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

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Introduction

- **"Vote with your wallet"** trend is growing. (Boström et al., 2019)
- Companies are following by taking stances on political and social matters. (Stolle and Micheletti, 2013)
- Nike and Pepsi have produced ad campaigns inspired by the Black Lives Matter movement. (Liaukonytė et al., 2023)

Introduction

- **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.

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

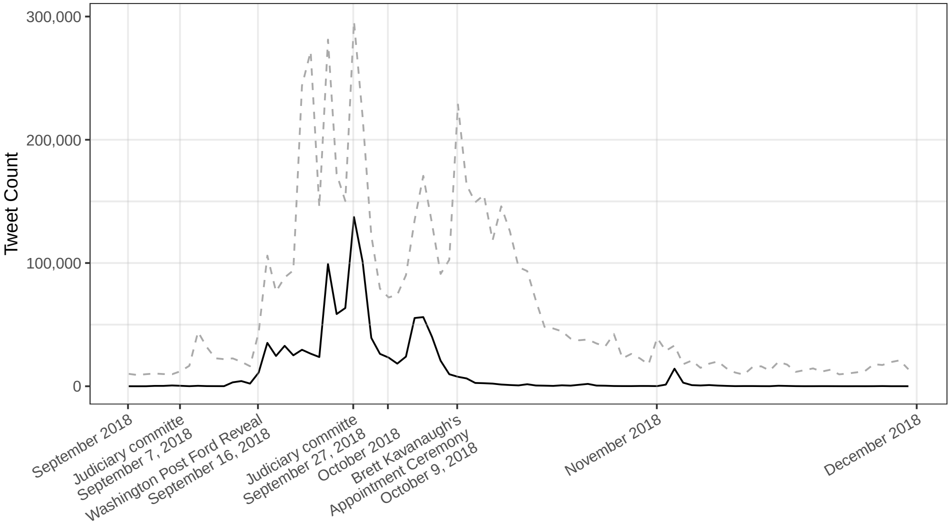
Who is Brett Kavanaugh?

- **Brett Kavanaugh** is a federal judge nominated to the US Supreme Court by President Donald Trump on **6th 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 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

- The dataset contains **significantly more observations for male** artists (14,103) than for female artists (2,120).
- This imbalance **reflects a broader disparity** in the representation of male and female artists **in the music industry.**
- **Why this research matters:**
  - → Addresses the **under-representation** and **gender disparities** in the music industry.
  - → **Understand how social and political events influence consumer behaviour.**

The Model

Difference-in-Difference Specification:

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

Where:

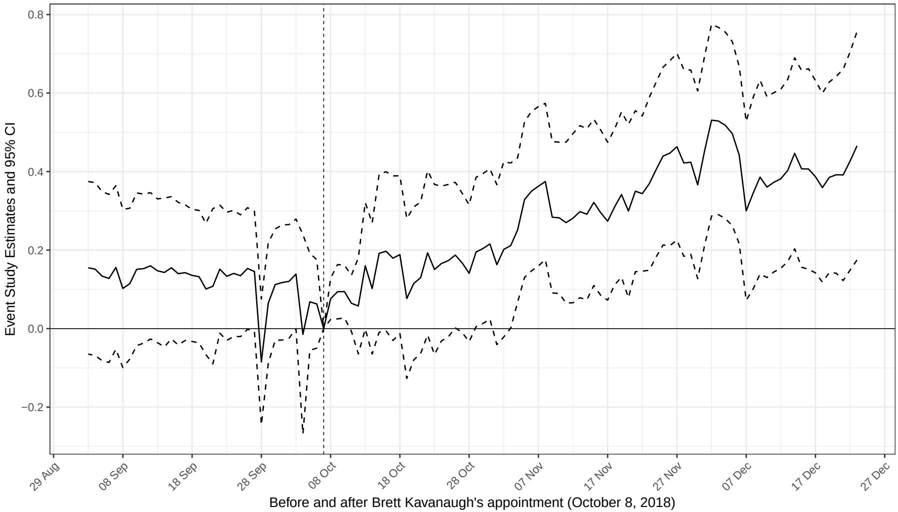
i is the item observation at **song** level

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

- The coefficient β_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 (3) September** to the **last Sunday before Christmas in (23) December 2018**.

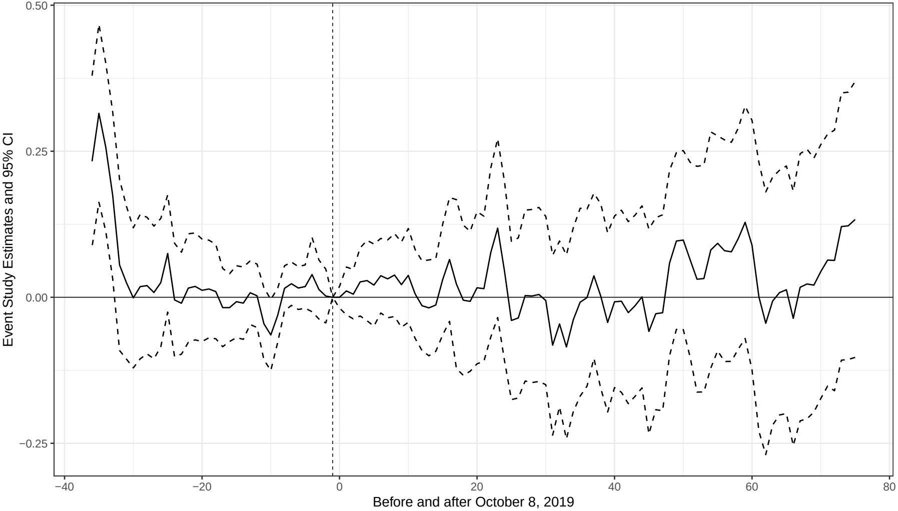
Event Study: Female and Male artists



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

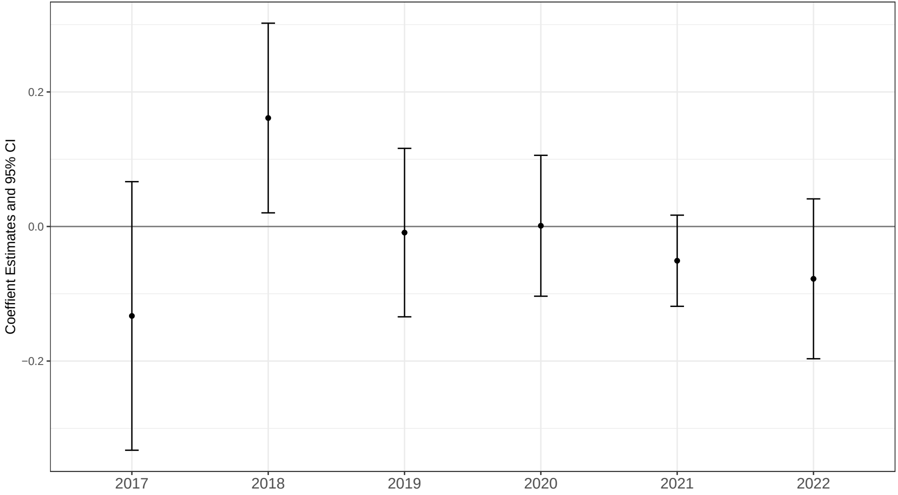
Event Study: Placebo



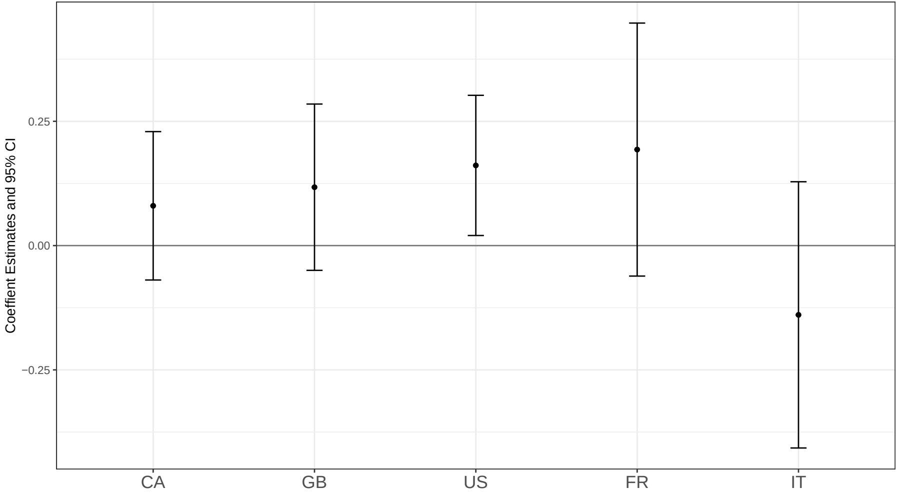
Placebo Diff-in-Diff

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: $Post_t \times Female_i$



Coefficient plot per country: $Post_t \times Female_i$



A platform induced effect?

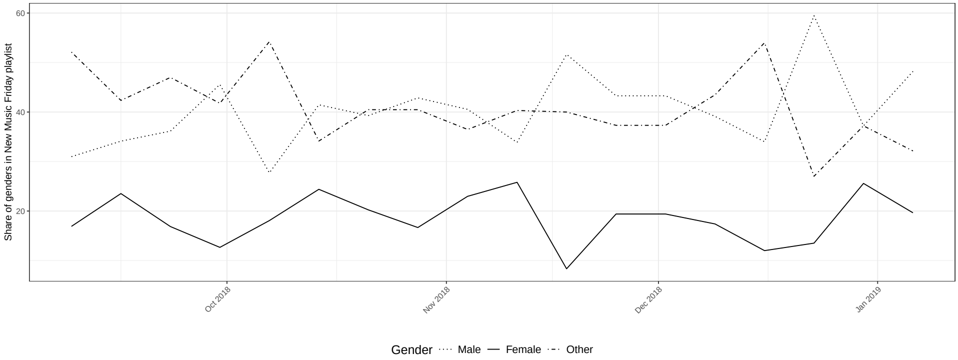


Figure: Share of songs among single artists in the New Music Friday Playlist, per gender

Is it all about gender?

- Kavanaugh's nomination raised awareness on **discourse on sexual misconduct.**
- **Far-reaching implications for gender politics** in the United States (Lawless, 2018).
- Enabled **empowerment and sexism** in various domains, including music.

Sexism and Empowerment

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

1. **Sexism**: BERTModel to identify **sexist verses** (Nguyen et al., 2020)
2. **Female Empowerment**: LLM (LLAMA3 from Meta) to identify whether a song is considered **empowering** or not.

Lyrics: Sexism

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				
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

Lyrics: Empowerment

- An LLM was asked if a song was empowering.
- Responses ranged from 0 (not empowering) to 1 (highly empowering).
- This enabled quantifying empowerment in song lyrics.
- Different specifications were tested:
  - → various thresholds [0.65, 0.70, 0.75]
  - → prompt engineering techniques

Lyrics: LLM prompt engineering

- if "blind":

  Perform text analysis to recognize language and assess empowerment.

- if "sighted":

  Perform text analysis to recognize language and assess empowerment knowing the performer is a `Female/Male`

- if "examples":

  Perform text analysis to recognize language and assess empowerment knowing the performer is a `Female/Male` and use these as examples for empowerment:

  → "Who run the world? Girls!"

  → "My persuasion can build a nation..."

Lyrics: Empowerment with prompt engineering

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			
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

Label effect?

- Belongingness to a **Major Label** was added as a robustness check
- A diff-in-diff-in-diff was performed adding label as a layer
- **Result:** Major labels are not pushing female artists

Lyrics: Label

Dependent Variable:	Log(Streams)
Model:	(1)
$Post_t \times Female_i \times Label = Universal$	-0.427***
	(0.115)
$Post_t \times Female_i \times Label = Warner$	-0.335**
	(0.138)
$Post_t \times Female_i$	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

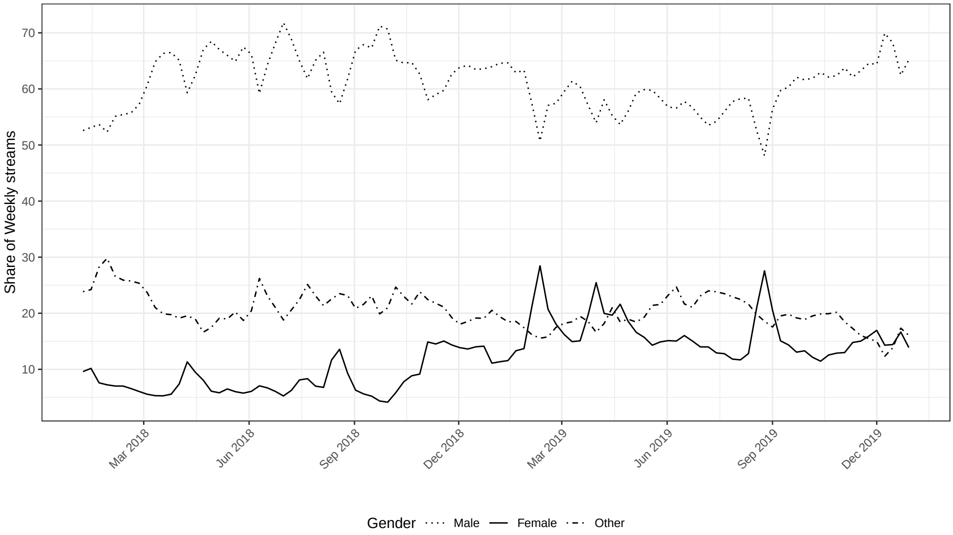
Key Takeaways

- **Kavanaugh's appointment** led to a **16% increase** in the consumption of music performed by **women** over the following **70 days** in the US.
- 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.
- **Major labels** are **not** pushing female artists

Thank you !!

Appendix

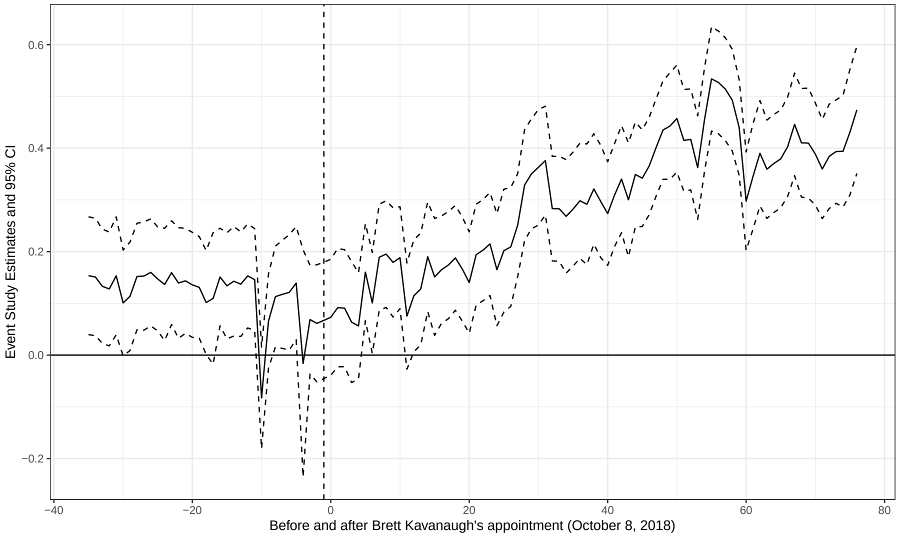
Gender share in charts



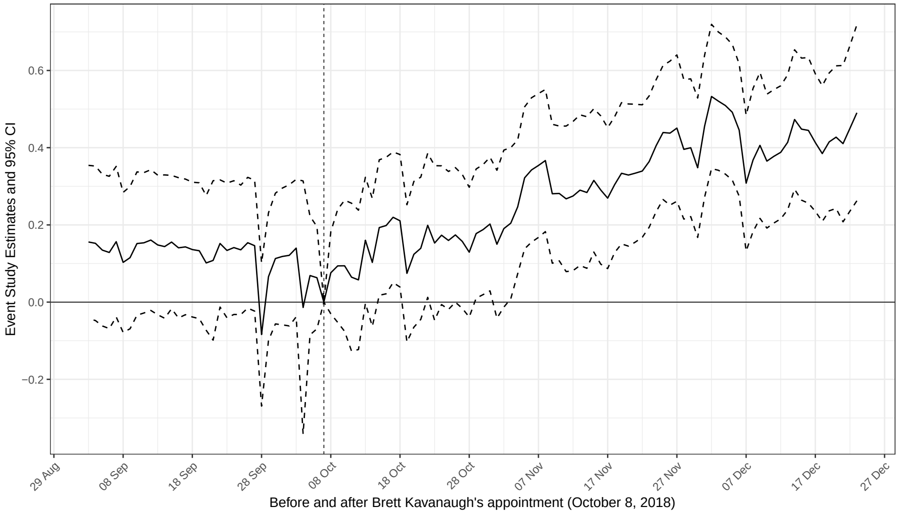
Descriptive statistics

	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
Number of observations:	2,120		14,103		-11,983	

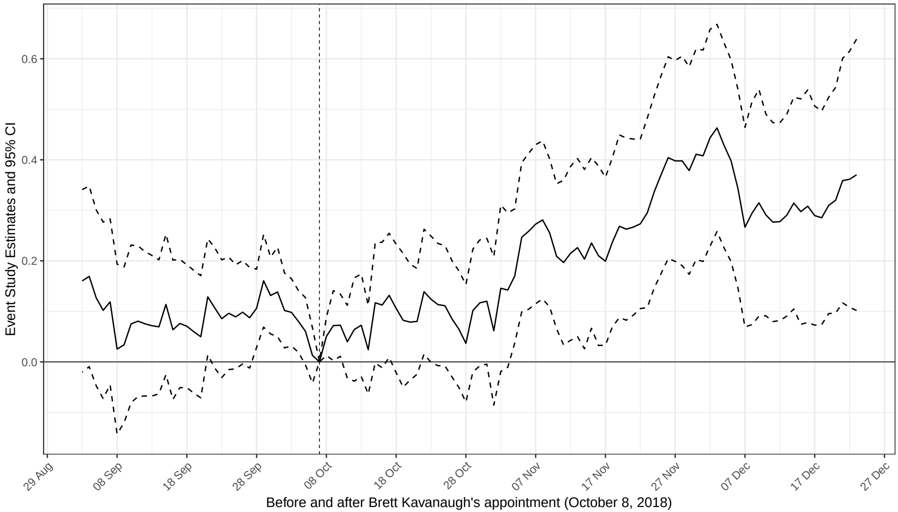
Bootstrap Results removing 1/4 observations



Removing Female Stars Releases



Removing New Releases



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 under-representation in the music industry.
- Kelley (2019) article pointing out gender inequality in music industry
- Bossi (2020) article analysing 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.