaming numbers of the top 200 songs in the US on Spotify. Using a difference-in-differences approach, I show an increase of at least 16% in the number of streams of songs by female artists, as opposed to male artists, within more than 60 days following Kavanaugh's appointment. An event-study analysis shows that songs by female and male artists followed comparable trends in terms of streaming numbers in the weeks before Brett Kavanaugh's appointment (October 8, 2018), with an increase in streams right after October 8 for songs performed by female artists. This increase in streaming is most pronounced in the first weeks after the appointment and persists for at least eight weeks into the winter holiday season. My results are robust to the inclusion of artists, songs, and time fixed effects. Moreover, they retain their robustness regardless of the method used to define treated and control groups, particularly when considering collaborations between artists of the same gender or individual female and male artists. With a back-of-the-envelope calculation, I estimate that this shift in music consumption is equivalent to an increase of at least US$120 in daily Spotify royalties for female artists associated with the increased streaming of their songs.

In this analysis, I show that significant events that draw media attention to issues of sexual misconduct and women's rights can influence everyday consumption decisions. This finding is consistent with previous research documenting the significant societal impact of the #MeToo movement. Luo and Zhang (2022) find that the hiring of female film writers by producers significantly increased following the Weinstein scandal in October 2017, especially for producers related to Harvey Weinstein. Additionally, Levy and Mattsson (2023) show a surge in the reporting of sexual crimes in countries with prominent #MeToo movements. More closely related to Kavanaugh's appointment, Gelman (2021) shows that US senators' communications changed after Kavanaugh's confirmation, with senators becoming more inclined to engage in partisan behaviour and get involved in partisan disputes. In comparison to these studies, my research explores a different aspect of behaviour and consumption that is not limited to specific groups (such as film producers, or senators) and examines an activity that is less critical but far more widespread than the reporting of sexual abuse.

The music industry provides a compelling context to study the impact of social movements on consumption patterns. First, changes in music consumption can be directly measured through the streaming of songs by different artists. Additionally, the gender of the artist is typically a distinct and easily identifiable aspect of his artistic output. Unlike other forms of consumption goods or artistic expression, such as movies, a song is performed by an individual or group of artists, leading listeners to commonly associate a song with the artists and their traits.

My estimates capture the relative increase in streaming numbers for songs by female artists compared to their male counterparts. In doing so, my approach also accounts for potential negative effects on male artists. However, I believe that the magnitude of these negative effects is minimal. Throughout the analysis period, streaming numbers for male artists remained stable. In addition, my analysis did not find significant differences when comparing male artists' songs with similar characteristics to those of female artists and may be more susceptible to being replaced by female artists' songs. Finally, the observed increase in streams for female artists' songs holds up even when I use songs by groups or multi-artist collaborations as a control group.

My data come from the US Spotify charts. While I cannot rigorously test the possibility that the platform may have promoted certain artists during this period, such promotion did not appear to occur through Spotify's most prominent "New Music Friday" playlist, which did not feature a higher number of female artists during my analysis period. Additionally, I can rule out seasonal effects or the presence of confounding effects related to the new entry of a few songs by top artists. Placebo analyses conducted in 2017 and 2019 show similar streaming patterns for male and female artists, with no notable changes over the same months. The robustness of my results is also confirmed when I restrict my analysis to artists outside the top five daily streams.

Finally, the music industry is particularly appealing for this study because I can analyse the lyrics of each song. This allows us to examine whether the impact is more pronounced for songs with sexist terms in their lyrics. When I focus on such songs, I observe an effect that is larger in magnitude and longer lasting, suggesting that sexist terms play a different role for female and male artists, and that media attention to gender issues had a specific impact on this subset of songs.

My research contributes to the understanding of gender imbalances in the music industry. Previous studies have primarily focused on describing gender representation in the field (Smith, Choueiti, Pieper, Clark, Case and Villanueva, 2018; Epps-Darling, Cramer and Bouyer, 2020; Aguiar, Waldfogel and Waldfogel, 2021). In contrast, my work examines how these gender imbalances, particularly in terms of consumer preferences for different artists, are not static but can be influenced by external events. Given the significant political implications of the Kavanaugh appointment, my study also adds to the emerging literature on political consumerism and how politics affect consumer preferences.

Brett Kavanaugh's confirmation process was highly contentious, marked by allegations of sexual assault, intense political debate, and extensive media coverage.[1] The confirmation to the Supreme Court was finalized with a particularly narrow Senate vote of 50-48, one of the closest margins in American history for a Supreme Court nominee. His appointment shifted the ideological balance of the Court, as Kavanaugh is perceived to have a more conservative stance on various issues, including abortion. This shift was considered pivotal in the context of abortion rights, increasing the likelihood of the Supreme Court adopting positions less supportive of the precedent set by Roe v. Wade.[2]

Given the nature of Kavanaugh's accusations and his ideological leanings, my work shows that the heightened political polarization had an impact on consumer preferences, particularly regarding goods such as songs that are easily associated with the gender of artists. This is in line with the recent work by Schoenmueller, Netzer and Stahl (2023), which shows increased polarization in preferences and purchase decisions after the election of Donald Trump in 2016. In this case, the change in consumption did not regard brands or products that take a stance on a specific topic or endorse a political figure (Hydock, Paharia and Blair, 2020; Hambrick and Wowak, 2021; Bondi, Burbano and Dell'Acqua, 2022; Liaukonytė, Tuchman and Zhu, 2023). Rather, it concerned products associated with a particular movement or ideology due to a product feature, irrespective of the ideology of the sellers or producers. In this respect, my work is akin to previous studies demonstrating the boycott of French products by American consumers during the dispute between France and the US over the Iraq War (Chavis and Leslie, 2009; Pandya and Venkatesan, 2016).

Finally, my work contributes to the literature on the design of digital marketplaces and how gender or racial imbalances affect these platforms. Platform design choices, including algorithms and featured content, have a significant impact on the popularity of products, such as songs in this context. These platforms must recognize and adapt to external factors and events that may exacerbate or mitigate existing imbalances. In my case, the political climate following Kavanaugh's confirmation provided a positive boost to female artists, thereby reducing gender imbalances. However, platforms must remain proactive, employing adaptive strategies when certain events risk exacerbating gender or racial discrimination (Luca, Pronkina and Rossi, 2022).

2. Empirical Setting and Dataset

The data comes from Spotify's publicly available charts and it contains daily snapshots from September 3, 2018, to December 23, 2018, about the top 200 songs in the US, ranked according to streaming numbers.[3] The data includes metrics such as the number of days a song has appeared on the charts, its daily ranking (from 1,

[1]According to Nielsen's data, the viewership for Brett Kavanaugh's testimony before the US Senate Judiciary Committee on September 27, 2018, exceeded 20 million people. For further reference, see: https://apnews.com/article/caa510f21dcd4c569a4c8ea91f587a44.

[2]For more information, see: https://www.bbc.com/news/world-us-canada-45774174 and https://www.bostonglobe.com/news/politics/2018/07/11/how-judge-brett-kavanaugh-confirmation-could-affect-roe-wade/s1ZbShSQk6rcFfjrV6x1m0/story.html.

[3]For more information, see: https://charts.spotify.com.

the highest, to 200, the lowest), and the number of streams. I enrich my dataset with additional information about songs and albums from Spotify's public APIs. This approach allows us to obtain detailed features for each song. I also gathered copyright holder details, release dates, and other relevant information from Spotify. To determine artist gender, I employed a two-step approach. First, I use the MusicBrainz APIs to retrieve the gender of artists.[4] Then, in case of missing information from MusicBrainz, I retrieve manually the artist's gender using the artist Wikipedia's page or the artist's picture shown on Spotify.[5] Doing so, I identify 57 unique songs performed by a female artist or a collaboration between two female artists, and 385 songs performed by a male artist or a collaboration between two male artists. These songs are performed by 164 unique artists, consisting of 37 female artists and 127 male artists. I also identify 189 songs performed by groups or collaborations of more than two artists.

In the remainder of this Section, I explore the evolving dynamics of public discourse on sexual misconduct, with a particular focus on the appointment of Brett Kavanaugh to the Supreme Court. This high-profile event serves as a pivotal point in my study, as I examine its impact on music consumption patterns. I conclude the Section by presenting descriptive statistics.

2.1. The Kavanaugh Appointment and Its Impact on Public Discourse on Sexual Misconduct

The appointment of Brett Kavanaugh to the Supreme Court represented a pivotal moment in the discourse about sexual misconduct, particularly within the context of the #MeToo movement. Originally sparked to combat sexual harassment and assault, this movement has emerged as a critical force in challenging entrenched societal norms and empowering survivors to voice their experiences.[6] However, Kavanaugh's nomination shifted the focus from the entertainment industry to the upper echelons of political power, highlighting the broader societal implications of these issues (Rhode, 2019, Grover, 2019).

An analysis of the use of the #MeToo hashtag from October 2017 to January 2020 (Appendix Figure A.3) reveals three notable spikes in public engagement. The first spike, in October 2017, coincided with Alyssa Milano's endorsement of the #MeToo hashtag. A subsequent surge occurred on January 7, 2018, following Oprah Winfrey's speech at the Golden Globes.[7] The spike with the longer span coincides with the period of Kavanaugh's nomination (September to October 2018). Figure 1, which narrows the focus to September 2018 to February 2019, shows how the spike in tweets associated with the #MeToo movement in the fall of 2018 is particularly related to Kavanaugh's nomination, as a significant portion of them include the hashtag

[4] MusicBrainz is an open music encyclopedia that collects and makes music metadata publicly available. See: `https://MusicBrainz.org/`.

[5] Solo artists are assigned a gender based on their self-identified gender. See Appendix Figures A.1 and A.2 for screenshots of MusicBrainz and Spotify artist webpages used to retrieve artists' gender.

[6] For an overview, see: `https://en.wikipedia.org/wiki/MeToo_movement`.

[7] See `https://twitter.com/Alyssa_Milano/status/919659438700670976` and `https://www.nytimes.com/2018/01/07/movies/oprah-winfrey-golden-globes-speech-transcript.html` for more details.

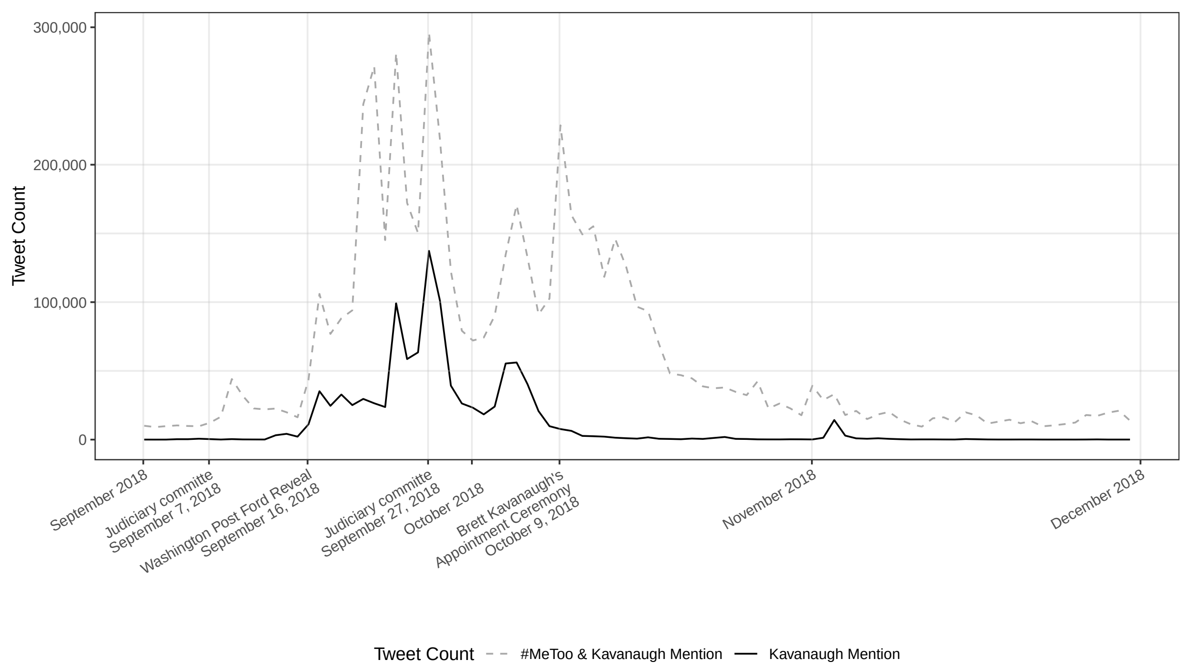

Figure 1. #MeToo and #Kavanaugh Tweet Counts Over Time

Notes: This figure shows the daily number of tweets containing the #MeToo hashtag (solid line) and the number of tweets containing the #MeToo and #Kavanaugh hashtags or mentioning the word "Kavanaugh" in the tweet (dotted line) from September 2018 to February 2019, as extracted from the public Harvard Dataverse (Maiorana, Morales Henry and Weintraub, 2023).

#Kavanaugh or mention the word “Kavanaugh” in the tweet.

The sexual assault allegations against Kavanaugh during this period intensified media scrutiny and sparked widespread public discourse.[8] These events marked a critical expansion of the movement's scope beyond the confines of the entertainment industry to address broader social and political concerns. This expansion is consistent with the findings of Levy and Mattsson (2023), which found that while the spike in Google searches about the #MeToo movement began in October 2017, media coverage of sexual assault spiked in the months leading up to Kavanaugh's confirmation.

Kavanaugh's nomination thus marked a pivotal point in the discourse on sexual misconduct, with significant implications for gender politics in the United States. Jennifer Lawless, Commonwealth Professor of Politics at the University of Virginia, underscored the broader implications: “The stakes here go beyond our societal perceptions of women's roles to the future of Roe v. Wade and women's reproductive rights.”[9]

Taking advantage of the heightened focus on gender-related policies during Kavanaugh's nomination to the Supreme Court, my study seeks to examine how increased public interest in specific issues might influence consumer behaviour, with a particular focus on music consumption patterns.

2.2. Data Description

My analysis spans from Monday, September 3, 2018 to Sunday, December 23, 2018. I select this time window to examine the impact of Brett Kavanaugh's public appointment ceremony on October 7, 2018 and avoid the variability often observed in summer chart movements.

Table 1 presents summary statistics derived from the Spotify chart dataset during this period. Here, I compare songs by female and male artists, focusing on various aspects such as average song performance on Spotify, artist popularity, and song characteristics. In Appendix Table A.3, I perform a similar analysis, this time comparing songs by female artists with those by groups. My unit of observation remains at the song/daily snapshot level throughout my analysis.

Songs performed by female artists account for 2,120 observations in the daily top 200 charts, while those performed by male artists account for 14,103 observations. This is consistent with the findings by Smith et al. (2018), who show that of the top 600 songs in the Spotify billboards from 2012 to 2017, only 22.4% are performed by female artists, and only 12.3% are written by female artists. Appendix Figure A.4 provides a visual representation of the gender distribution in the charts from 2017 to 2020. A notable increase in the proportion of female artists in the charts starts after October 2018, and remained stable since then. Female artists generally experience a shorter chart duration, about 83 days less on average, which is a 50% difference compared to male artists. Despite the relatively lower representation of female artists compared to male

[8] For detailed coverage of these allegations, see: `https://www.nytimes.com/2018/10/02/us/politics/kavanaugh-news-fbi-investigation.html`.

[9] This quote from Professor Lawless was reported in an article by Sabrina Siddiqui for The Guardian, cited in Siddiqui (2018). For an examination of the impact of Brett Kavanaugh's confirmation on Roe v. Wade, see `https://www.bostonglobe.com/news/politics/2018/07/11/how-judge-brett-kavanaugh-confirmation-could-affect-roe-wade/s1ZbShSQk6rcFfjrV6x1m0/story.html`.

artists, songs by female artists that make it into the top 200 charts receive, on average, approximately the same number of streams, and female artists typically have more than two times as many Spotify followers as their male counterparts.

Yet, only 15% of chart entries for female artists occur during the week of the song's release, in stark contrast to the 54% for male artists. This discrepancy may indicate different marketing strategies or release tactics employed by the music industry for male versus female artists. In line with this point, I observe some notable disparities between male and female artists in the proportion of songs associated with a major record label, that are single tracks, contain explicit lyrics, or lyrics with at least one sexist verse. To measure the presence of sexism in lyrics, I use the BERTweet classification algorithm (Nguyen, Vu and Nguyen, 2020), which analyzes song content for offensive or derogatory language. The algorithm defines a term as sexist following the Explainable Detection of Online Sexism (EDOS) dataset (Kirk, Yin, Vidgen and Röttger, 2023).[10]

Female artists have a higher frequency of major label affiliation, tend to release more singles, and their songs generally contain less explicit and sexist lyrics than their male counterparts. Finally, Spotify proposes a set of features to describe the sound and the rhythm of each song. In Appendix 5., I provide a complete description of each feature following Spotify definitions. Some of these variables show statistically significant differences between male and female artists, with varying magnitudes and directions. For instance, female artists' songs have lower danceability and tempo than male artists. These findings suggest that songs by female and male artists have different features and may attract audiences with different tastes.

3. Identification Strategy

I use a difference-in-differences design to measure the effect on music consumption of the increased interest in gender-related policies during Kavanaugh's nomination to the Supreme Court. To do that, I compare the Spotify streams for songs by female and male artists over time. The main estimating equation is as follows:

$$\log(\text{streams}_{it}) = \theta_i + \gamma_t + \beta_1 Female_i \times Post_t + \beta_2 \mathbf{X}_{it} + \epsilon_{it}, \tag{1}$$

where $\log(\text{streams}_{it})$ denotes the natural logarithm of the streaming count for song i at day t; and θ_i and γ_t capture song-specific and day-specific fixed effects.[11] The variable Female_i is a dummy variable taking value 1 if song i is performed by a female artist or two female artists' collaborations, and 0 if it is performed by a male artist or two male artists' collaborations. The variable Post_i is equal to 1 for dates after October 8, 2018, the day after the public ceremony of appointment at the White House of Brett Kavanaugh as Supreme

[10] For more information about the BERTweet classification algorithm and the EDOS dataset, see: `https://huggingface.co/NLP-LTU/distilbert-sexism-detector`.

[11] I use the International Standard Recording Code (ISRC) as a unique identifier for each song. This is necessary since a single song could have multiple Spotify IDs.

Table 1. Summary Statistics - Songs by Female and Male Artists in US

	Female		Male		Difference	
	Mean	SD	Mean	SD	Δ	P-value
Charts						
Days on Chart	78	76	161	176	-83	0
Chart Rank	101	58	98	58	3	0.02
Week of Release	0.04	0.19	0.13	0.33	-0.09	0
Streams	449,715	386,390	439,051	288,533	10,664	0
Artists						
Artist Followers	51,544,874	40,983,042	24,882,703	26,019,201	26,662,171	0
Song Characteristics						
Song Duration (Seconds)	203	27	194	51	9	0
Is Explicit	0.32	0.46	0.81	0.39	-0.5	0
Major Record Label	0.72	0.45	0.5	0.5	0.22	0
Is Empowering	0.34	0.48	0	0.06	0.34	0
Is Sexist	0.18	0.38	0.61	0.49	-0.44	0
Is Single Release	0.56	0.5	0.2	0.4	0.36	0
Song Features						
Acousticness	0.3	0.3	0.25	0.26	0.06	0
Danceability	0.62	0.13	0.73	0.14	-0.11	0
Energy	0.58	0.17	0.58	0.15	0	0.7
Musical Mode	0.6	0.49	0.62	0.49	-0.02	0.09
Speechiness	0.08	0.06	0.16	0.12	-0.08	0
Tempo (BPM)	119.21	28.2	125.64	29.07	-6.42	0
Time Signature	3.9	0.3	3.97	0.22	-0.07	0
Valence	0.38	0.17	0.43	0.2	-0.05	0
Number of observations:	2,120		14,103		-11,983	

Notes: The table shows summary statistics about songs present in the Spotify top 200 us billboard between September 03, 2 018 and December 23, 2 018. Comparisons made between 57 (4) songs by female and 385 (164) songs from male artists. Gender identification based on publicly available data on MusicBrainz, Spotify, or Wikipedia.

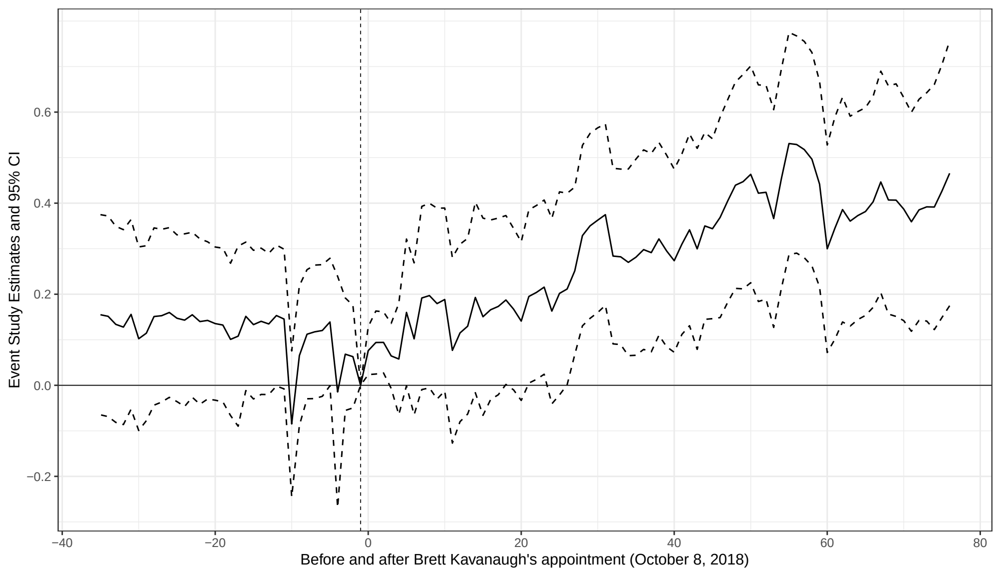

Figure 2. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

Court Judge. I use this date as it marks the official conclusion of the nomination process. However, as illustrated in Figure 1, interest in the movement and the topic of sexual abuse had already started to rise a few days prior, suggesting that there might have been anticipation of media and public attention beginning a few days earlier. Finally, the set of controls, grouped in $\mathbf{X}_{it}$, includes factors such as whether song i was newly released that week or if it was present on the chart the day before.

The coefficient β_1 captures the effect of the increased interest in gender-related policies and sexual misconduct on the consumption of music performed by female artists. This is under the assumption that songs performed by male artists, serving as the control group, provide a suitable counterfactual for the dynamics of music streams after October 8, 2018. To test the absence of pre-trends between treated (songs by female artists) and control (songs by male artists) groups, I illustrate the evolution of $\log(\text{streams}_{it})$ over time with an event-study approach. I regress $\log(\text{streams}_{it})$ over the product between the dummy Female_i and a full set of dummy variables for each day from Monday, September 3, 2018, to Sunday, December 23, 2018. The model controls for song fixed effects, day fixed effects, and dummy variables indicating whether the song is already present on the chart the day before, and whether it is a new release of that week:

$$\log(streams_{it})_{it} = \alpha_i + \rho_t + \sum_{\tau=Sept18,3}^{Jan19,6} \beta_\tau Female_i \times 1(t=\tau) + \epsilon_{it}. \tag{2}$$

I present the results of the estimates of Equation 2 in Figure 2, where I plot the estimated β_τ from September 3, 2018, to December 23, 2019. The coefficients corresponding to days before October 8, 2018, are close to zero and do not exhibit a clear trend. Thus, the stream's dynamics for songs performed by female or male artists was similar before the appointment of Brett Kavanaugh as Supreme Court Judge. This finding supports the parallel trend assumption, which is necessary for my analysis. Instead, after October 8, 2018, the estimated β_τs show a positive trend, meaning that the streams for songs by female artists increase relative to songs by male artists. The effect persists for more than 60 days and declines during the period of the Christmas holidays. In Appendix Figure A.5, I present the estimated β_τ from an event study analysis covering the period from September 2018 to August 2019 (250 days). This analysis confirms that the effect diminishes as public attention to the issue of sexual misconduct wanes.

4. Main Results

In this Section, I present the main results of my analysis. Table 2 shows four specifications of the DiD estimates of Equation 1. I focus on songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018. I employed four different specifications. Columns (1) and (2) use artist and day fixed effects, and controls including dummy variables about whether the song was released that week or whether it appeared in the chart the day before. In Column (2) I add song features controls, providing insights into the impact of time-invariant song characteristics. In Column (3), I incorporate song fixed effects. Finally, I focus on songs from single artists in Column (4) to avoid potential confounders related to collaborations of multiple artists. Standard errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4).

In each specification, the coefficient β_1 in Equation 1 is positive and significant. This suggests that the increased media focus on discussions of sexual misconduct is having a positive impact on female artists, as evidenced by the increase in streams of their songs in the weeks following Brett Kavanaugh's appointment to the Supreme Court. The stronger effect observed with artist fixed effects can be partly attributed to the limitations of the specifications with song fixed effects. My panel of songs is highly unbalanced with many songs present in the charts for a few days or weeks. Thus, with song fixed effects, the coefficient β_1 is only estimated using songs present in the charts before and after October 8, 2018, which significantly limits the power of the empirical model and focuses on a specific set of songs. Similarly, excluding collaborations between artists of the same gender from the sample shrinks the sample by 30% and further reduces the group of (treated) songs by female artists, which is already a minority of the total songs.

My analysis spans from early September 2018 to December 2018. This timeframe allows us to establish a sufficient number of days to detect parallel trends prior to October 8, 2018 (avoiding the inclusion of the summer period, which could be influenced by summer hits and potentially confound my analysis). It also provides enough days to observe the effect unfolding over the first 50 days and then being absorbed during the Christmas holiday period (see Figure 2). The period between Summer and Christmas in 2018 is expected to be relatively uneventful for the music industry, and I believe that seasonal dynamics should not

Table 2. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.295***	0.291***	0.176**	0.157**
	(0.088)	(0.066)	(0.072)	(0.072)
Fixed-effects				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
Fit statistics				
Standard-Errors	Artist		Song	
Observations	16,223	16,223	16,223	16,223
R^2	0.360	0.441	0.801	0.828
Within R^2	0.009	0.134	0.008	0.145

This table presents regression results analyzing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 16,223 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

significantly affect my estimates. To validate this assumption, I conducted a placebo analysis by repeating the event study specification as outlined in Equation 2 in 2017 and 2019 (Appendix Figures A.6 and A.7). In the corresponding period one year earlier or later, the difference in streaming for songs by female and male artists remains relatively constant over time.[12] This leads us to conclude that seasonal events are unlikely to be highly influential and confound my estimates.

Similar to exogenous seasonal events, the effect of Kavanaugh's appointment could have been confounded by the release of singles or albums by a few top artists. The specifications in Table 2 already include time-

[12]In the fall of 2017, I observed the initial notable spikes in interest regarding the #MeToo movement, particularly in response to Alyssa Milano's tweet. However, there was no significant change in streams for either female or male artists during this period. This suggests that the scandals igniting the movement in 2017 were more closely associated with the movie industry and did not directly affect music consumption.

varying controls to account for songs that chart in the first week. However, to ensure that the effect is not primarily driven by a handful of top tracks, I rerun the four specifications presented in Table 2 without accounting for the top five songs in terms of daily streams. Appendix Table A.6 illustrates the results of this analysis, which shows a positive and statistically significant effect of similar size to the coefficients obtained with the full sample. Furthermore, to test the robustness of these findings, bootstrapping was performed on the sample by randomly removing 500 songs performed by female artists and re-running the event study for 1,000 iterations, shown in A.8. This additional bootstrapping analysis further supports the reliability of the results, providing confidence that the observed effects are not solely attributable to variations in individual high-performing tracks.

In all these specifications, the effect is not only statistically significant, but its size is also economically relevant. Following Brett Kavanaugh's appointment to the Supreme Court, songs by female artists saw a significant increase in streaming of at least 16%, which translates to over 50,000 additional Spotify streams per day. Given that the average length of songs by female artists is 3 minutes and 22 seconds, this translates to an additional 2,200 hours of songs by female artists per day.

I can also propose a back-of-the-envelope calculation of the financial impact of increased attention related to Kavanaugh's appointment to the Supreme Court. Spotify does not explicitly disclose per-stream royalties, and the platform's royalty structures appear to encompass more than just the number of song streams. However, various unofficial sources have suggested that Spotify pays artists an average of between 0.003 and 0.005 US dollars per stream.[13]

Based on this estimate, and assuming it is accurate, an increase of 43,000 Spotify streams per day would translate into a 129-219 US dollars increase in artists' daily earnings for at least 8 weeks after Brett Kavanaugh's appointment, for a total of more than 10,000 US dollar.

4.1. Spillover Effects

Using my identification design, I compare the evolution of streaming numbers between songs performed by female and male artists. The previous results indicate that the difference in streaming numbers between female and male artists favours female artists after October 8, 2018. However, based on the results in Table 2 and Figure 2, I cannot rule out that this change comes at the expense of reduced streams for songs by male artists. While this is not problematic for my design, it is critical to interpret correctly the results and understanding the impact of Kavanaugh's appointment on music consumption.

My dataset only includes songs that appear in the top 200 US Spotify charts from September 3, 2018 to December 23, 2019. Thus, the increase in streams for a particular category of songs (such as those by female artists) can directly influence the composition of the top 200 songs on the platform over time. As

[13] For more information about the Spotify royalty structure, see https://support.spotify.com/us/artists/article/royalties/, https://loudandclear.byspotify.com/, https://dittomusic.com/en/blog/how-much-does-spotify-pay-per-stream/, and https://www.musicgateway.com/blog/music-distribution/how-much-does-spotify-pay-per-stream.

shown in Appendix Figure A.11, the share of songs by female artists in the US top 200 Spotify charts has increased, resulting in the displacement of songs by male artists and groups. However, the presence of this displacement effect within the top 200 charts does not necessarily imply that the coefficients presented in Table 2 capture the positive effects experienced by female artists together with the potentially negative consequences faced by male artists. This is due to my design, which involves comparing songs that are consistently present on the charts over time. While some songs by female artists may have replaced songs by male artists on the charts, this may not necessarily have affected artists who consistently maintain songs in the top 200.

To assess the potential spillover effect on songs within the charts, I analyse the streaming dynamics of songs by male artists before and after October 8, 2018. Appendix Figure A.12 illustrates the average values of $\log(\text{streams}_{it})$ for songs by male artists from September 3, 2018 to December 23, 2019. I do not observe a decrease in the number of streams following Kavanaugh's appointment for songs by male artists. Instead, I observe a few isolated positive daily spikes before and after the October 8, 2018 "shock". This finding suggests that the social movement-induced increase in streams for songs by female artists did not impact negatively songs by male artists in the US top 200 Spotify charts.

In Appendix Table A.5, I replicate the four specifications from Table 2, using songs performed by groups or collaborations of more than two artists as controls. Consistent with the main results, I also observe a positive effect in this case, indicating that streams of songs by female artists increased relative to those by groups after Kavanaugh's appointment.

It is also important to recognize that songs by female artists are a minority. Thus, even if some listeners switched from songs by male artists or groups to those by female artists, the impact is unlikely to be significant given the significantly larger pool of songs by male artists. This is especially true given the differences in musical styles between male and female artists, as highlighted in Table 1. To account for these differences, I conduct a more focused analysis by narrowing my analysis to a subset of songs by male artists that share similar musical characteristics with those by female artists. To achieve this, I calculate a propensity score utilizing all Spotify song features and metadata. Then, for each day, I pair each song by a female artist with a song by a male artist using a nearest neighbour approach.[14] With this approach, I significantly reduce the group of songs by male artists used as a control group. Yet, when I estimate Equation 1 for this restricted sample, the results are similar to the ones using the whole sample of songs. As shown in Appendix Table A.4, the effect remains consistently positive and significant, with slightly larger estimates when artist fixed effects are included. Restricting to songs with similar characteristics does not pose a problem for pre-trends, as shown in Appendix Figure A.13. Here, the positive dynamics appear more pronounced, especially within the first 50 days, but I also see a decreasing trend that is consistent with the full sample analysis. Taken to-

[14] As distance metric to calculate the nearest neighbour I use the scaled Euclidean distance. This is to mimic the Euclidean distance of normalized vectors used and implemented by Spotify in the Approximate Nearest Neighbour package: https://github.com/spotify/annoy.

gether, these results suggest that even when examining songs with similar characteristics - an aspect that might suggest an increased spillover potential - the magnitude of the effect remains comparable to the previous case.

4.2. A Platform-Induced Effect?

Up to this point, I have interpreted the increase in music streams as a sign of changing preferences among Spotify users for songs by female artists. However, Spotify's recommendation system also influences the music users come across on the platform, and the surge in streams may be partly due to platform recommendations. Unfortunately, I do not have enough data to directly evaluate if Spotify's recommendation algorithm changed during the Fall of 2018.

However, I do have some knowledge about the songs the platform promotes to its listeners through the "New Music Friday" playlist. This playlist is considered a key platform for promoting newly released tracks across various genres. It is highly visible and often listened to by Spotify users eager to discover new music tracks. The playlist is updated every week and includes a variety of well-known and unknown songs. Previous studies have demonstrated the significance of the "New Music Friday" playlist and how it can be used by Spotify to effectively promote independent or female artists (Hukal, Henfridsson, Shaikh and Parker, 2020; Aguiar and Waldfogel, 2021; Aguiar et al., 2021).

Appendix Figure A.14 shows the percentage of male and female artists and groups featured in the "New Music Friday" playlist over time. During the Fall of 2018, there was no significant increase in female artists showcased. If anything, male artist representation increased in November and December 2018. This observation alone cannot rule out the platform's impact on more song streams by female artists. However, it suggests that Spotify did not actively promote female artists through one of their main playlists during my study period.

4.3. Songs Lyrics and Sexism

My analysis has focused primarily on the impact of Kavanaugh's appointment on the streams of songs by female artists. However, the increasing attention in gender-related policies and sexism may have some impact on the language used in songs, regardless of the gender of the artist. This raises the question of whether the lyrical content of songs plays a role in determining their success. While it is unlikely that a sudden surge of non-sexist songs will be produced in the immediate aftermath of Kavanaugh's appointment, I can examine whether lyrics might influence listener preferences.

In Appendix Figure A.15, I show the daily proportion of songs with at least one sexist line in the lyrics by female and male artists and groups from September 2018 to January 2019. Songs by female artists are significantly less likely to contain sexist language than those by male artists or groups. Yet, I do not observe a large change in the proportion of songs with sexist lyrics before and after October 2018. There is a sharp decrease in sexism around the Christmas holiday season, likely due to the release of more festive tunes that tend to be less controversial. If, instead of focusing on the presence of at least one sexist lyric, I examine the proportion of sexist lyrics, I still observe that songs by female artists are less sexist and the presence of sexism in songs does not change much over time (Appendix Figure A.16).[15]

Despite the lack of a pronounced change in overall lyrical sexism, the effect I observed for women's songs could still be partially attributed to the language of their songs. To investigate this possibility, I repeated my analysis, dividing the sample into songs with and without sexist lyrics. I found that songs with sexist content (with at least one sexist word in the song's lyrics) accounted for 49% of the total, with 320 songs containing sexism by male artists and 10 by female artists.

In my analysis of songs by male and female artists that contain at least one sexist line, I observe a stronger positive effect. Specifically, songs by female artists experience a 50% increase in daily streams following Kavanaugh's appointment, regardless of the specification used (see Table A.7). This more pronounced effect is consistent with the temporal patterns identified in the previous event studies. Figure A.17 illustrates this trend, repeating the specification from Equation 2 but focusing only on songs with at least one sexist line in their lyrics. I observe a significant increase in streams for female artists immediately after October 9, 2018. In this scenario, the uptick is not only more robust in the first few weeks, but also continues to grow over time. Conversely, when looking at songs without sexist lyrics, the effect remains positive but only reaches statistical significance when artist fixed effects are applied. This effect is much less pronounced and mostly localized to the first weeks after Kavanaugh's appointment (as shown in the Appendix Table A.8 and Figure A.18).

These results support the hypothesis that the presence of sexism in lyrics is a relevant channel of the observed effect. Specifically, songs by female artists receive more streams than those by male artists in the context of lyrics containing sexist terms. This differential effect may arise because when female artists incorporate sexist terms, the valence and interpretation of these words may be perceived differently, potentially less offensively, than when used by male artists (Galinsky, Wang, Whitson, Anicich, Hugenberg and Bodenhausen, 2013; Cervone, Augoustinos and Maass, 2021).

4.4. Song Lyrics and Female Empowerment

In this analysis, I employ a difference-in-differences (DiD) approach to evaluate the impact of songs classified as "empowering" on music streaming volumes, distinguishing between songs by female and male artists. Using the LLAMA 3 model, songs are classified as empowering based on varying threshold levels and prompt configurations to assess robustness and sensitivity of the results.

As shown in Table A.9, I begin by examining the effect of empowerment on streaming with samples

[15] The lack of a clear post-Kavanaugh pattern in lyrical content may reflect the limitations of my analysis timeframe. While user preferences may have shifted toward less sexist material, the pool of songs available during the weeks of interest may not have changed significantly. This shift is more likely to manifest itself over a longer period.

restricted to male and female artists at a threshold of 0.75. This table also distinguishes results by prompt type, allowing us to isolate the gender-specific influence of empowering content while accounting for potential sampling biases. The results reveal that empowering songs by female artists have a distinct impact on streaming, with positive and statistically significant interaction terms. For instance, the interaction coefficient between $\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$ is 0.315, significant at 5%, indicating that empowering songs by female artists are associated with a 31.5% increase in streaming compared to the baseline.

Next, Table A.10 explores the effect of empowerment classification with progressively stricter thresholds set at 0.65, 0.7, and 0.75. This variation in thresholds helps examine how increasingly stringent definitions of "empowerment" influence streaming outcomes. The coefficients in this table show a significant interaction between the post-event period, female artist, and empowerment status, with the highest threshold of 0.75 yielding a significant coefficient of 0.288 at 5%. This result suggests that the impact of empowering content for female artists becomes more pronounced as the empowerment threshold increases, reinforcing the interpretation that higher streaming levels are tied to stricter empowerment criteria.

Finally, in Table A.11, I analyze the effect of different prompt engineering configurations (blind, sighted, and examples) on the classification of songs as empowering by the LLAMA 3 model, while maintaining a constant threshold of 0.75. Prompt engineering plays a critical role in refining the model's classification process. In the "blind" configuration, the model is not provided with any information about the gender of the performer, ensuring a neutral assessment that does not rely on gender-specific cues. The "sighted" configuration introduces the performer's gender as additional information, enabling the model to contextualize its classification based on gender. Lastly, the "examples" configuration includes illustrative samples of empowering language for both male and female artists, helping the model identify empowerment characteristics in a more gender-tailored manner. This design allows us to evaluate how these different prompt setups influence the model's classification accuracy and the corresponding regression coefficients. The results reveal that prompt engineering significantly impacts the magnitude and significance of the interaction terms.

Overall, these findings suggest that empowering songs by female artists experience higher streaming levels post-event, particularly when classified with a high threshold and appropriate prompt engineering. This pattern, consistently observed across multiple model specifications, underscores the robustness of the positive interaction effect of empowering content by female artists on streaming volumes.

4.5. Robustness checks

The analysis presented in Figures A.9 and A.10 explores the robustness of the estimated treatment effects from the Difference-in-Differences regression described in Equation 1 by examining variations across both geographical and temporal dimensions.

Figure A.9 illustrates the results of the event study for songs by female and male artists, stratified by country. The coefficients, along with their 95% confidence intervals, are estimated for Canada (CA), Great Britain

(GB), the United States (US), France (FR), and Italy (IT). This country-level disaggregation highlights the consistency of the treatment effects across distinct geographical contexts. The inclusion of standard errors clustered at the song level ensures robust inference, mitigating potential biases arising from within-song correlation.

Figure A.10, on the other hand, focuses on the temporal dimension by stratifying the analysis by year within the US. The yearly estimates provide insights into the stability of the treatment effects over time. As with the country-level analysis, standard errors are clustered at the song level to maintain the reliability of the inference. This temporal disaggregation allows us to observe whether the effect of the treatment is persistent or varies across different years. Together, these analyses provide compelling evidence of the robustness of the treatment effects, both across countries and over time, reinforcing the validity of the findings.

5. Conclusion

Based on my analysis of Spotify streaming data, I find that the appointment of Brett Kavanaugh to the Supreme Court led to a notable increase in the consumption of music performed by female artists. Specifically, my analysis indicates a 16% rise in streaming numbers for songs by female artists on Spotify, a shift that persisted for several weeks. This change, robust against various confounding factors, highlights a significant alteration in consumer behaviour in response to a major socio-political event.

Notably, this increase in streaming is not merely reflective of changing music preferences, but also signals consumer alignment with broader social movements focused on gender issues. My findings align with and extend the work of Luo and Zhang (2022), who noted changes in the hiring of female film writers following the Weinstein scandal, and Levy and Mattsson (2023), who documented a surge in reporting sexual crimes in countries with prominent #MeToo movements. This parallel suggests a broader societal shift towards acknowledging and addressing gender-related concerns.

This behavioural shift towards content created by female artists underscores a significant opportunity for businesses. By aligning their offerings with evolving consumer values, particularly in contexts where gender and social issues are prominent, businesses can not only stay relevant but also contribute positively to societal change. For platform designers and managers, it is crucial to understand and anticipate how external events might shape consumer preferences. This foresight is essential for ensuring that their platforms can swiftly adapt to these changes, thereby fostering an environment that is both responsive and responsible.

Ultimately, my study adds a new dimension to the discourse on political consumerism and the design of digital marketplaces. It highlights the dynamic nature of consumer preferences influenced by external events and underscores the importance of businesses and platforms in being attentive to these shifts, especially in the context of gender and social issues.

Appendices

Tables and Figures

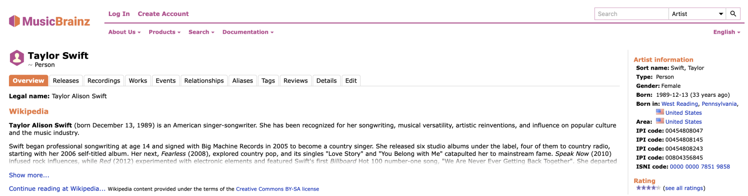

Figure A.1. Screenshot of a MusicBrainz Artist Webpage (Taylor Swift)

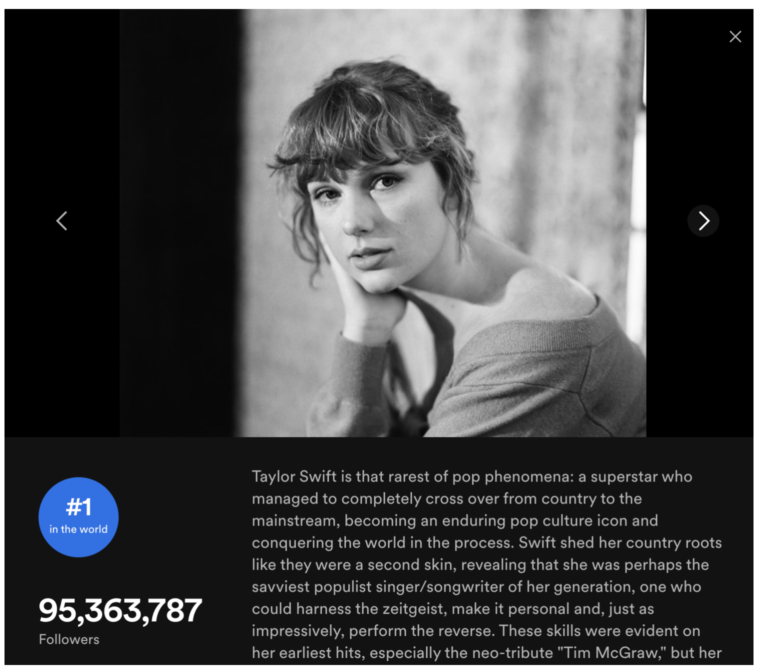

Figure A.2. Screenshot of a Spotify Artist Webpage (Taylor Swift)

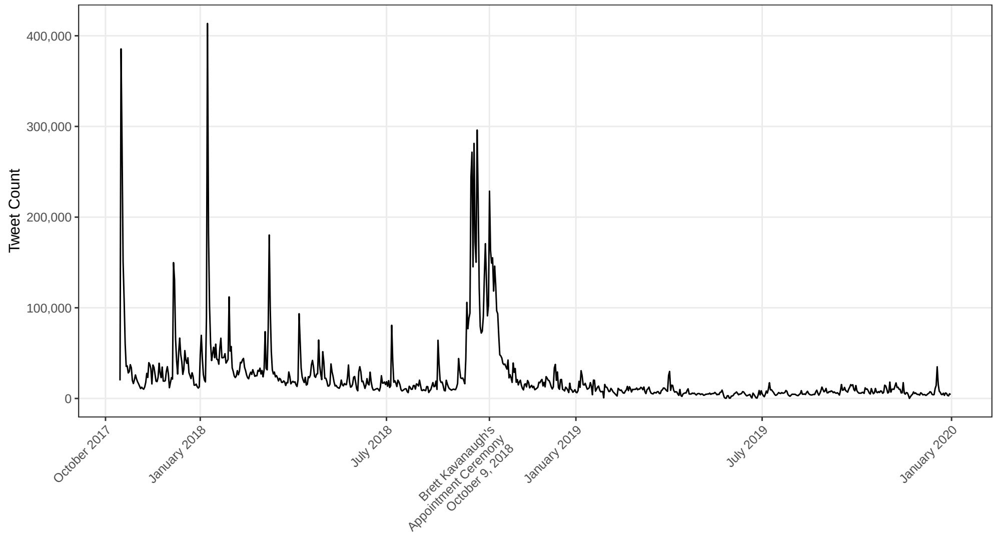

Figure A.3. #MeToo Tweet Count over Time

Notes: This figure illustrates the daily count of tweets containing the #MeToo hashtag from 2017 to January 2020, sourced from the public Harvard Dataverse (Maiorana et al., 2023). Three spikes can be seen: the first in October 2017 with Alyssa Milano's tweet, the second in January 2018 related to Oprah Winfrey's speech at the Golden Globes, and the third and longer corresponding to Brett Kavanaugh's nomination period.

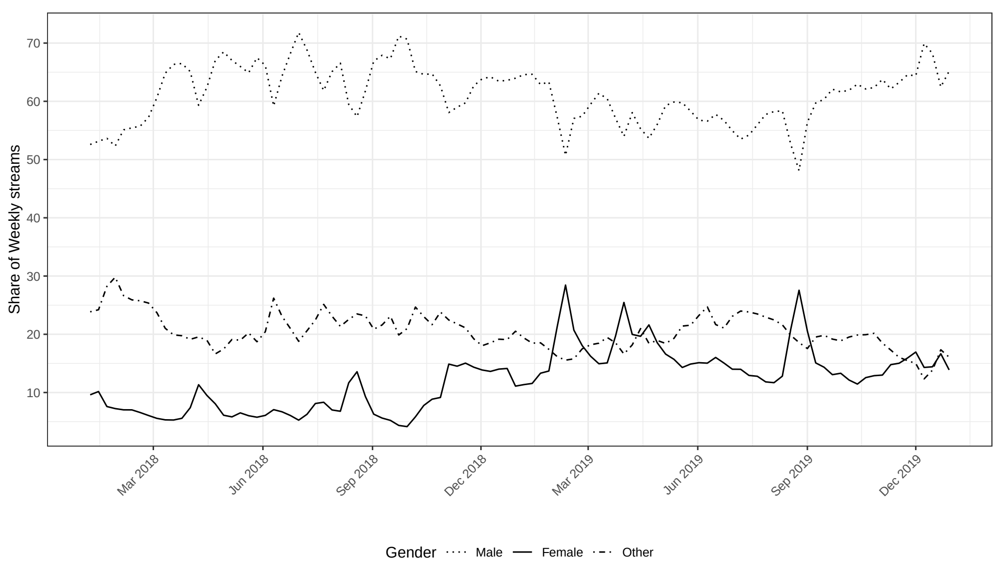

Figure A.4. Share of Weekly Streams in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from January 2018 to January 2020

Table A.3. Summary Statistics - Songs by Female Artists and Groups in US

	Female		Groups		Difference	
	Mean	SD	Mean	SD	Δ	P-value
Charts						
Days on Chart	136	144	78	76	58	0.00
Chart Rank	104	59	101	58	3	0.03
Week of Release	0.11	0.32	0.04	0.19	0.08	0.00
Streams	410 344.93	251 351.92	449 715.08	386 390.24	-39 370.15	0.00
Artists						
Artist Followers	20 672 179	20 682 732	51 544 874	40 983 042	-30 872 695	0.00
Song Characteristics						
Song Duration (Seconds)	222	50	203	27	19	0.00
Is Explicit	0.48	0.5	0.32	0.46	0.16	0.00
Major Record Label	0.62	0.49	0.72	0.45	-0.1	0.00
Is Sexist	0.39	0.49	0.18	0.38	0.22	0.00
Is Single Release	0.39	0.49	0.56	0.5	-0.17	0.00
Acousticness	0.18	0.2	0.3	0.3	-0.12	0.00
Song Features						
Danceability	0.69	0.14	0.62	0.13	0.07	0.00
Energy	0.66	0.15	0.58	0.17	0.08	0.00
Musical Mode	0.64	0.48	0.6	0.49	0.05	0.00
Speechiness	0.13	0.12	0.08	0.06	0.05	0.00
Tempo (BPM)	123.08	30.47	119.21	28.2	3.87	0.00
Time Signature	4	0.22	3.9	0.3	0.09	0.00
Valence	0.48	0.2	0.38	0.17	0.1	0.00
Number of observations:	2,120		1,634		486	

Notes: The table shows summary statistics about songs present in the Spotify top 200 us billboard between September 03, 2 018 and December 23, 2 018. Comparisons made between 57 (4) songs by female and 90 songs from groups. Gender identification based on publicly available data on MusicBrainz, Spotify, or Wikipedia.

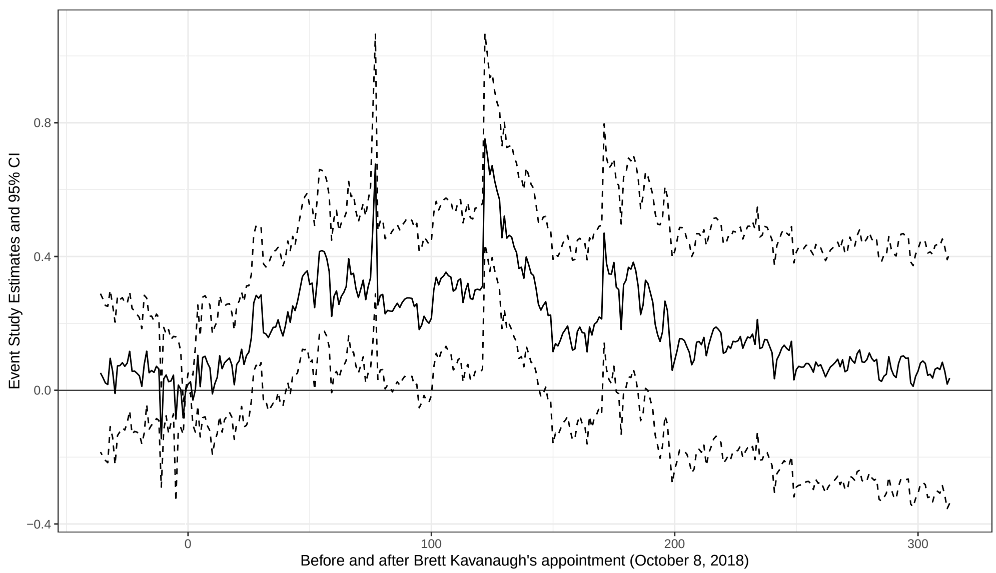

Figure A.5. Event Study: $\log(streams_{it})$ - Songs by Female and Male Artists (Longer Time Window)

Notes: In line with Equation 2, $\log(streams_{it})$ is regressed on song fixed effect and on the products between $Female_i$ and a full set of dummy variables for each day from September 3, 2018, to July 9, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

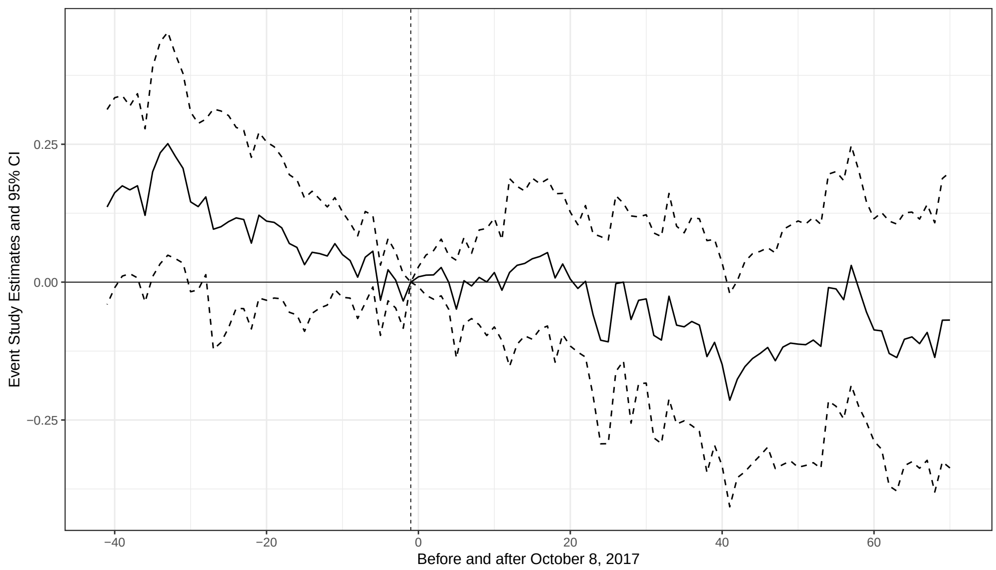

Figure A.6. Placebo Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists in 2017

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female$_i$ and a full set of dummy variables for each day from September 3, 2017, to December 23, 2017. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2017, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

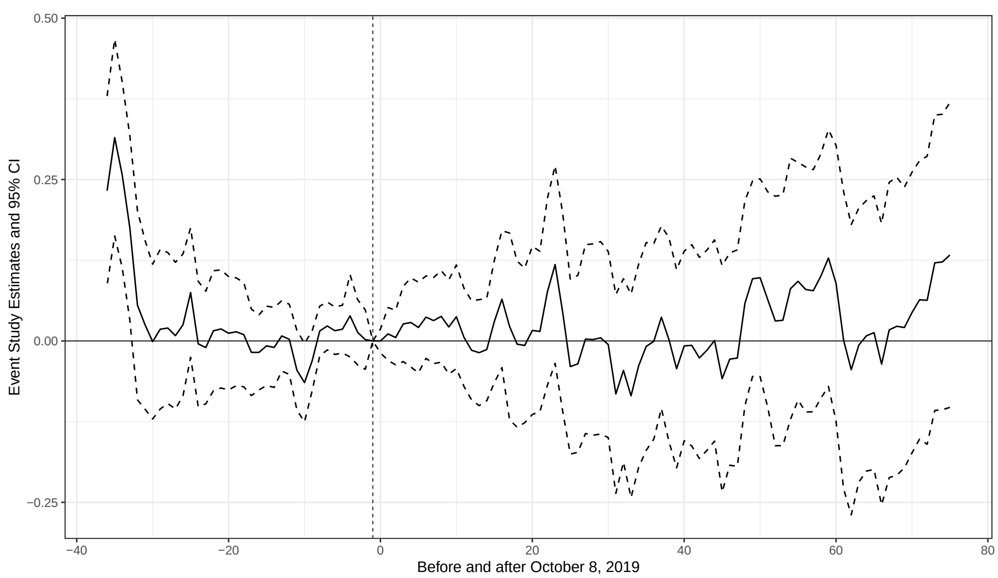

Figure A.7. Placebo Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists in 2019

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female$_i$ and a full set of dummy variables for each day from September 3, 2019, to December 23, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2019, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

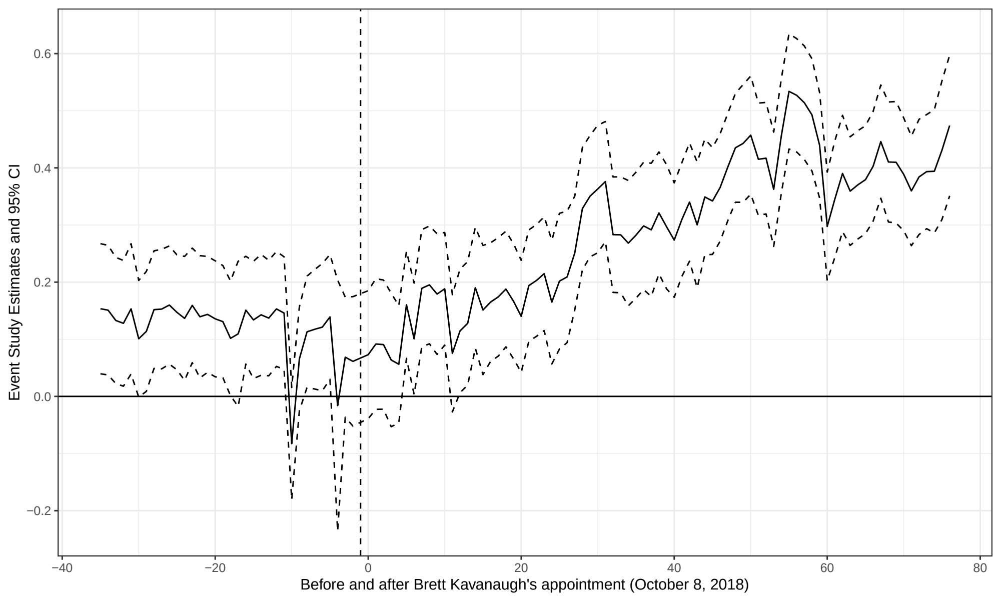

Figure A.8. Bootstrapped Event Study of $\log(\text{streams}_{it})$: Comparison of Songs by Female and Male

Notes: To ensure robustness in the event study analysis, we conducted bootstrapping by randomly removing 500 songs performed by female artists from the sample. This process was repeated 1,000 times.

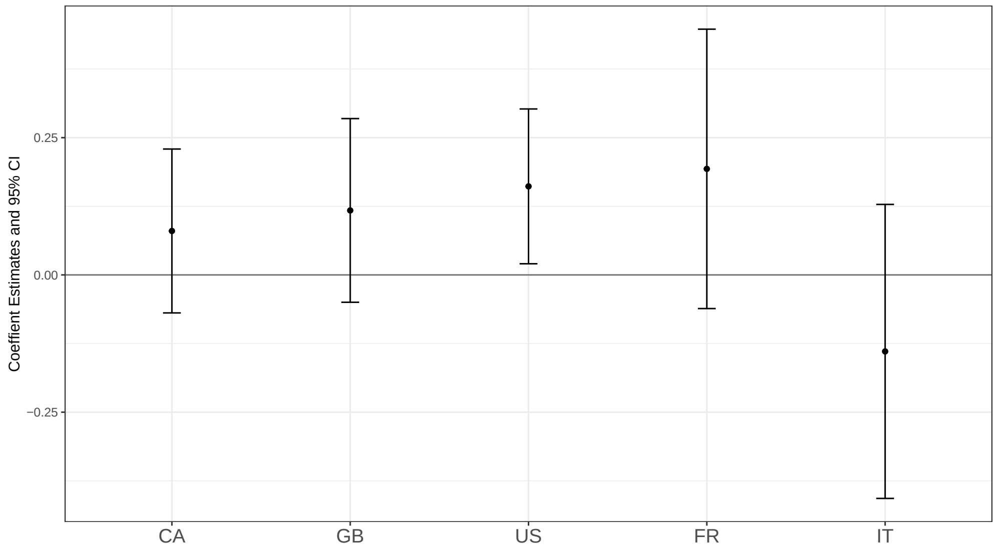

Figure A.9. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists by Country

Notes: As an additional robustness check, we estimate the Difference-in-Differences regression described in Equation 1, incorporating data from Canada (CA), Great Britain (GB), the United States (US), France (FR), and Italy (IT). The coefficients, along with their corresponding 95% confidence intervals, are displayed for each country-specific estimate. Standard errors are clustered at the song level to ensure robust inference. This approach allows us to examine the consistency of the treatment effects across different geographical contexts.

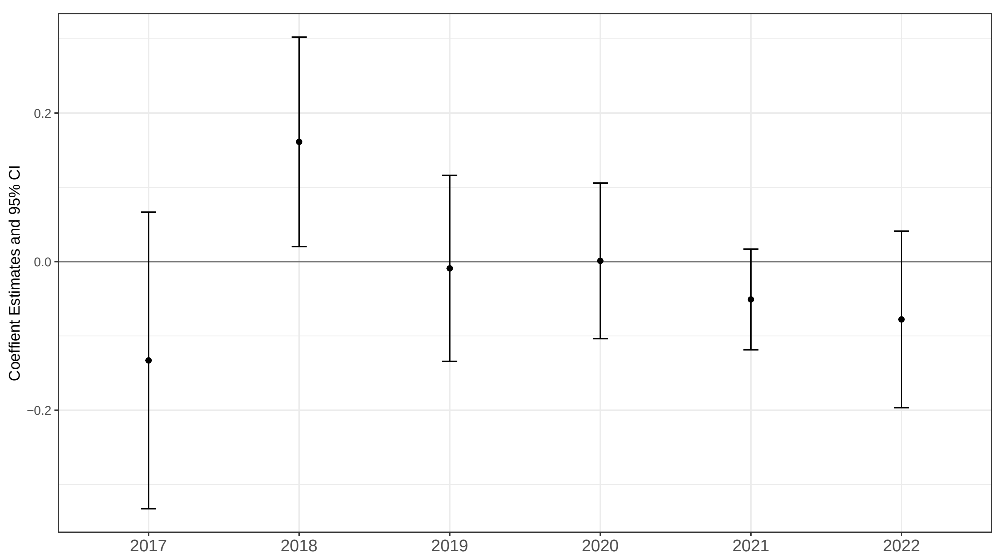

Figure A.10. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists by Year

Notes: As an additional robustness check, we estimate the Difference-in-Differences regression described in Equation 1, stratifying the analysis by year in the US. The coefficients, along with their corresponding 95% confidence intervals, are displayed for each yearly estimate. Standard errors are clustered at the song level to ensure robust inference. This approach allows us to assess the stability of the treatment effects over time.

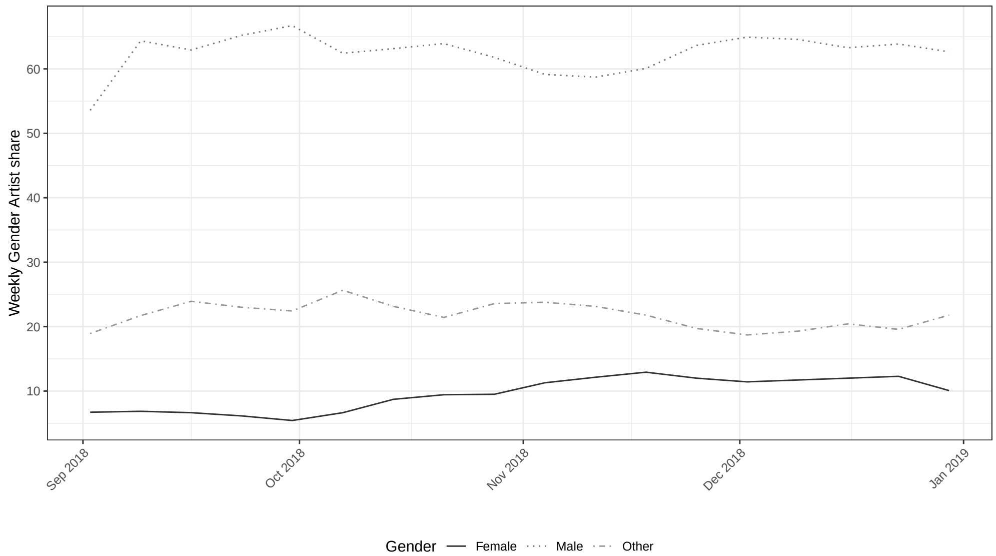

Figure A.11. Share of Weekly Presence of Female, and Male Artists and Groups in the Spotify Top 200 US Spotify Charts

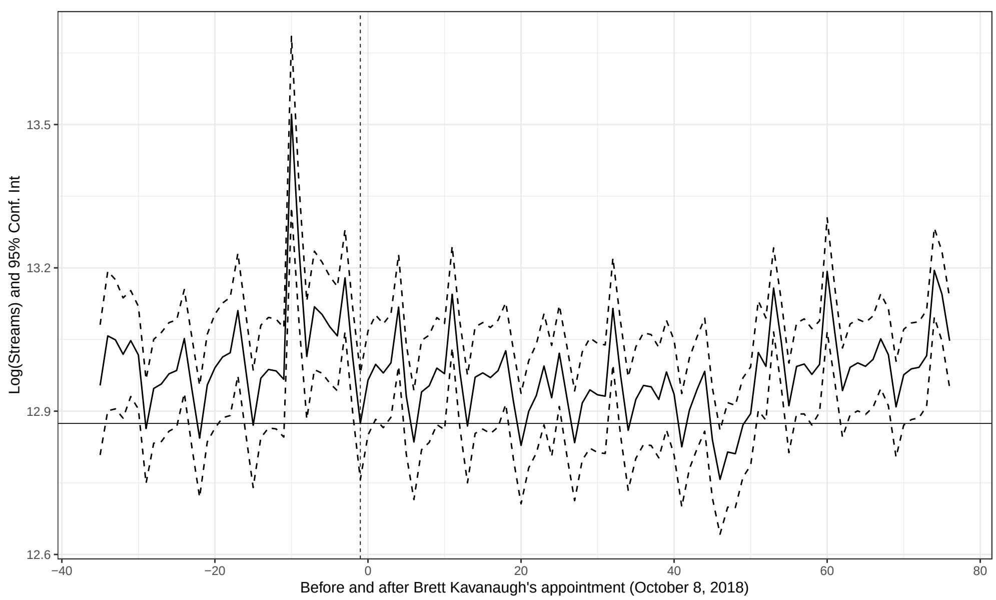

Figure A.12. Average $\log(\text{streams}_{it})$ for Songs by Male Artists

Notes: We plot the average value of $\log(\text{streams}_{it})$ for songs performed by male artists for each day from September 3, 2018, to December 23, 2018 with 95% confidence intervals.

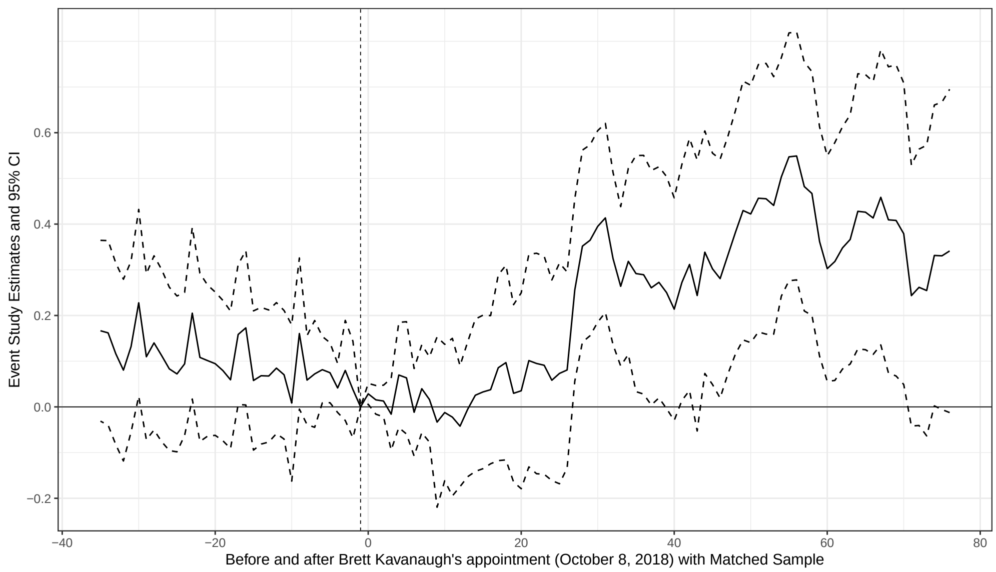

Figure A.13. Event Study: $\log(\text{streams}_{it})$ - Songs by Female Artists and Matched Songs by Male Artists

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. The songs by male artists in the control group have been restricted to match the Spotify song features by songs by female artists. We calculate a propensity score utilizing all Spotify song features and metadata. Subsequently, for each day, we pair each song by a female artist with a song by a male artist using a nearest neighbour approach. Standard Errors (5%) are clustered at song level.

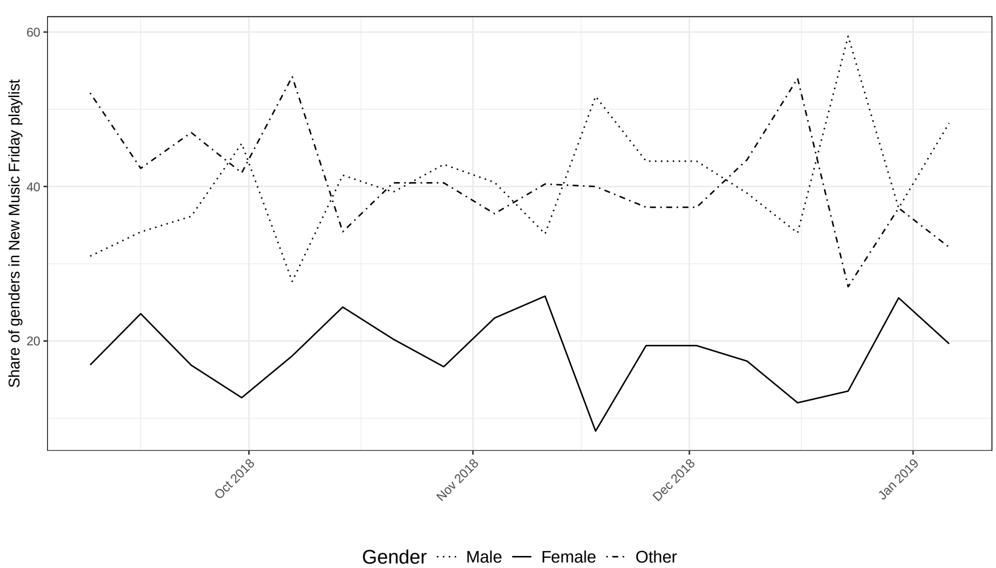

Figure A.14. Share of Female, and Male Artists and Groups in the Spotify New Music Friday Playlist

Table A.4. Difference-in-Differences: $\log(\text{streams})$ - Songs by Female and Matched Songs by Male Artists: US.

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.308**	0.308***	0.121*	0.101
	(0.128)	(0.101)	(0.069)	(0.070)
Fixed-effects				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls	✓	✓	✓	✓
Fit statistics				
Observations	4,204	4,204	4,204	3,539
R^2	0.58564	0.63154	0.85773	0.85275
Within R^2	0.23317	0.31811	0.03510	0.02214

The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to December 23, 2019. The songs by male artists in the control group have been restricted to match the Spotify song features by songs by female artists. We calculate a propensity score using all Spotify song features and metadata. Then, for each day, we pair each song by a female artist with a song by a male artist using a nearest neighbor approach. Columns (1) and (2) use artist and day fixed effects, and in Column (2) we add song features controls. In Column (3), we incorporate song fixed effects. Columns (4) focus on songs from single artists. Standard errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female Artists and Groups or Collaborations of More than Two Artists

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.264	0.257***	0.168**	0.048
	(0.203)	(0.082)	(0.074)	(0.088)
Fixed-effects				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Fit statistics				
Standard-Errors	Artist		Song	
Observations	7,069	7,069	7,069	3,668
R^2	0.52049	0.67220	0.85266	0.83294
Within R^2	0.02224	0.33159	0.01966	0.03776

The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to December 23, 2018 by female artists and groups or collaborations of more than two artists. Columns (1) and (2) use artist and day fixed effects, and in Column (2) we add song features controls. In Column (3), we incorporate song fixed effects. Columns (4) focus on songs from single female artists. Standard errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists without Top 5

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.189^{*}	0.192^{**}	0.148^{**}	0.138^{**}
	(0.099)	(0.089)	(0.070)	(0.070)
Fixed-effects				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
Fit statistics				
Standard-Errors	Artist		Song	
Observations	15,749	15,749	15,749	15,749
R^2	0.37097	0.42969	0.78236	0.80456
Within R^2	0.00464	0.09755	0.00701	0.10833

This table presents regression results analyzing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 15,749 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

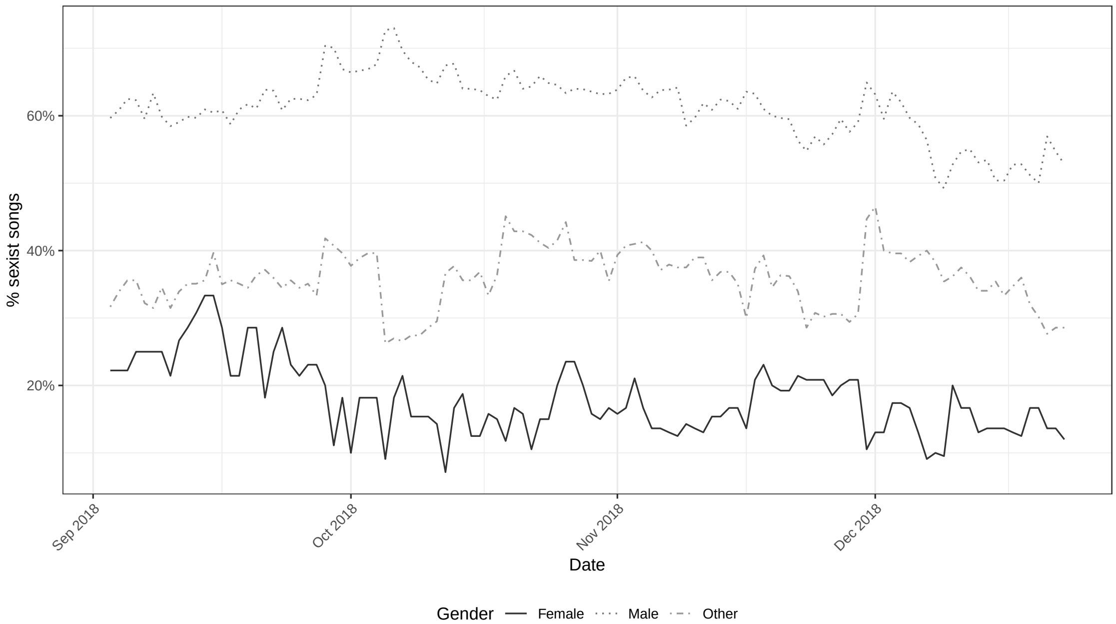

Figure A.15. Daily Share of Songs with at least one Sexist Term in the Lyrics in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from September 3, 2018 to December 23, 2018

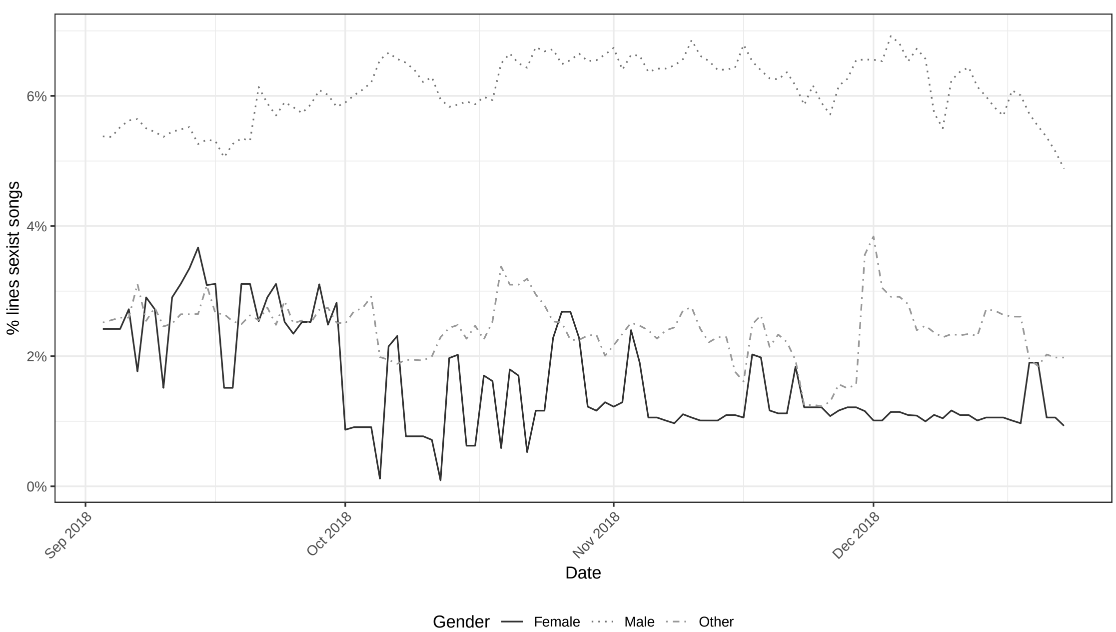

Figure A.16. Daily Share of Lines in Songs' Lyrics with at least one Sexist Term in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from September 3, 2018 to December 23, 2018

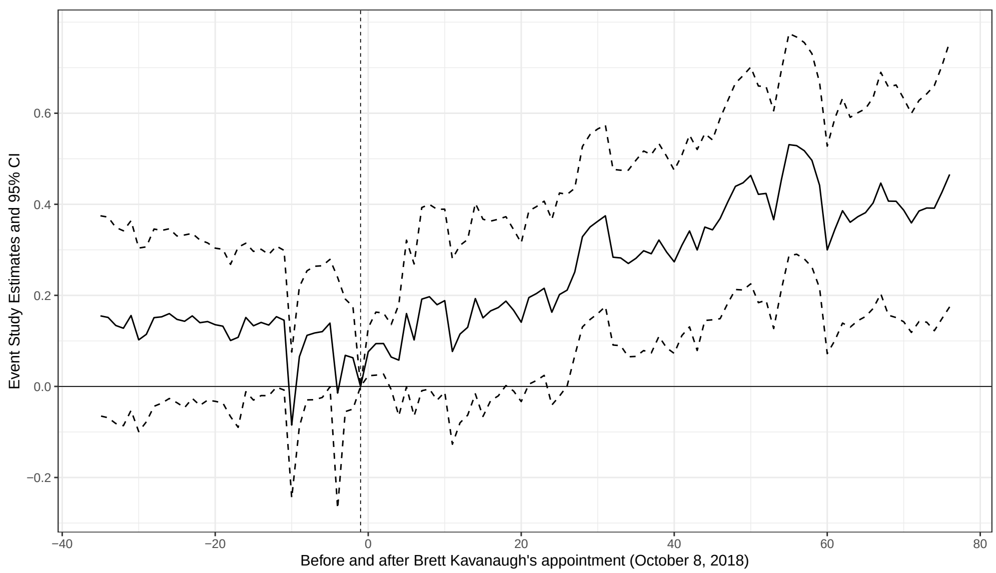

Figure A.17. Event Study: $\log(\text{streams}_{it})$ - Songs with Sexist Terms by Female and Male Artists

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen et al., 2020). We restrict the sample to songs with no sexist lines in their lyrics. Standard Errors (5%) are clustered at song level.

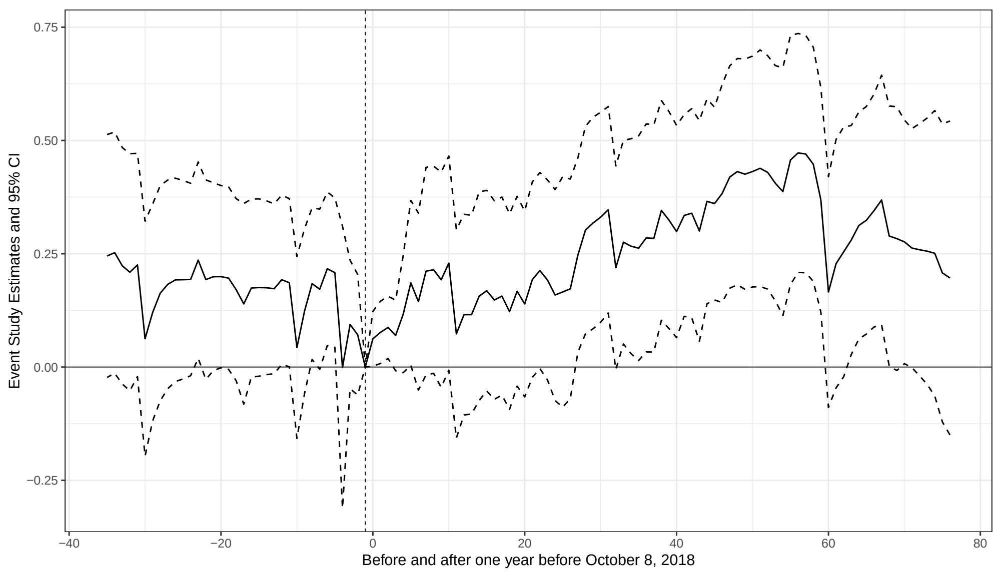

Figure A.18. Event Study: $\log(\text{streams}_{it})$ - Songs with no Sexist Terms by Female and Male Artists

Notes: In line with Equation 2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen et al., 2020). We restrict the sample to songs with no sexist lines in their lyrics. Standard Errors (5%) are clustered at song level.

Table A.7. Difference-in-Differences: $\log$ (streams) - Songs by Female and Male Artists with at least one Sexist Line in the Lyrics.

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Sexist}_t$	0.381^{***}	-0.027	-0.033	-0.046
	(0.119)	(0.048)	(0.046)	(0.046)
$\text{Post}_t \times \text{Sexist}_t \times \text{Female}_i$				0.491^{***}
				(0.123)
Fixed-effects				
Charts Controls	✓	✓	✓	✓
Song	✓	✓	✓	✓
Day	✓	✓	✓	✓
Fit statistics				
Standard-Errors	Song			
Observations	2,102	14,081	16,183	16,183
R^2	0.85303	0.83123	0.82730	0.82941
Within R^2	0.06072	0.16601	0.13859	0.14912

The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to December 23, 2018. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen et al., 2020). We restrict the sample to songs with at least one sexist term in their lyrics. Column (1) models the effect of sexism on song streams for female artists, incorporating Song and Day fixed effects. Column (2) presents the same model but for male artists, controlling for Song and Day fixed effects. Column (3) analyses the effect of sexism on streams across all artists, using Song and Day fixed effects. Column (4) incorporates an interaction between sexism and gender (female) to capture gender-differentiated effects. In all models, standard errors are clustered by ISRC. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists with No Sexist Line in the Lyrics.

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.295***	0.291***	0.176**	0.157**
	(0.088)	(0.066)	(0.072)	(0.072)
Fixed-effects				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
Fit statistics				
Standard-Errors	Artist		Song	
Observations	16,223	16,223	16,223	16,223
R^2	0.36002	0.44093	0.80071	0.82825
Within R^2	0.00857	0.13392	0.00828	0.14532

This table presents regression results analyzing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 16,223 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9. Difference-in-Differences: $\log(\text{streams})$ - Songs by Female and Male Artists considered empowering by LLAMA 3 model for different thresholds.

Dependent Variable:	Log(Streams)		
Model:	(1)	(2)	(3)
$\text{Post}_t \times \text{Female}_i$	0.087	0.107	0.111
	(0.117)	(0.112)	(0.077)
$\text{Post}_t \times \text{Empowering}_i$	-0.207***	-0.207***	-0.207***
	(0.022)	(0.022)	(0.022)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$	0.285**	0.286**	0.311**
	(0.136)	(0.137)	(0.137)
Fixed-effects			
Song	✓	✓	✓
Day	✓	✓	✓
Empowerment Threshold	0.650	0.700	0.750
Fit statistics			
Observations	16,172	16,172	16,172
R^2	0.82853	0.82858	0.82865
Within R^2	0.14500	0.14527	0.14563

The sample includes songs within the top 200 charts on Spotify from September 3, 2018, to December 23, 2018. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10. Difference-in-Differences: $\log(\text{streams})$ - Songs by Female and Male Artists considered empowering by LLAMA 3 model for: US.

Dependent Variable:	Log(Streams)		
Model:	(1)	(2)	(3)
$\text{Post}_t \times \text{Empowering}_i$	0.079	-0.222***	-0.207***
	(0.138)	(0.021)	(0.022)
$\text{Post}_t \times \text{Female}_i$			0.111
			(0.077)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$			0.311**
			(0.137)
Fixed-effects			
Song	✓	✓	✓
Day	✓	✓	✓
Sample	Females	Males	All
Empowerment Threshold	0.750	0.750	0.750
Prompt Type	Examples	Examples	Examples
Fit statistics			
Observations	2,102	14,070	16,172
R^2	0.846	0.831	0.829
Within R^2	0.017	0.166	0.146

The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018.. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11

Dependent Variable:	Log(Streams)		
Model:	(1)	(2)	(3)
$\text{Post}_t \times \text{Female}_i$	0.268***	0.102	0.111
	(0.100)	(0.066)	(0.077)
$\text{Post}_t \times \text{Empowering}_i$	0.045	-0.144	-0.207***
	(0.081)	(0.129)	(0.022)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$	-0.263*	0.393**	0.311**
	(0.140)	(0.195)	(0.137)
Fixed-effects			
Song	✓	✓	✓
Day	✓	✓	✓
Prompt Type	Blind	Sighted	Examples
Threshold	0.750	0.750	0.750
Fit statistics			
Observations	16,172	16,172	16,172
R^2	0.82919	0.82929	0.82865
Within R^2	0.14832	0.14882	0.14563

The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018.. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12. Difference-in-Differences: $\log(\text{streams})$ - Empowering songs by Label: US.

Dependent Variable:	Log(Streams)
Model:	(1)
$\text{Post}_t \times \text{Female}_i \times \text{Label} = \text{Universal}$	-0.427***
	(0.115)
$\text{Post}_t \times \text{Female}_i \times \text{Label} = \text{Warner}$	-0.335**
	(0.138)
$\text{Post}_t \times \text{Female}_i$	0.476***
	(0.107)
Fixed-effects	
Song	✓
Day	✓
Fit statistics	
Observations	16,223
R^2	0.83001
Within R^2	0.15410

The sample includes songs within the top 200 US charts on Spotify between September 03, 2018 and December 23, 2018.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Spotify Songs' Features

We provide here the full list of Spotify songs' features with their definition in line with the Spotify website:[16]

- Acousticness: A variable from 0.0 to 1.0 that indicates the likelihood of the track being acoustic.
- Danceability: This assesses how suitable a track is for dancing, based on tempo, rhythm stability, beat strength, and regularity. It ranges from 0.0 to 1.0.
- Duration: The length of the track in milliseconds.
- Energy: A value from 0.0 to 1.0 that represents the intensity and activity of a track, influenced by aspects like dynamic range, perceived loudness, and timbre.
- Explicit: Whether or not the track has explicit lyrics, 1 equals True, 0 equals False.
- Instrumentalness: Predicts the absence of vocals in a track, with values closer to 1.0 indicating higher likelihood of no vocal content.
- Key: The musical key of the track, using Pitch Class notation.
- Liveness: Indicates the probability of the track being recorded live.
- Loudness: The average loudness of the track in decibels (dB).
- Mode: Specifies the modality (major or minor) of a track.
- Speechiness: Assesses the presence of spoken words in a track.
- Tempo: The overall estimated tempo of a track in beats per minute (BPM).
- Time Signature: An estimated time signature indicating the number of beats in each bar.
- Valence: A measure describing the musical positiveness conveyed by a track, ranging from 0.0 to 1.0.

[16]For more information, see: https://developer.spotify.com/documentation/web-api/reference/get-audio-features.

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