

How Valuable is a Super Bowl Halftime Performance?

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Abstract— This paper aims to determine how much value a musical artist receives from performing in the NFL Super Bowl. To do so we will be using a Difference in Difference approach to see the effect of the performance on their streams, album sales, and chart rankings. Due to the imbalanced treatment and control groups our initial findings lacked significance, however after bootstrapping with oversampling of the treated group we saw significantly positive effects of treatment.

Keywords—*Music Industry, Sports, Marketing, Streaming, Spotify, NFL*

I. INTRODUCTION

In this paper we attempt to quantify the value of the publicity artists receive when performing in the NFL Super Bowl half time show. No previous work that we could locate attempts to answer this question. The majority of prior literature instead examines the dynamics between marketability and artistic integrity, or changing trends in how music is marketed.

The primary obstacle in compiling this report was data availability. Most relevant data including exact financial payouts, historical album sales, and streams are confidential and/or proprietary. Due to this issue we were forced to adjust the original scope of this paper and omit the analysis of impacts in NFL viewership based on the artist performing. Also due to this issue we were forced to restrict our analysis to 2015-2024 which impacted the significance of our findings. In order to address this issue we utilized a bootstrap sampling method with oversampling of the artists who had performed in that years Super Bowl. Our MLE estimates for the value of the publicity are within [\$170,000, \$284,000] depending on the exact payout rate they receive.

II. METHOD

The majority of this project was spent collecting and preprocessing our data. Due to budget constraints we were prevented from accessing in-depth long run historical records and were forced to limit our scope. We were fortunately able to collect artist chart ranking, streams, and album sales from 2015-2024 with few structural issues. Data volume and granularity remain the limiting factors of our analysis. All of the data we collected was scraped from the sites referenced below. This scraping process presented numerous difficulties such as requiring the usage of a Chrome WebDriver to log in to a Spotify account which was required to view the necessary charts. This on its own would not have been too burdensome, but during the analysis Chrome released version 124 without releasing a

WebDriver compatible with that version. We were then forced to utilize the beta development instances in order to collect the data which did not work as expected some portion of the time. The next challenge we faced required us to scrape archived historical versions of the Hits Daily Double site that were preserved as a part of the Internet Archive initiative. Since the versions of the site spanned 2015-2024 our HTML parsing process was quite labor intensive due to site structure updates.

Once the data had been collected from the web and parsed from the HTML and stored in CSV files we were able to begin preprocessing our data. Due to the lack of standard formatting for artist names, featured artists, track names, and album names this process required complex logic, and a significant amount of manual formatting. Our first step was to create new rows to individually represent each artist on tracks that included multiple artists. This required us to recognize tokens such as “with”, “&”, “and”, “ft.”, and “feat.” as well as distinguish when they were genuinely part of the artist's name.¹ Once this step had been completed we verified that all punctuation was consistent across sources and then converted all letters to uppercase to ease matching. We next stripped all quantitative values of punctuation and converted percentages to decimals and values measured in multiples of base 10 to integers. Then we inserted the attributes chart movement from the previous week, a dummy variable indicating whether the artist had performed in that year's Super Bowl, and another dummy variable indicating whether the chart was dated before or after the Super Bowl. Finally we added observations for the performers that showed up in only one of the pre and post treatment groups. Artists that only showed up in the pre-treatment group had their values set to 90% of the last ranked artists for their post-treatment observation. While artists that were only present in the post-treatment group had their values set to 90% of the bottom ranked prior artist. This approach lead to some highly suspect outliers, so we have assumed some level of data entry errors and opted to drop they filled in values for our simulations.

In order to capture the effect of performing in the Super Bowl, while also controlling for other market factors we elected to utilize a Difference-in-Difference (DD) model. This approach compares the pre and post treatment means of the control and treatment group. The effects can either be estimated by hand after calculating the means as such:

$$DD = \Delta Treatment - \Delta Control$$

Alternatively a linear regression with the structure:

1. Earth, Wind, & Fire being an example.

$$y_i = \beta_0 + \beta_1 Post_i + \beta_2 Treat_i + \beta_3 (Post_i * Treat_i)$$

has the DD estimate as the β_3 coefficient. In our initial estimates we observed economically significant outcomes that were statistically insignificant due high standard errors resulting from the treated groups sample size of 25. Which is insufficient on its own, but is even more so in the face of the controls 1003 samples. As an attempt to address this we performed several bootstraps with replacement and specified ratios of control and treated observations. Since our data included the total album and album equivalent sales (SPS) we converted these values to streams using the common ratio of one album:3500 streams by free accounts. We used the ratio for free accounts rather than paid accounts due to lack of transparency about the premium paid for the latter. We then calculated the expected royalty amount using Spotify's published average range of \$0.003 to \$0.005 per stream. We have assumed Spotify's payment plan for all streams since it holds by far the largest market share, while also sitting near the median of reported rates.

Our data simulation included 1,000 iterations of 1,000 randomly sampled data points where 10%-25% of data points were halftime performers. A random state seed was set in order to improve reproducibility. We then used the distribution of results to make an argument of causal inference.

III. EXPERIMENTAL RESULTS

The results of our simulation report both strongly significant economic and statistical results. Table I shows summary values of our simulation.

Table I	Ratio	Mean	SE
0.003 Earnings	0.10	\$170,451.42**	73,756.09
0.005 Earnings	0.10	\$284,085.70**	122,926.82
0.003 Earnings	0.25	\$169,552.12***	51,373.64
0.005 Earnings	0.25	\$282,586.87***	85,622.73
Total SPS	0.10	16,205.01 ***	6,976.43
Total SPS	0.25	16,121.50**	5,050.52

**Significant at 5% level

***Significant at 1% level

The earnings estimates are likely lower than reality since are approximations use the standard rate, whereas the top-level performers that are chosen for the Super Bowl likely receive

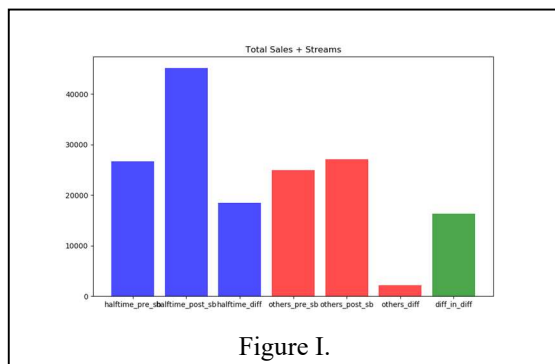


Figure I.

higher payouts. While our initial findings held no significance, the magnitude of change shown in Figures I. and II. convinced us to explore variance reduction techniques to continue our analysis.

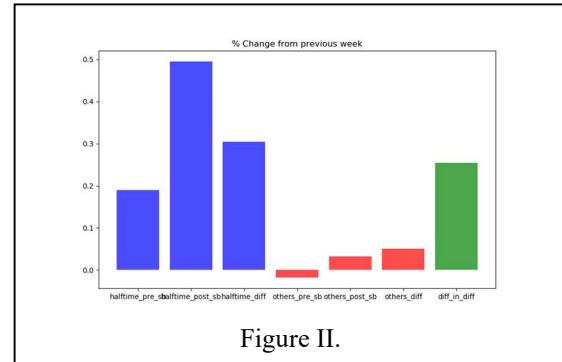


Figure II.

Figures III. and IV. show the distribution of earnings generated from our simulation.

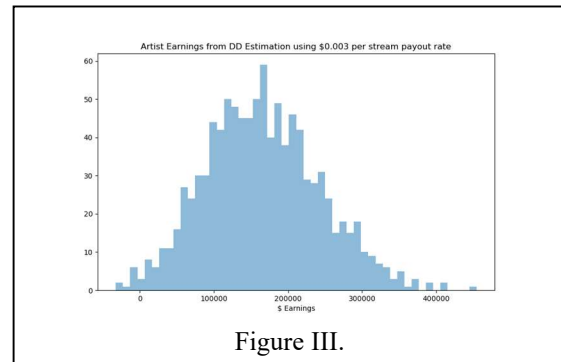


Figure III.

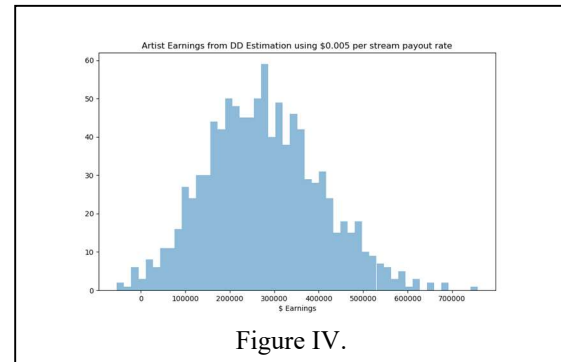


Figure IV.

IV. CONCLUSION

In summary, based on our estimates an artist who performs in the NFL Super Bowl halftime show will on average earn an extra \$170,000 to \$284,000 from an extra 16,000 album sales and streams in the first week afterwards alone. Future work on this topic would be simple for those with the ability to access granular music industry data going farther back, or those with access to similar data about NFL viewership numbers. Extensions may still be made without access to that information. Additions such as collecting more data from the

dates surrounding the Super Bowl could be collected over a longer period to abide by the website's restrictions. This may help with the issues posed by artists leaving the top 50. Alternatively utilizing metrics across the data sources we have collected may allow for a predictive model to be built to estimate some of the missing values.

The findings of this paper hint at a fascinating trend that would prove invaluable to the marketing and publicity industries. Data availability due to budget constraints and lack of corporate affiliation severely hinder any conclusions we may attempt to make about causality. The only true way to move forward and circumvent these issues is access to the required data.

REFERENCES

- [1] [1] Statista. (2024). Statista: Home. [Online]. Available: <https://www-statista-com.dist.lib.usu.edu/>. Accessed on: May 1, 2024.
- [2] Wikipedia. (2024, May 1). List of most-watched television broadcasts. [Online]. Available: https://en.wikipedia.org/wiki/List_of_most-watched_television_broadcasts#United_States. Accessed on: April 19, 2024.
- [3] Spotify. (2024). Spotify Charts: Regional Global Daily. [Online]. Available: <https://charts.spotify.com/charts/view/regional-global-daily/latest>. Accessed on: April 1, 2024.
- [4] Hits Daily Double. (2024). Sales Plus Streaming. [Online]. Available: https://hitsdailydouble.com/sales_plus_streaming. Accessed on: April 15, 2024.
- [5] Internet Archive. (2024). Wayback Machine. [Online]. Available: <https://web.archive.org/>. Accessed on: April 15, 2024.
- [6] Official Charts Company. (2024). Official Charts. [Online]. Available: <https://www.officialcharts.com/>. Accessed on: March 18, 2024.
- [7] Ditto Music. (2024). How Much Does Spotify Pay Per Stream? [Online]. Available: <https://dittomusic.com/en/blog/how-much-does-spotify-pay-per-stream>. Accessed on: April 20, 2024.
- [8] Digital Music News. (2018, December 25). How Much Do Music Streaming Services Pay Musicians in 2019? [Online]. Available: <https://www.digitalmusicnews.com/2018/12/25/streaming-music-services-pay-2019/>. Accessed on: April 20, 2024.