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

Abstract

This study examines the impact of Brett Kavanaugh's Supreme Court appointment on U.S. music consumption, specifically exploring changes in streaming patterns on Spotify. With a difference-in-differences approach, we analyze the streaming data of the top 200 songs, revealing a significant increase of at least 13% in the streams of songs by female artists post-appointment. This sustained shift in consumer behaviour suggests a reaction to heightened media attention on gender issues. Our findings are robust against confounding factors such as seasonal trends and Spotify's promotional activities. Further, the study delves into the role of sexist lyrics, finding a more pronounced effect in songs with sexist terms. 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.

JEL-Codes: J160, L820.

Keywords: gender equality, music industry, social movements, political consumerism.

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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 behavior 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 behavior?

To explore, we 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, we analyze how the increased media coverage of this event affected music consumption patterns. Specifically, we 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, we show an increase of at least 13% 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. Our 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, we 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, we 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 U.S. senators' communications changed after Kavanaugh's confirmation, with senators becoming more inclined to engage in partisan behavior and get involved in partisan disputes. In comparison to these studies, our research explores a different aspect of behavior 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.

Our estimates capture the relative increase in streaming numbers for songs by female artists compared to their male counterparts. In doing so, our approach also accounts for potential negative effects on male artists. However, we believe that the magnitude of these negative effects is minimal. Throughout the analysis period, streaming numbers for male artists remained stable. In addition, our 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 we use songs by groups or multi-artist collaborations as a control group.

Our data come from the US Spotify charts. While we 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 our analysis period. Additionally, we 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 our results is also confirmed when we restrict our analysis to artists outside the top five daily streams.

Finally, the music industry is particularly appealing for this study because we can analyize 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 we focus on such songs, we 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.

Our 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, our 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, our 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, our 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 our 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, our 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, our 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

[1]According to Nielsen's data, the viewership for Brett Kavanaugh's testimony before the U.S. 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/s1ZbShSQk6rcFfjrV6x1mO/story.html`.

recognize and adapt to external factors and events that may exacerbate or mitigate existing imbalances. In our 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 January 6, 2019, about the top 200 songs in the U.S., 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, the highest, to 200, the lowest), and the number of streams. We enrich our dataset with additional information about songs and albums from Spotify's public APIs. This approach allows us to obtain detailed features for each song. We also gathered copyright holder details, release dates, and other relevant information from Spotify. To determine artist gender, we employed a two-step approach. First, we use the MusicBrainz APIs to retrieve the gender of artists.[4] Then, in case of missing information from MusicBrainz, we retrieve manually the artist's gender using the artist Wikipedia's page or the artist's picture shown on Spotify.[5] Doing so, we identify 79 songs performed by a female artist or a collaboration between two female artists, and 593 songs performed by a male artist or a collaboration between two male artists. These songs are performed by 195 unique artists, consisting of 43 female artists and 152 male artists. We also identify 229 songs performed by groups or collaborations of more than two artists.

In the remainder of this Section, we 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 our study, as we examine its impact on music consumption patterns. We conclude the Section by presenting descriptive statistics.

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

[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 A1 and A2 for screenshots of MusicBrainz and Spotify artist webpages used to retrieve artists' gender.

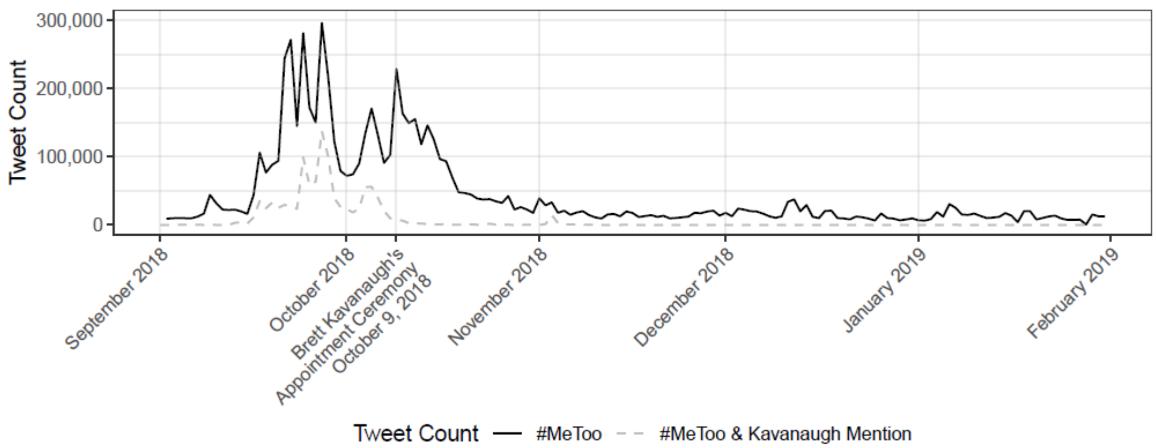

Figure 1. #MeToo and #Kavanaugh Tweet Counts Over Time

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).

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 A3) 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 #Kavanaugh or mention the word "Kavanaugh" in the tweet.

[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.

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, our study seeks to examine how increased public interest in specific issues might influence consumer behavior, with a particular focus on music consumption patterns.

2.2. Data Description

Our analysis spans from Monday, September 3, 2018 to Sunday, January 6, 2019. We select this time window to examine the impact of Brett Kavanaugh's public appointment ceremony on October 9, 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, we 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 A1, we perform a similar analysis, this time comparing songs by female artists with those by groups. Our unit of observation remains at the song/daily snapshot level throughout our analysis.

Songs performed by female artists account for 2,395 observations in the daily top 200 charts, while those performed by male artists account for 15,761 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 A4 provides a visual representation of the gender distribution in the charts from 2017 to 2020. A notable

[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`.

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

		Female		Male		Difference	
		Mean	SD	Mean	SD	Δ	p-value
Charts	Days on chart	82.69	80.02	164.57	178.54	-81.89	0.00
	Rank	66.20	66.67	71.68	62.31	-5.47	0.39
	Is release week	0.15	0.36	0.54	0.50	-0.39	0.00
	Streams	454,680	384,440	437,407	290,557	17,272	0.04
Artists	Followers	43,615,027	33,608,450	19,800,296	18,727,070	23,814,730	0.00
Song Characteristics	Duration (m:ss)	3:22	0:26	3:13	0:50	9.05	0.00
	Is explicit	0.32	0.47	0.81	0.39	-0.48	0.00
	Is major label	0.87	0.33	0.63	0.48	0.25	0.00
	Is sexist	0.18	0.39	0.61	0.49	-0.43	0.00
	Is single	0.34	0.47	0.16	0.36	0.18	0.00
Song Features	Acousticness	0.30	0.30	0.24	0.25	0.06	0.00
	Danceability	0.62	0.14	0.73	0.14	-0.12	0.00
	Energy	0.58	0.16	0.58	0.15	0.00	0.51
	Mode	0.65	0.45	0.61	0.48	0.04	0.00
	Speechiness	0.08	0.06	0.16	0.12	-0.08	0.00
	Tempo	119.39	27.19	125.30	28.71	-5.91	0.00
	Time Signature	3.92	0.26	3.98	0.17	-0.06	0.00
	Valence	0.38	0.17	0.43	0.20	-0.05	0.00
	Number of Observations	2,395	-	15,761	-	-	-

Notes: The table shows summary statistics about songs present in the Spotify top 200 US billboard between September 3, 2018, and January 6, 2019. The table compares 79 songs by female (43) and 593 songs from male (152) artists. We retrieve artists' genders using their self-identified gender on MusicBrainz, Spotify, or Wikipedia.

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 82 days less on average, which is a 50% difference compared to male artists. Despite the relatively lower representation of female artists compared to male 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, we 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, we 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 B, we 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

We 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, we compare the Spotify streams for songs by female and male artists over time. The main estimating equation is as follows:

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

where $\log(streams_{it})$ 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 $Post_t$ is equal to 1 for dates after October 9, 2018, the day after the public ceremony of appointment at the White House of Brett Kavanaugh as Supreme Court Judge. We 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

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

[11] We 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.

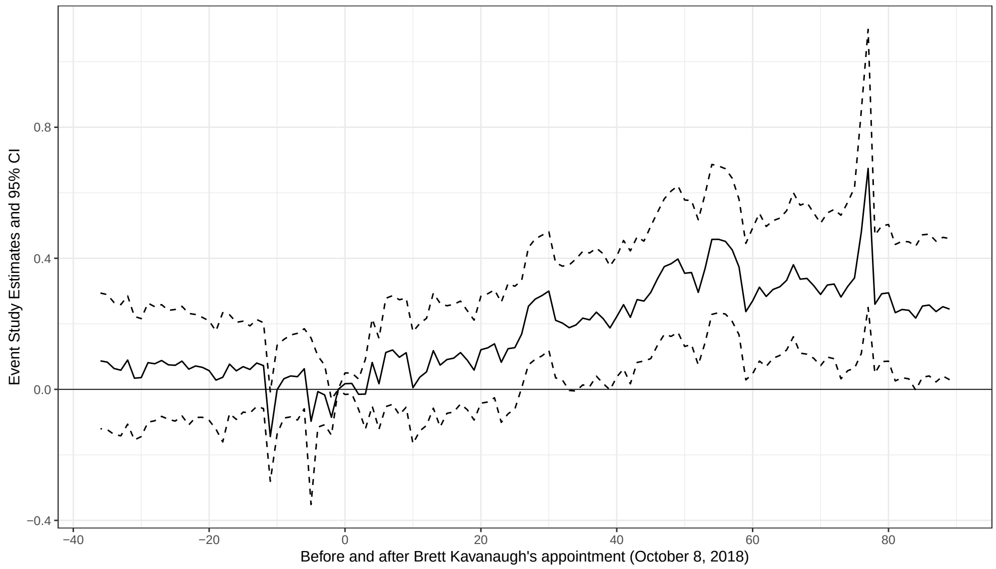

Figure 2. Event Study: $\log(streams_{it})$ - Songs by Female and Male Artists

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 January 6, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 2018, is normalized to 0. The sample includes songs in the US top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

songs performed by male artists, serving as the control group, provide a suitable counterfactual for the dynamics of music streams after October 9, 2018. To test the absence of pre-trends between treated (songs by female artists) and control (songs by male artists) groups, we illustrate the evolution of $\log(streams_{it})$ over time with an event-study approach. We regress $\log(streams_{it})$ 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, January 6, 2019. 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:

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

We present the results of the estimates of Equation 2 in Figure 2, where we plot the estimated β_τ from September 3, 2018, to January 6, 2019. The coefficients corresponding to days before October 9, 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 our analysis. Instead, after October 9, 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 A5, we 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, we present the main results of our analysis. Table 2 shows four specifications of the DiD estimates of Equation 1. We focus on songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 2019. We 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) we add song features controls, providing insights into the impact of time-invariant song characteristics. In Column (3), we incorporate song fixed effects. Finally, we 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. Our 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 9, 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.

Our analysis spans from early September 2018 to January 2019. This timeframe allows us to establish a sufficient number of days to detect parallel trends prior to October 9, 2018 (avoiding the inclusion of the summer period, which could be influenced by summer hits and potentially confound our 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 we believe that seasonal dynamics should not

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

	$\log(streams_{it})$			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.297***	0.303***	0.166**	0.129*
	(0.093)	(0.091)	(0.075)	(0.074)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Day FE	✓	✓	✓	✓
Observations	18,156	18,156	18,156	12,876
R^2	0.366	0.398	0.813	0.826
Within R^2	0.051	0.098	0.137	0.107

Notes: The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 2019. 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). $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

significantly affect our estimates. To validate this assumption, we conducted a placebo analysis by repeating the event study specification as outlined in Equation 2 in 2017 and 2019 (Appendix Figures A6 and A7). 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 our 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-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, we rerun the four specifications presented in Table 2 without accounting for the top five songs in terms of daily streams. Appendix Table A2 illutrates the results of this analysis, which shows a positive and statistically significant effect of similar size to the coefficients obtained with the full sample.

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 13%, which translates to over 43,000 additional Spotify streams

[12] In the fall of 2017, we 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.

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.

We 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 dollar 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 our identification design, we 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 favors female artists after October 9, 2018. However, based on the results in Table 2 and Figure 2, we cannot rule out that this change comes at the expense of reduced streams for songs by male artists. While this is not problematic for our design, it is critical to interpreting correctly the results and understanding the impact of Kavanaugh's appointment on music consumption.

Our dataset only includes songs that appear in the top 200 US Spotify charts from September 3, 2018 to January 6, 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 shown in Appendix Figure A8, 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 necessarely 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 our 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, we analyze the streaming dynamics of songs by male artists before and after October 9, 2018. Appendix Figure A9 illustrates the average values

[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.

of $\log(streams_{it})$ for songs by male artists from September 3, 2018 to January 6, 2019. We do not observe a decrease in the number of streams following Kavanaugh's appointment for songs by male artists. Instead, we observe a few isolated positive daily spikes before and after the October 9, 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 A3, we 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, we 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, we conduct a more focused analysis by narrowing our analysis to a subset of songs by male artists that share similar musical characteristics with those by female artists. To achieve this, we calculate a propensity score utilizing 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.[14] With this approach, we significantly reduce the group of songs by male artists used as a control group. Yet, when we 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 A4, 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 A10. Here, the positive dynamics appear more pronounced, especially within the first 50 days, but we also see a decreasing trend that is consistent with the full sample analysis. Taken together, 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, we 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

[14]As distance metric to calculate the nearest neighbour we 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.

music users come across on the platform, and the surge in streams may be partly due to platform recommendations. Unfortunately, we do not have enough data to directly evaluate if Spotify's recommendation algorithm changed during the Fall of 2018.

However, we 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 A11 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 our study period.

5. Songs Lyrics and Sexism

Our 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, we can examine whether lyrics might influence listener preferences.

In Appendix Figure A12, we 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, we 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, we examine the proportion of sexist lyrics, we still observe that songs by female artists are less sexist and the

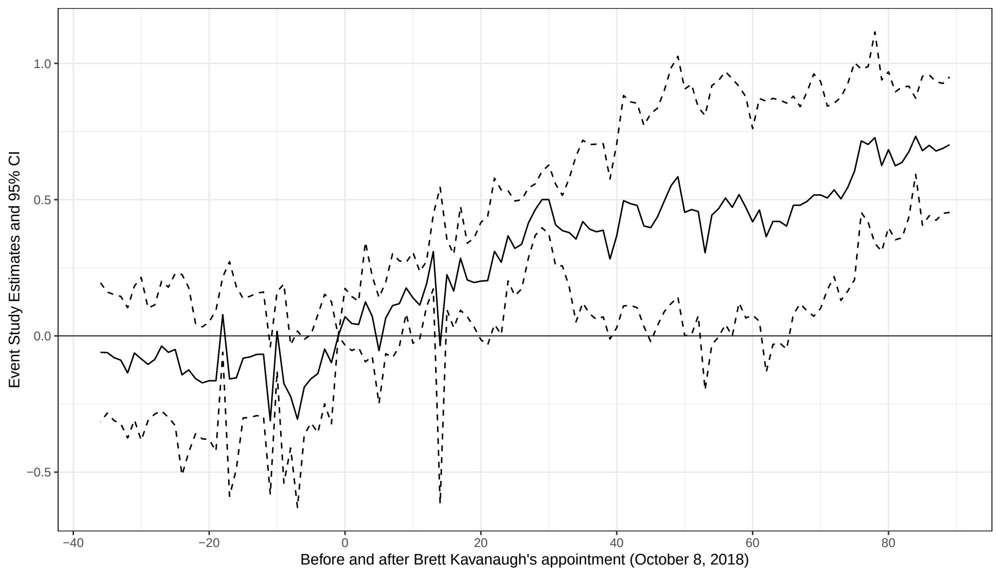

Figure 3. Event Study: $\log(streams_{it})$ - Songs with at least one Sexist Line by Female and Male Artists

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 January 6, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 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 at least one sexist line in their lyrics. Standard Errors (5%) are clustered at song level.

Table 3. Difference-in-Differences: $\log(streams_{it})$ - Songs by Female and Male Artists with at least one Sexist Line in the Lyrics.

	$\log(streams_{it})$			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.658***	0.610***	0.510***	0.464***
	(0.136)	(0.139)	(0.139)	(0.140)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Day FE	✓	✓	✓	✓
Observations	10,001	10,001	10,001	6,024
R^2	0.446	0.493	0.841	0.874
Within R^2	0.054	0.134	0.187	0.180

Notes: The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 2019. 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. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

presence of sexism in songs does not change much over time (Appendix Figure A13).[15]

Despite the lack of a pronounced change in overall lyrical sexism, the effect we observed for women's songs could still be partially attributed to the language of their songs. To investigate this possibility, we repeated our analysis, dividing the sample into songs with and without sexist lyrics. We 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 our analysis of songs by male and female artists that contain at least one sexist line, we 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 3). This more pronounced effect is consistent with the temporal patterns identified in the previous event studies. Figure 3 illustrates this trend, repeating the specification from Equation 2 but focusing only on songs with at least one sexist line in their lyrics. We 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 A5 and Figure A14).

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).

6. Conclusion

Based on our analysis of Spotify streaming data, we 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, our analysis indicates a 13% 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

[15] The lack of a clear post-Kavanaugh pattern in lyrical content may reflect the limitations of our 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.

significant alteration in consumer behavior 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. Our 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 behavioral 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, our 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.

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A APPENDIX - Tables and Figures

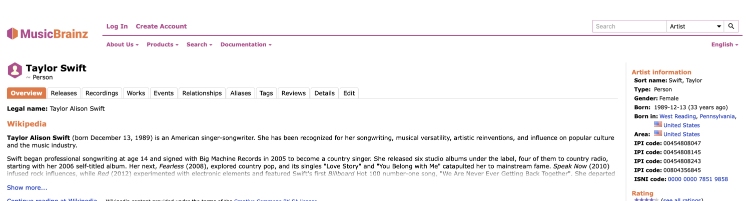

Figure A1. Screenshot of a MusicBrainz Artist Webpage (Taylor Swift)

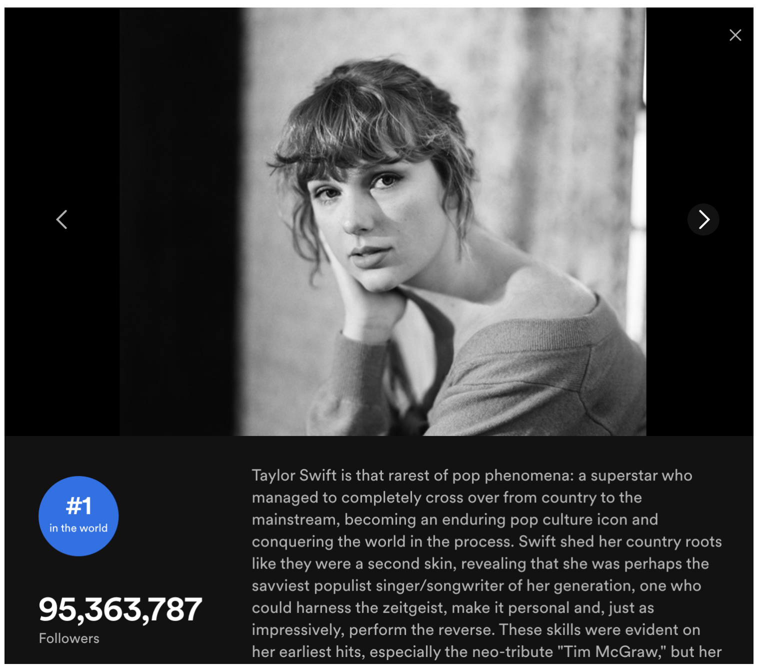

Figure A2. Screenshot of a Spotify Artist Webpage (Taylor Swift)

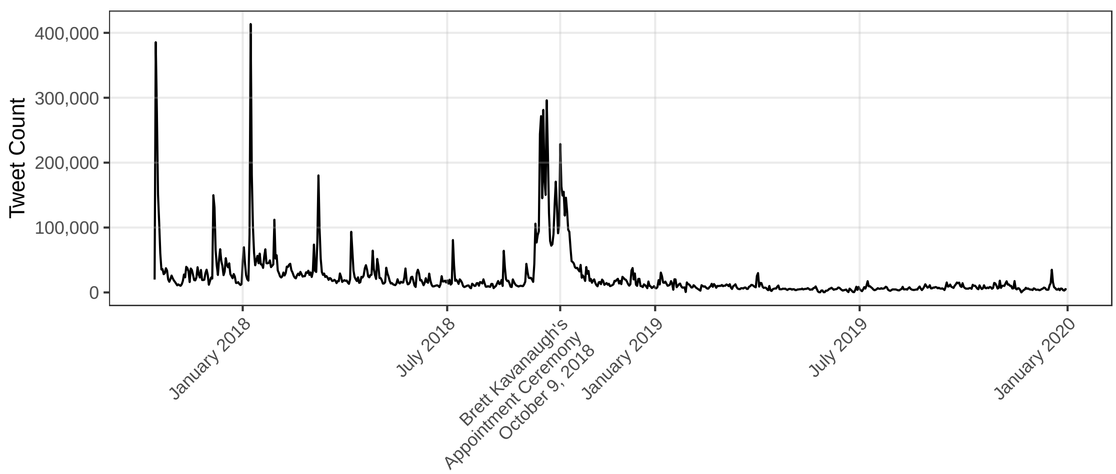

Figure A3. #MeToo Tweet Count over Time

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.

Table A1. Summary Statistics: Songs by Female and Other Artists

		Female		Other		Difference	
		Mean	SD	Mean	SD	Δ	p-value
Charts	Days on chart	82.69	80.02	137.18	145.79	-54.49	0.00
	Rank	99.94	58.81	104.45	58.37	-4,52	0.00
	Is release week	0.03	0.18	0.10	0.30	-0.07	0.00
	Streams	454,680	384,440	407,521	247,877	47,158	0.00
Artists	Followers	43,615,027	33,608,450	15,797,567	13,440,493	27,817,459	0.00
Song Characteristics	Duration (m:ss)	3:22	0:26	3:40	0:51	-0:17	0.00
	Is explicit	0.32	0.47	0.09	0.47	0.50	0.00
	Is major label	0.87	0.33	0.85	0.35	0.02	0.01
	Is sexist	0.18	0.39	0.10	0.31	0.08	0.00
	Is single	0.34	0.47	0.10	0.35	0.48	0.38
Song Features	Acousticness	0.30	0.30	0.20	0.22	0.10	0.00
	Danceability	0.62	0.14	0.69	0.14	-0.07	0.00
	Energy	0.58	0.16	0.65	0.17	-0.07	0.00
	Mode	0.65	0.45	0.73	0.65	0.48	0.00
	Speechiness	0.08	0.06	0.13	0.11	0.11	0.00
	Tempo	119.39	27.19	122.70	30.79	-3.30	0.00
	Time signature	3.92	0.26	3.98	0.32	-0.06	0.00
	Valence	0.38	0.17	0.49	0.20	-0.10	0.00
	Number of Observations	2,395	-	5,703	-	-	-

Notes: The table shows summary statistics about songs present in the Spotify top 200 US billboard between September 3, 2018, and January 6, 2019. The table compares 79 songs by female and 229 songs from groups or collaborations of more than two artists. We retrieve artists' genders using their self-identified gender on MusicBrainz, Spotify, or Wikipedia.

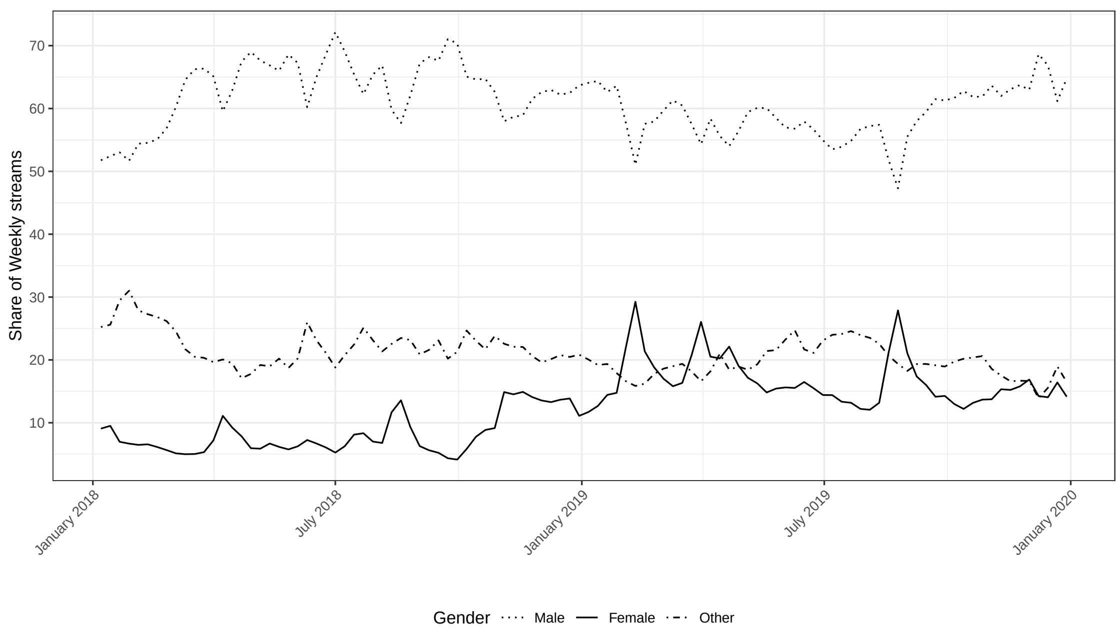

Figure A4. Share of Weekly Streams in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from January 2018 to January 2020

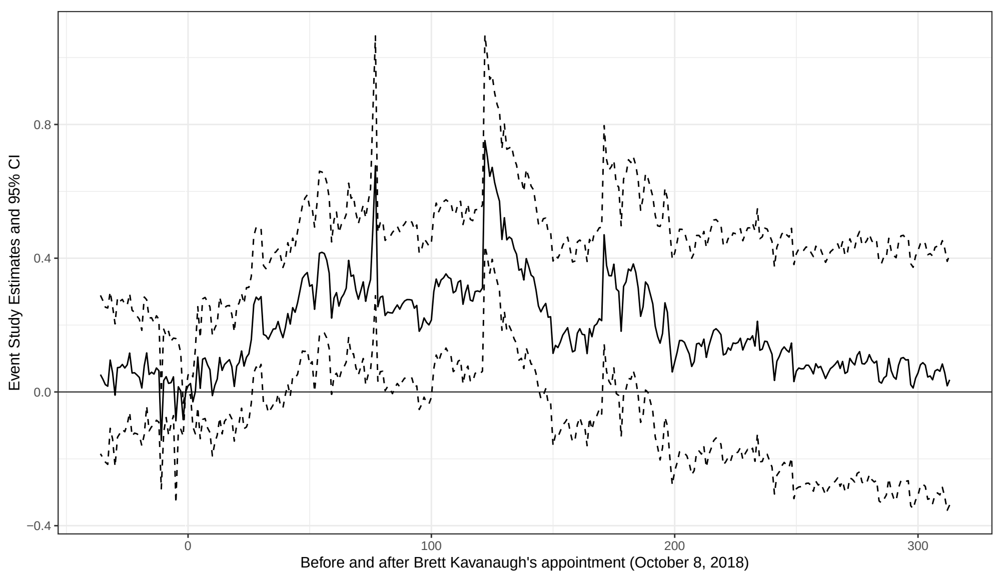

Figure A5. Event Study: $\log(streams_{it})$ - Songs by Female and Male Artists (Longer Time Window)

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 9, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

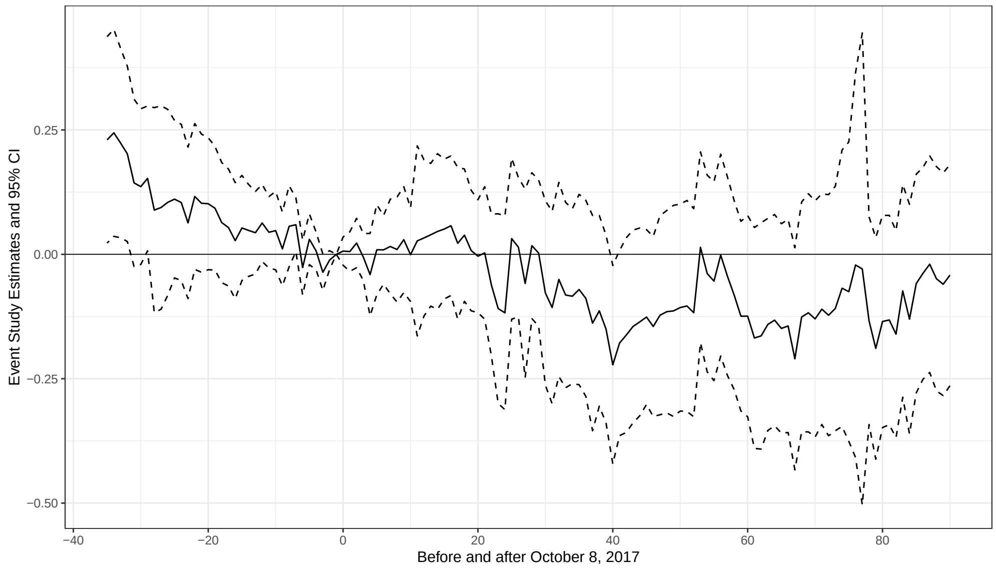

Figure A6. Placebo Event Study: $\log(streams_{it})$ - Songs by Female and Male Artists in 2017

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, 2017, to January 6, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 2017, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

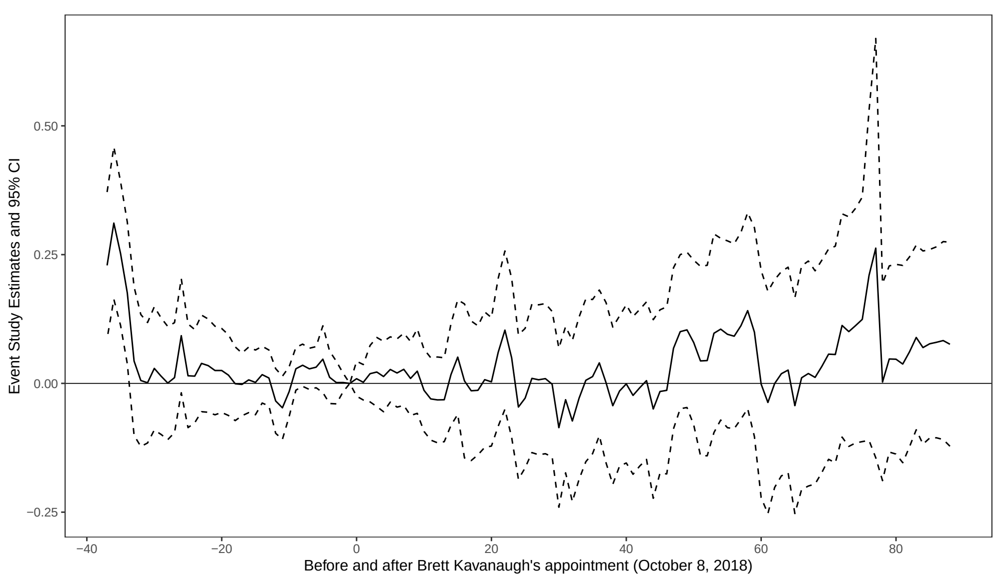

Figure A7. Placebo Event Study: $\log(streams_{it})$ - Songs by Female and Male Artists in 2019

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, 2019, to January 6, 2020. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 2019, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

Table A2. Difference-in-Differences: $\log(streams_{it})$ - Female and Male Artists - No Top 5 Daily Songs

	$\log(streams_{it})$			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.207**	0.208**	0.144**	0.130*
	(0.102)	(0.096)	(0.073)	(0.074)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Date FE	✓	✓	✓	✓
Observations	17,612	17,612	17,612	12,555
R^2	0.376	0.403	0.787	0.795
Within R^2	0.036	0.077	0.104	0.092

Notes: The sample includes songs within the top 200 U.S. charts from the top 6 to the top 200 on Spotify from September 3, 2018, to January 6, 2019. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

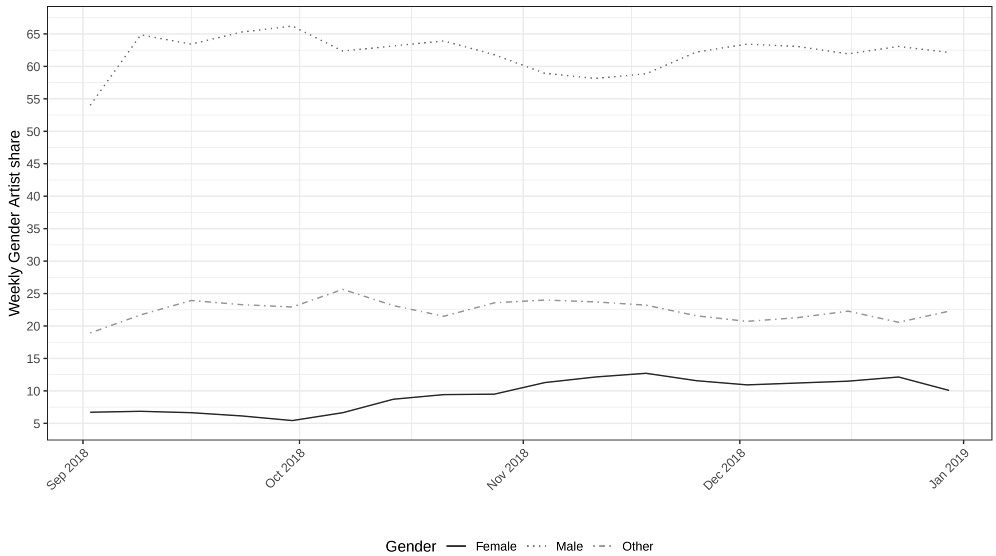

Figure A8. Share of Weekly Presence of Female, and Male Artists and Groups in the Spotify Top 200 US Spotify Charts

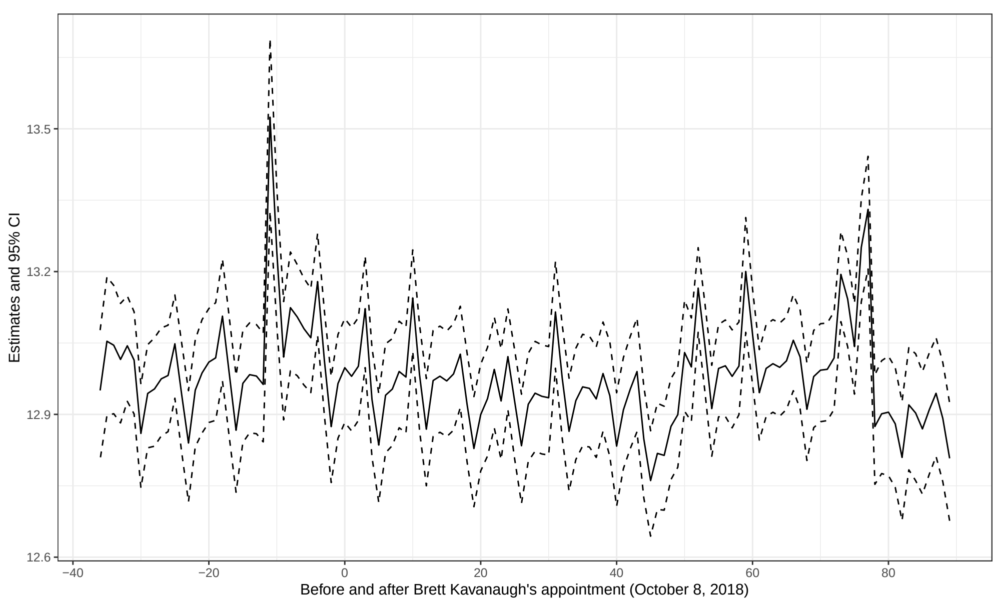

Figure A9. Average $\log(streams_{it})$ for Songs by Male Artists

Notes: We plot the average value of $\log(streams_{it})$ for songs performed by male artists for each day from September 3, 2018, to January 6, 2019 with 95% confidence intervals.

Table A3. Difference-in-Differences: $\log(streams_{it})$ - Songs by Female Artists and Groups or Collaborations of More than Two Artists

	log(streams)			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.235**	0.219***	0.157**	0.027
	(0.100)	(0.079)	(0.076)	(0.090)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Day FE	✓	✓	✓	✓
Observations	8,146	8,146	8,146	4,202
R^2	0.623	0.679	0.835	0.822
Within R^2	0.067	0.205	0.052	0.054

Notes: The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 2019 by female artists and groups or colloborations 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

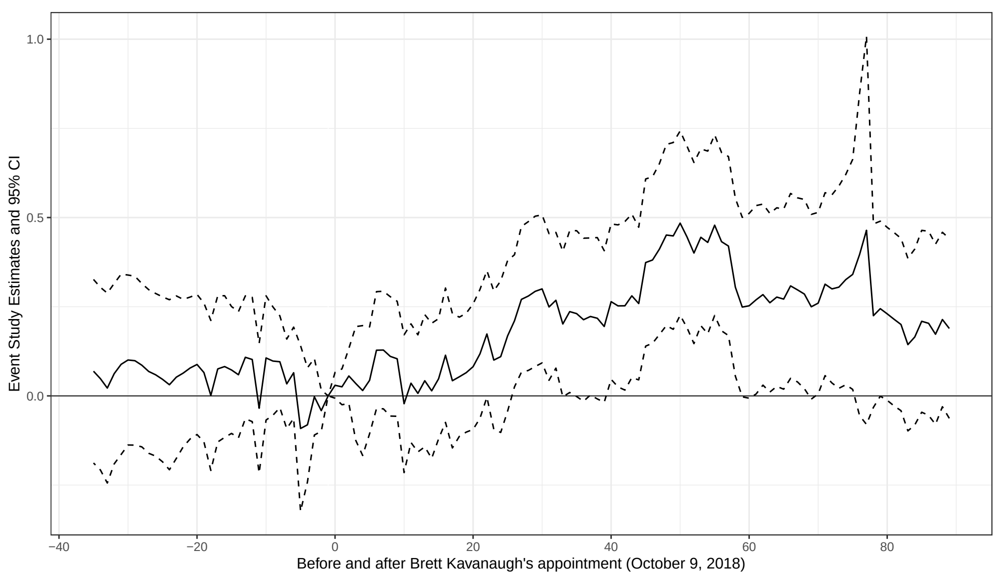

Figure A10. Event Study: $\log(streams_{it})$ - Songs by Female Artists and Matched Songs by Male Artists

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 January 6, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 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 neighbor approach. Standard Errors (5%) are clustered at song level.

Table A4. Difference-in-Differences: $\log(stream_{it})$ - Songs by Female and Matched Songs by Male Artists

	$\log(stream_{it})$			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.400***	0.362***	0.190**	0.131*
	(0.109)	(0.110)	(0.088)	(0.079)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Date FE	✓	✓	✓	✓
Observations	4,754	4,754	4,754	4,602
R^2	0.495	0.582	0.844	0.850
Within R^2	0.086	0.244	0.060	0.045

Notes: The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

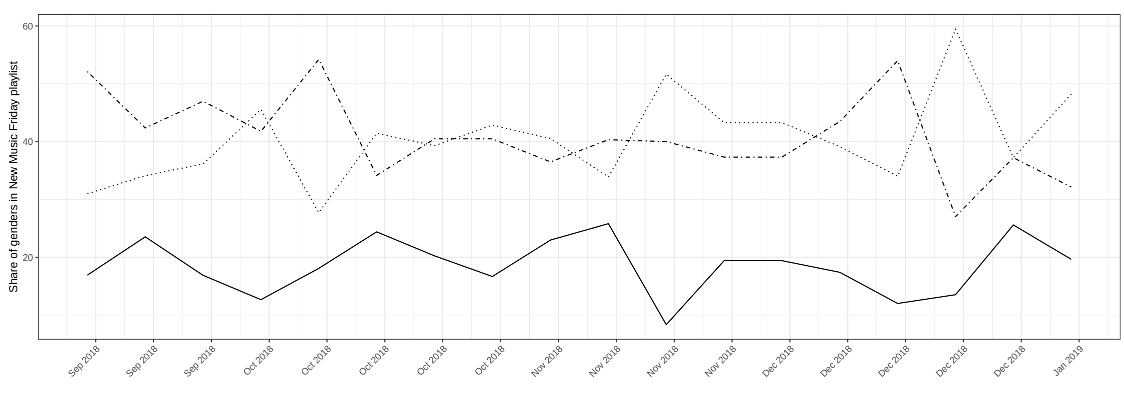

Figure A11. Share of Female, and Male Artists and Groups in the Spotify New Music Friday Playlist

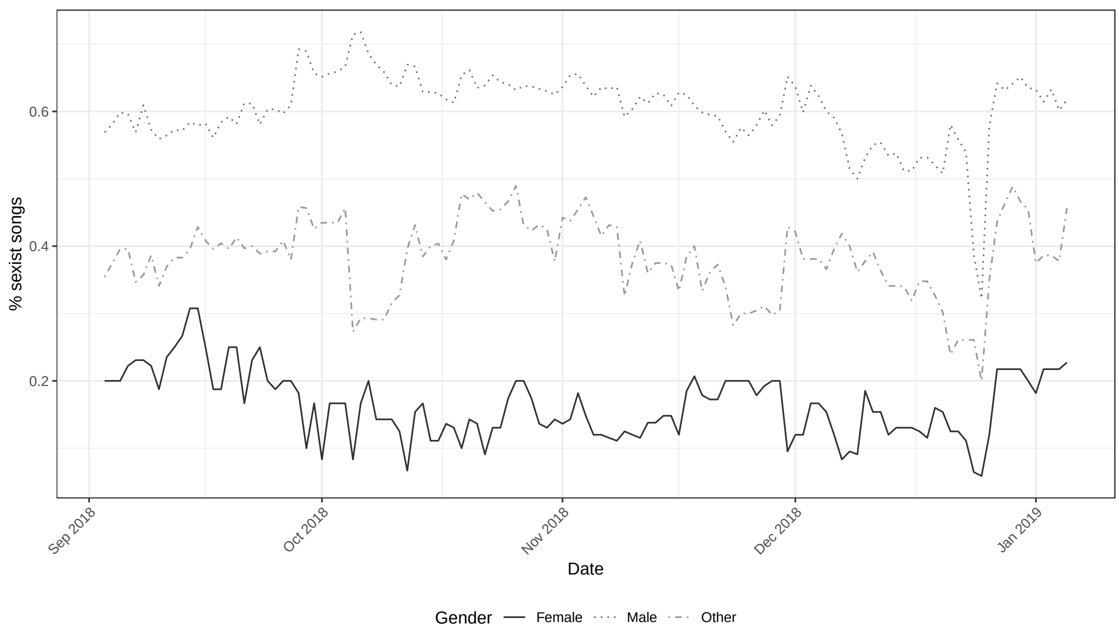

Figure A12. Daily Share of Songs with at least one Sexist Term in the Lyrics in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from September 3, 2018 to January 6, 2019

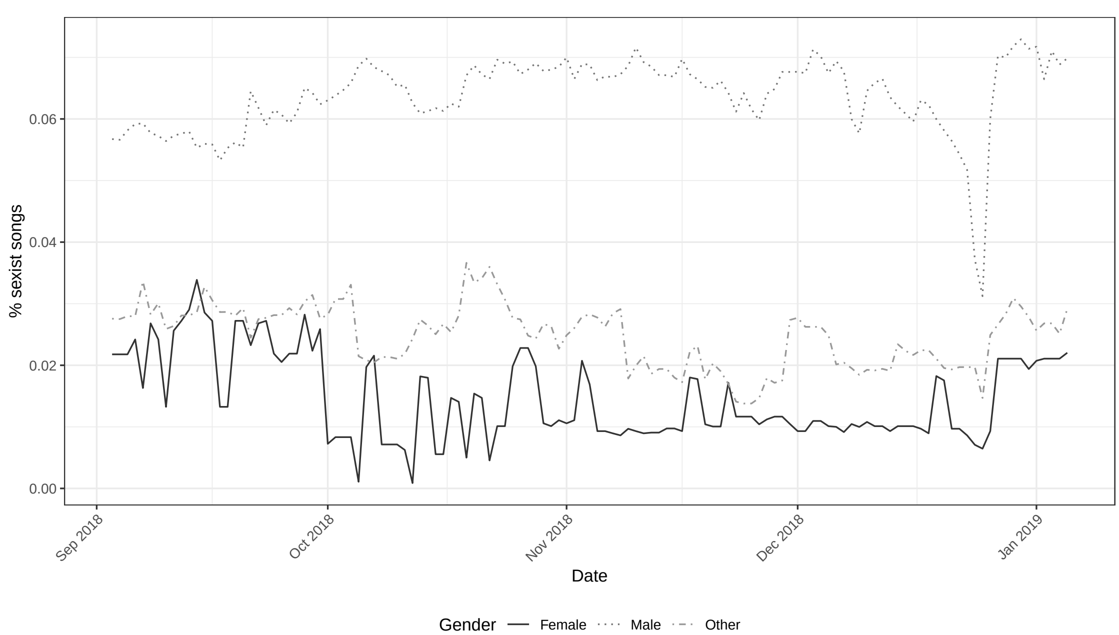

Figure A13. Daily Share of Lines in Songs' Lyrics with at least one Sexist Term in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from September 3, 2018 to January 6, 2019

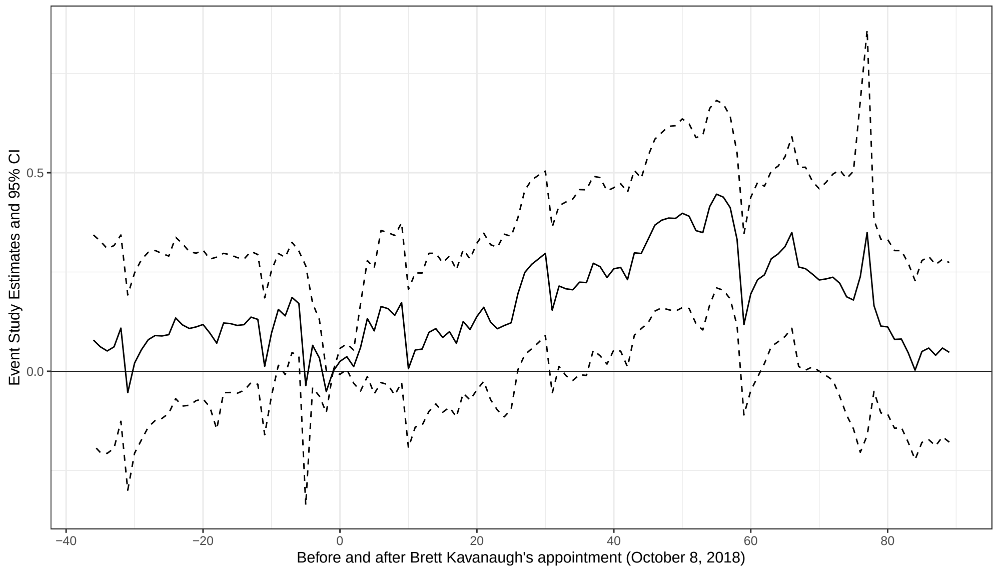

Figure A14. Event Study: $\log(streams_{it})$ - Songs with no Sexist Terms by Female and Male Artists

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 January 6, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 9, 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 A5. Difference-in-Differences: $\log(streams_{it})$ - Songs by Female and Male Artists with No Sexist Line in the Lyrics.

	$\log(streams_{it})$			
	(1)	(2)	(3)	(4)
$Post_t \times Female_i$	0.207**	0.200**	0.108	0.070
	(0.101)	(0.089)	(0.072)	(0.072)
Song features controls		✓		
Charts controls	✓	✓	✓	✓
Artist FE	✓	✓		
Song FE			✓	✓
Day FE	✓	✓	✓	✓
Observations	8,507	8,507	8,507	7,164
R^2	0.462	0.513	0.826	0.828
Within R^2	0.052	0.142	0.073	0.046

Notes: The sample includes songs within the top 200 U.S. charts on Spotify from September 3, 2018, to January 6, 2019. 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 no sexist terms in their lyrics. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B APPENDIX - 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.