The Value of Silence: The Effect of UMG's Licensing Dispute with TikTok on Music Demand

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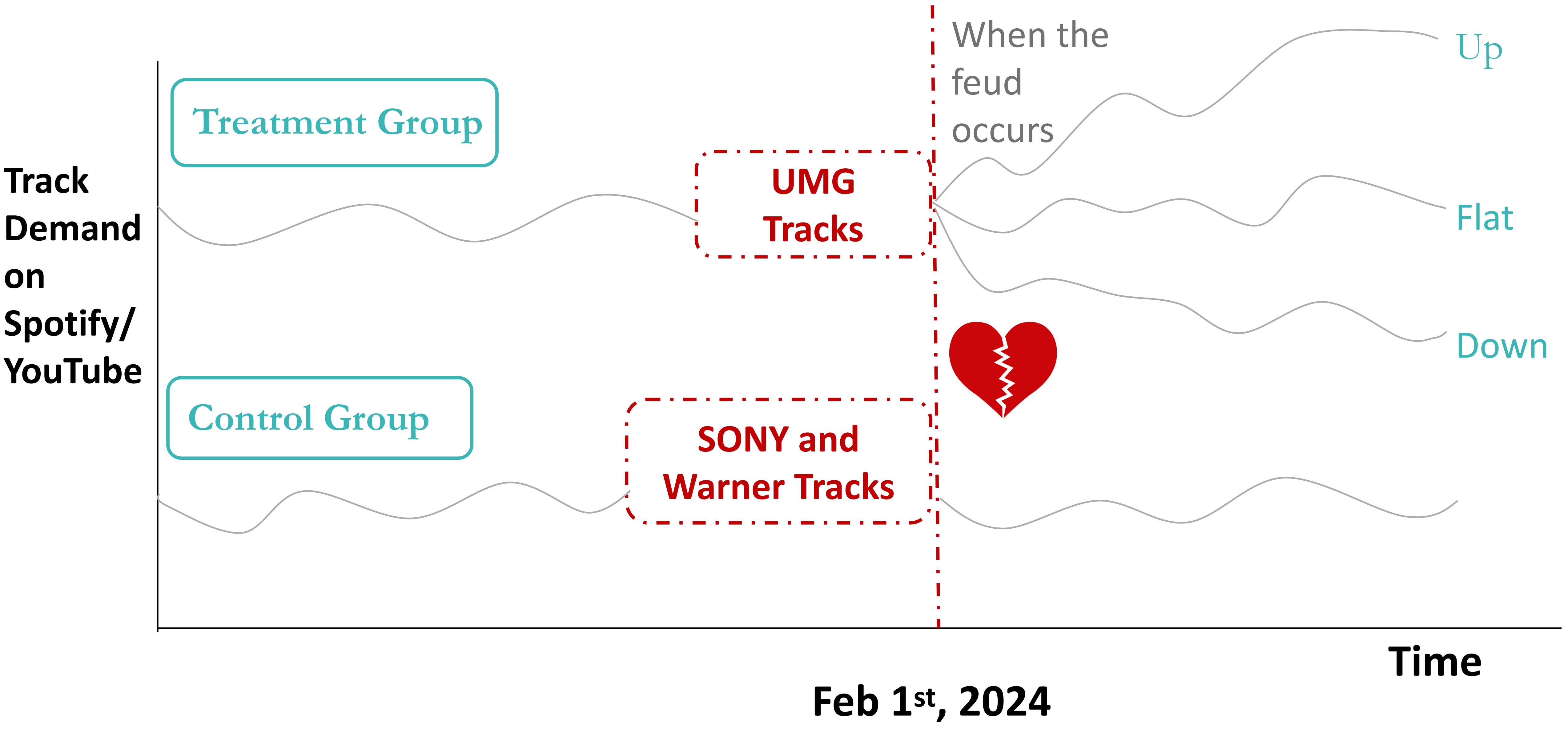
Research Questions

How Does Excluding Music Tracks from Social Media Platforms (e.g., TikTok) Affect Music Demand on Streaming Services (e.g., Spotify, YouTube)?

- Is there an overall impact?
- Are there any heterogeneous effects across tracks?
- Can we quantify this impact and offer economic implications for the parties involved?

DiD Empirical Framework



Main Effects

$$log(Demand_{it} + 1) = \alpha + \beta * UMG_i * Post_t + Track_i + Date_t + \epsilon_{it},$$

Table 3: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Log-Specification)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	-0.00293	(0.00219)	-0.00684	(0.00738)
_cons	5.572***	(0.000383)	5.908***	(0.00140)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
N	24653297		1611685	
R^2	0.9475		0.8838	
AIC	56223334.0		4565598.3	
BIC	56223349.0		4565610.5	

Standard errors are presented in parentheses and clustered at the track level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

<u>Null effects</u> on streaming demand at both Spotify and YouTube!

Heterogeneity by availability on TikTok

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_Youtube_views	(3) log_Spotify_streams	(4) log_Youtube_views
1.UMG#1.post	0.0229***	0.0216+	-0.0142***	-0.0266**
	(0.00405)	(0.0112)	(0.00257)	(0.00869)
_cons	7.741***	6.820***	4.593***	4.914***
	(0.000676)	(0.00227)	(0.000459)	(0.00157)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	7670998	804222	16982133	787275
R^2	0.9429	0.8634	0.9351	0.8976
AIC	16724381.7	2384634.5	38388391.9	1938692.4
BIC	16724395.5	2384646.1	38388406.5	1938704.0

Standard errors are presented in parentheses and clustered at the track level

$^{+}\ p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Tracks on TikTok prior to the dispute: Positive effect (*Substitution* effect)

Tracks not on on TikTok prior to the dispute: Negative effect (*Complementary* effect)

Economic Impact and Aftermath

$$\text{Gain}^S = \sum_{i=1}^{N_{\text{OnTikTok}}} \beta^S_{\text{OnTikTok}} \times BaselineDemand^S_i \times 0.003 \times 365$$
$$\text{Loss}^S = \sum_{i=1}^{N_{\text{NotOnTikTok}}} \beta^S_{\text{NotOnTikTok}} \times BaselineDemand^S_i \times 0.003 \times 365,$$

- Removal of UMG's music from TikTok lead to about $900 million USD/year in revenue gain
- Greater than renumeration under prior agreement (approx. $111 USD/year)
- What happened eventually — On May 1st 2024, UMG and TikTok announced new licensing agreement with increased compensation for UMG artists

Overall positive effect is consistent with eventual resolution of the dispute.

Subsequent Work

- Us — Null effects
- Winkler et al. 2024— Positive effects
- Bairathi et al. 2024 — Negative effects

Question — why the difference and what can we credibly take away in terms of policy?

What are the possible sources of differences

- Data sources and panel length
- All tracks vs. tracks on TikTok prior to dispute
- Model used (DiD vs. synthetic/matching with DiD)
- Use of logged dependent variable
- Level of data aggregation (weekly vs. daily)

Possible sources of differences

- Data sources and panel length
- All tracks vs. tracks on TikTok prior to dispute
  - Winkler et al. 2024 and our paper use data on all tracks
  - Bairathi et al. 2024 exclusively focus on tracks on TikTok
- Model used (DiD vs. synthetic/matching with DiD)
  - Other two papers use matching/synthetic DiD
  - Parallel trends largely satisfied (trends, if any, are about 1—3% of TEs)
- Level of data aggregation (weekly vs. daily)
  - To do matching — but significant loss of power and matching can add its own sources of bias
- Use of logged dependent variable
  - Bairathi et al. 2024 use levels instead of log (see McConnell 2024)
  - Even with levels, we see positive/null effects for tracks on TikTok, but much poorer model fit and unstable TEs

Levels Estimates

Table 9: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Levels-Specification)

	(1) Spotify_streams		(2) YouTube_views	
1.UMG#1.post	684307.2***	(163345.7)	15855.4	(71044.9)
_cons	515134.4***	(28591.5)	582512.0***	(13467.0)
N	24653297		1611685	
R^2	0.0124		0.4281	
aic	993492724.8		57412769.5	
bic	993492739.9		57412781.8	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Levels-Specification, Dropping Observations Larger than 99 Percentile)

	(1) Spotify_streams		(2) YouTube_views	
1.UMG#1.post	312.3**	(98.41)	635.0	(566.3)
_cons	18112.6***	(17.18)	20820.0***	(108.0)
N	24406707		1595299	
R^2	0.9047		0.4214	
aic	571635472.8		41644196.7	
bic	571635487.9		41644209.0	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Effects still positive or null.
- Model fit is poor and magnitude of TEs is sensitive to outliers.
- Consistent with Winkler et al. 2024’s positive effect.

Levels estimates by availability on TikTok

Table A19: Main Effect of Excluding UMG Tracks from TikTok on Music Demand: Tracks on vs. Not on TikTok (Levels-Specification)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) Spotify_streams	(2) Youtube_views	(3) Spotify_streams	(4) Youtube_views
1.UMG#1.post	2931374.5***	53910.4	-225423.4**	62492.4
	(495362.8)	(112260.1)	(72121.8)	(33994.3)
_cons	1154299.6***	879572.2***	219572.9***	188057.3***
	(82678.5)	(22789.6)	(12888.9)	(6127.7)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	7671163	804253	16982133	787275
R^2	0.0185	0.4503	0.0145	0.5265
aic	316982804.1	28999886.7	655908557.8	26778734.6
bic	316982817.9	28999898.3	655908572.4	26778746.2

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- For tracks on TikTok, effects are still positive/null
  - Results consistent with earlier log specification and with the eventual resolution of the dispute.
  - Even with multiple other stress tests, we are not able see the negative effects in Bairathi et al. 2024.

Main Takeaways

- Empirical findings
  - Impact of silencing of UMG's music: Null/positive overall
  - Tracks on TikTok before the dispute — Positive Effects (*Substitution* Effect)
  - Tracks not on TikTok before the dispute — Negative Effect (*Complementary* Effect)
  - Overall economic impact — TikTok was undercompensating UMG
  - Use of logged dependent variable
- More broadly, lessons for empirical research (at least for me):
  - Null results are okay….
  - There are many researcher degrees of freedom — therefore consider multiple specifications and stress test findings
  - Simpler models + more data tend to be more robust
  - Model fit matters for policy implications

Thank You!

Details on Panel Length

- Data sources and panel length
  - Winkler et al. (2024)
    - 9 weeks total, 5 weeks before and 4 weeks after (Jan 1st — Feb 27th 2024)
  - Bairathi et al. (2024)
    - 10-week window, December 25,2023-March 5,2024
  - Our paper
    - 25 weeks/180-day period, from Oct. 10th 2023 to April 7th 2024