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

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# Context: Political Consumerism

In recent years, there has been an increase in **political consumerism**, a phenomenon where **consumers "vote" with their wallets**.

Companies followed by taking stances on political and social matters. (Stolle and Micheletti, 2013)

For example, Nike and Pepsi have produced ad campaigns inspired by the Black Lives Matter movement. (Liaukonytė et al., 2023)

# Context: Political Consumerism

Political consumerism became evident in the film industry following the **Weinstein scandal** and the **#MeToo movement** in 2017 (Luo and Zhang, 2022).

- **#MeToo** boosts Hollywood producer-female writer collaborations.
- Weinstein-associated producers were **35% more likely** to work with post-scandal **female writers**, especially those closely connected to him.

In the music industry, it is usually the **Artist** that takes a stance on **political and social issues**.

# This Paper

## Research question

Did Kavanaugh's appointment affect music consumption in the US?

As **setting** we chose:

- **Kavanaugh's Appointment** at Supreme Court - #MeToo
- Platform: **Spotify**

**Main Results:**

- Female artists' **streams increase** *w.r.t.* males' and groups' ones
- The effect is **short-term** - 3 Months

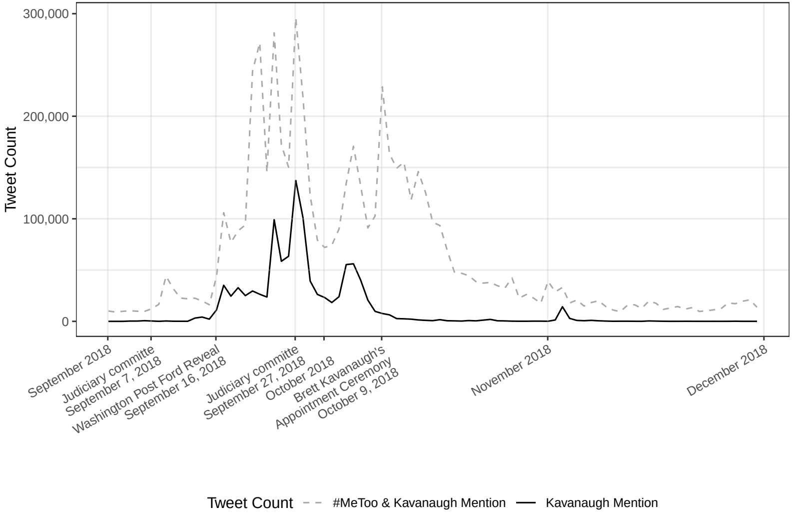
# Who is Brett Kavanaugh?

- **Brett Kavanaugh** is a federal judge nominated to the US Supreme Court by President Donald Trump on **6$^{\text{th}}$ October 2018**.
- Considered a **conservative** judge.
- Accused of sexual assault by **Christine Ford**, who testified before the Senate Judiciary Committee.
- His appointment gave the Supreme Court a **solid conservative majority**.

# Kavanaugh's Appointment media coverage

- In the **tweets text analysis** we have among the most common hashtags, #stopkavanaugh and #kavanaugh ▸ Tweets Hashtags
- #MeToo, had a significant increase in tweets in **September 2018**, returning to **previous levels in two months**.
- As a **proxy for general interest**, we use Tweets count about #MeToo and #stopkavanaugh and #kavanaugh

# #MeToo and Kavanaugh tweets



# Tweets

Most common hashtags in tweets in the selected period:

1. #metoo: 2 857 575
2. no hashtag: 2 458 176
3. #believesurvivors: 339 692
4. #whyididntreport: 293 834
5. #timesup: 176 026
6. #believewomen: 116 173
7. #stopkavanaugh: 114 948
8. KoreanTweets: 90 688
9. #kavanaugh: 86 591
10. #himtoo: 86 410

# Data

1. Charts: **200 most streamed songs** in the **US** on **Spotify**
   - → Number of streams
   - → Song rank (1-200)
   - → Days on chart
   - → Release week (0 -1)
   - → Release date
2. Song Features elaborated by Spotify:
   - → Danceability, Tempo (bpm), Energy, Key, Duration (length), etc.
3. Artists data:
   - → Gender: Female, Male, Group *(musicbrainz.com)*
   - → Followers

# Descriptive statistics

Summary Statistics - Songs by Female and Male Artists between September 3, 2018, and December 23, 2018

| | 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 | |

# The Model

Difference-in-Difference Specification:

$$\log\left(\text{streams}_{it}\right) = \theta_i + \gamma_t + \beta_1 \text{Female}_i \times \text{Post}_t + \beta_2 \boldsymbol{\chi}_{\mathbf{it}} + \epsilon_{it}$$

Where:

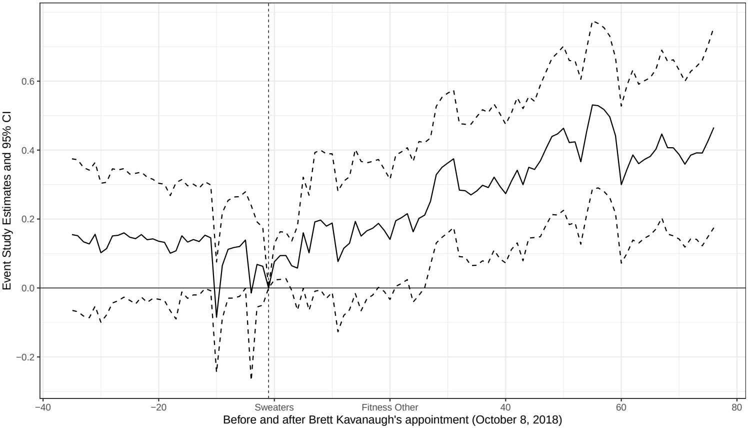
$i$ is the item observation at **song** level

$t$ is the time observation at **day** level

- The coefficient $\beta_1$ **captures the difference** between the log of the streams of **songs performed by male or female artists**.

The event study was conducted using observations from the **first Monday of September** to the **last Sunday before Christmas in December 2018**.

# Event Study: Female and Male artists



# Regression Table: 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 | | | ✓ | ✓ |
| *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 |

# Event Study: Placebo

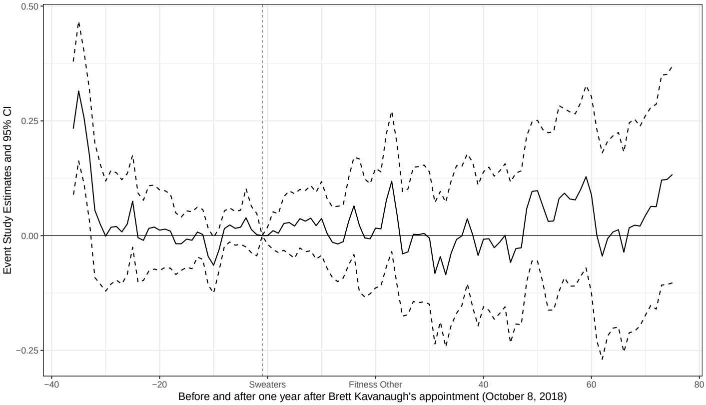



*Figure:* Event Study using 2019 as Placebo

# Placebo Diff-in-Diff

| Dependent Variable: | Log(Streams) | |
|---|---|---|
| Model: | (1) | (2) |
| $\text{Post}_t \times \text{Female}_i$ | 0.010 | -0.011 |
| | (0.076) | (0.063) |
| *Fixed-effects* | | |
| Artist | ✓ | |
| Day | ✓ | ✓ |
| Song | | ✓ |
| *Fit statistics* | | |
| Standard-Errors | Artist | Song |
| Observations | 16,614 | 16,614 |
| $R^2$ | 0.492 | 0.814 |
| Within $R^2$ | 0.149 | 0.128 |

# Coefficient plot per year: $Post_t \times Female_i$

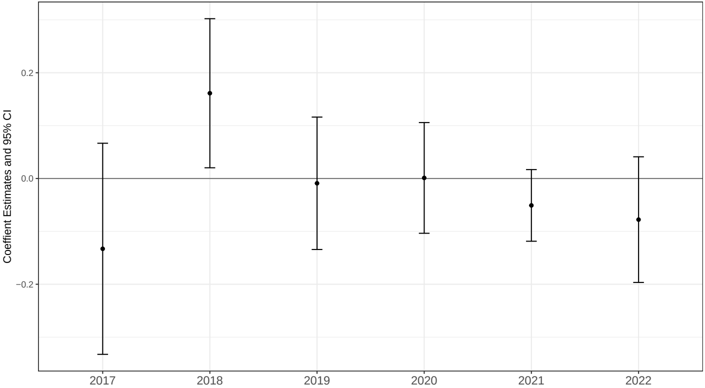



*Figure:* Annual Regression $Post_t \times Female_i$ Estimates in the US

# Coefficient plot per country: $Post_t \times Female_i$

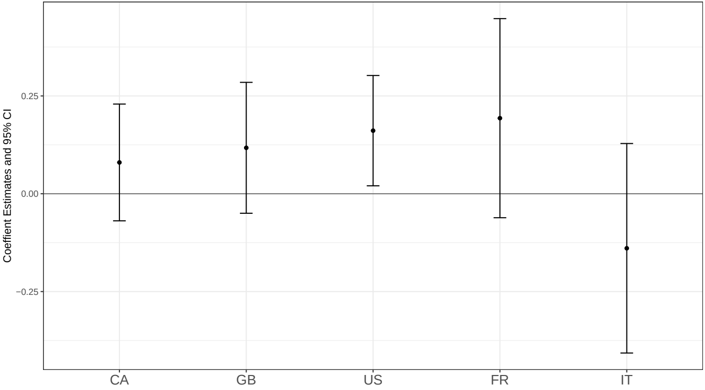



*Figure:* $Post_t \times Female_i$ Estimates Across Countries in 2018

# Gender share in Playlists

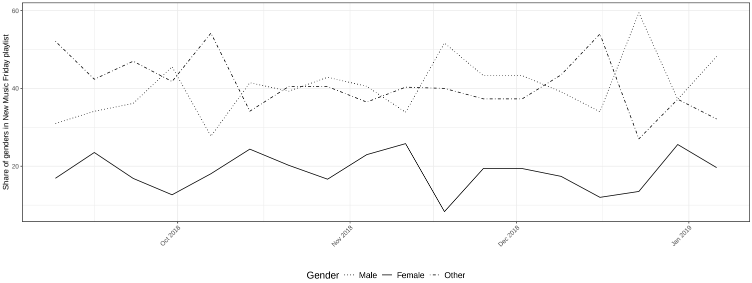



*Figure:* Share of songs among single artists in the New Music Friday Playlist, per gender

# Why females vs males?

Kavanaugh's nomination thus marked a **turning point in the discourse on sexual misconduct**, with significant implications for gender politics in the United States. (Lawless, 2018)

We **analyzed the lyrics of the songs** in the charts for:

1. **Sexism**: BERTModel to identify **sexist verses**
2. **Female Empowerment**: LLM (LLAMA3 from Meta) to identify whether a song is an **empowerment** song or not

# Examples: Female empowerment and sexism from females

## I'M THAT GIRL

*Beyoncé - RENAISSANCE*

**Lyrics**

I pull up in these clothes, look so good

'Cause I'm in that, hoe

You know all these songs sound good

'Cause I'm on that, hoe

Deadass, deadass, I'm deadass

It's not the diamonds

It's not the pearls

I'm that girl (I'm that girl)

# Examples: Female empowerment and sexism from males

## ALL OF THE LIGHTS

*Kanye West - My Beautiful Dark Twisted Fantasy*

**Lyrics**

Restraining order, can't see my daughter

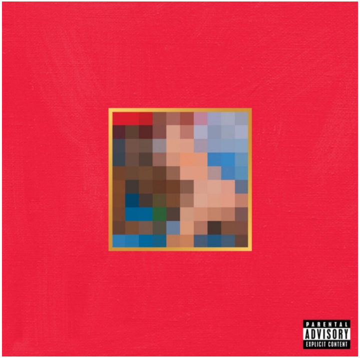
I made mistakes

I bumped my head

Them courts sucked me dry

I spent that bread

She need her daddy, baby, please



# Lyrics: Sexism

| God Made Girls - RaeLynn | |
|---|---|
| **Verse** | **Sexist (0/1)** |
| Somebody's gotta wear a pretty skirt | 1 |
| Somebody's gotta be the one to flirt | 1 |
| Somebody's gotta wanna hold his hand | 1 |
| So God made girls | 0 |
| Somebody's gotta make him get dressed up | 1 |
| Give him a reason to wash that truck | 1 |
| Somebody's gotta teach him how to dance | 1 |
| So God made girls | 0 |

*Table:* Sample Lyrics and Assigned Sexism Labels (0 = Not Sexist, 1 = Sexist)

# Lyrics: Sexism

| Dependent Variable: | Log(Streams) | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| $\text{Post}_t \times$ Sexist | 0.381*** | -0.027 | -0.033 | -0.046 |
| | (0.119) | (0.048) | (0.046) | (0.046) |
| $\text{Post}_t \times$ Sexist $\times\ \text{Female}_i$ | | | | 0.491*** |
| | | | | (0.123) |
| *Fixed-effects* | | | | |
| Song | ✓ | ✓ | ✓ | ✓ |
| Day | ✓ | ✓ | ✓ | ✓ |
| *Fit statistics* | | | | |
| Standard-Errors | Song | | | |
| Observations | 2,102 | 14,081 | 16,183 | 16,183 |
| $R^2$ | 0.853 | 0.831 | 0.827 | 0.829 |
| Within $R^2$ | 0.061 | 0.166 | 0.139 | 0.149 |

# Text Analysis Prompt Example

- Perform text analysis to recognize language and assess empowerment.
- Respond only with a JSON dictionary.

## Lyrics

To the old, and to the new, we dedicate this song...

**Consider these as examples of female empowerment:**

- "Who run the world? Girls!"
- "My persuasion can build a nation..."
- "Strong enough to bear the children..."

# Lyrics: Empowerment with prompt engineering

*Table:* 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) |
| $\text{Post}_t \times \text{Female}_i$ | 0.268*** | 0.102 | 0.111 |
| | (0.100) | (0.066) | (0.077) |
| $\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$ | -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* | | | |
| Standard-Errors | Song | | |
| Observations | 16,172 | 16,172 | 16,172 |
| $R^2$ | 0.829 | 0.829 | 0.829 |
| Within $R^2$ | 0.148 | 0.149 | 0.146 |

# Lyrics: Empowerment with different thresholds

*Table:* Difference-in-Differences: log(streams) - Songs by Female and Male Artists considered empowering by LLAMA 3 model for different thresholds.

| Dependent Variable: | Log(Streams) | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| $Post_t \times Female_i$ | 0.087 | 0.107 | 0.111 |
| | (0.117) | (0.112) | (0.077) |
| $Post_t \times Empowering_i$ | -0.207*** | -0.207*** | -0.207*** |
| | (0.022) | (0.022) | (0.022) |
| $Post_t \times Female_i \times Empowering_i$ | 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 |
| $R^2$ | 0.829 | 0.829 | 0.829 |
| Within $R^2$ | 0.145 | 0.145 | 0.146 |

# Lyrics: Empowerment with different samples

*Table:* Difference-in-Differences: log(streams) - Songs by Female and Male Artists considered empowering by LLAMA 3 model for: US.

| Dependent Variable: | Log(Streams) | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| $\text{Post}_t \times \text{Female}_i$ | | | 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* | | | |
| Standard-Errors | Song | | |
| Observations | 2,102 | 2,102 | 16,172 |
| $R^2$ | 0.846 | 0.846 | 0.829 |
| Within $R^2$ | 0.017 | 0.017 | 0.146 |

# Lyrics: Label

*Table:* Difference-in-Differences: log(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* | |
| Standard-Errors | Song |
| Observations | 16,223 |
| $R^2$ | 0.830 |
| Within $R^2$ | 0.154 |

# Key Takeaways

- The media attention on **Kavanaugh's Appointment** and on the **#MeToo movement** had an effect on music consumption in the United States in the following **70 days**.
- **Increase** of approximately **16%** in the consumption of music performed by **women**, compared to music performed by **men and groups**.
- Sexist songs from women **increase** of approximately **40%** w.r.t non-sexist songs.
- Songs that are **flagged as empowering** by LLAMA3, have a fairly significant increase of **30%** w.r.t non empowering songs.

Thank you !!

# Appendix

# Gender share in charts

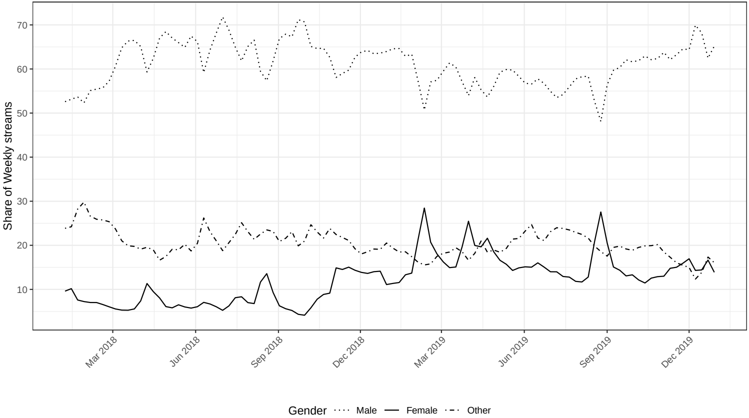



*Figure:* Share of daily streams among single artists, per gender

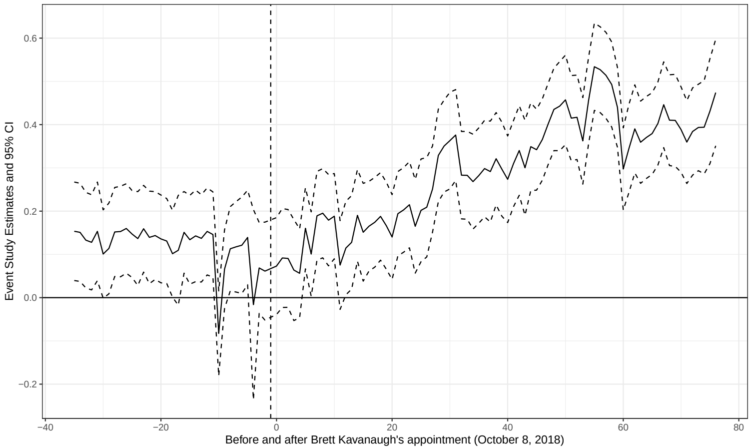



*Figure:* Bootstrapped results for main event study

# Literature review

Under-representation of female artists in the music industry:

- Smith et al. (2018) Report analyzing the presence in charts and prizes won by women
- D'Souza (2023) article reporting the women's underepresentation in the music industry.
- Kelley (2019) article pointing out gender inequality in music industry
- Bossi (2020) article analyzing the underlying factors for gender inequality.

Gender-bias in the movie industry:

- Ellis-Petersen (2014) Hollywood film crews 75—25 as Male—Female Ratio.

Bias in recommendation systems:

- Aguiar et al. (2021) Spotify favours women's songs in the positions of New Music Friday playlists.