Northeastern University
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# Beer Industry
# Advertising Elasticity of Demand Phenomena

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**MISM6203 Business Analytics Methods**
**Semester Project by Zinaida Dvoskina and Kirill Ilin**
**Budweiser**

Business problem

The beer industry has a unique phenomenon: the advertising elasticity of demand is zero. Simply put, total advertising has pretty much no effect on total beer consumption. However, AED differs significantly between brands. An increase in demand for one comes directly at the expense of the other. Therefore, brands like Budweiser still must invest millions in advertising to increase or, at least, keep market share.

Data Sources used in the research

Multiple data sources were collected and analyzed for our research. Since the Budweiser brand is a part of a public company AB InBev, its data is publicly available.

1. We used year-to-year financial reports from AB InBev, posted by Gurufocus and Advertising Age & Kantar Media. Financial reports provided deep insights into the company's advertising elasticity of demand.
2. The second source was the beer industry year-by-year statistics. Most of that data is publicly available via Statista and includes sales and AB InBev market share in the industry. That data allowed us to make comparisons of AB InBev to the market.
3. We used the data provided by exceptional marketing campaigns such as Superbowl 2020 and FIFA World Cup 2018. Budweiser and other beer brands are constantly sponsoring such events and we have looked into the possible causation of marketing expenses on marketing in such events and the overall performance of the company.
4. The fourth source we used was the data gathered from the competitors and substitutes such as spirits and wines. That allowed us to see how the demand for beer changed over the years compared to other drinks.

We also analyzed many different pieces of research on the elasticity of alcohol beverages topic in order to see any patterns and have a knowledge background on the methodology of such researches and past results.

Preliminary Work

These are the steps we took in order to pick out and structure the data from the available sources.

Step 1: We have searched for the relevant company and industry-related data. We were checking possible sources for the relevant and available data. Our priority was to pick out the complete databases with relevant statistical data on companies' performance over the last 5 years.

Step 2: In this step, we have matched variables from the picked data by time spans in order to achieve the time correlation between the data, which is essential for the analysis process with multiple sources.

Step 3: In this step, we have transformed data into the row-column format and changed the structure of certain databases via Python and R. In addition to that we got rid of irrelevant and incomplete data such as mid-seasons with low potential for affecting the performance of the company.

Step 4: In this step, we have analyzed the data we are working with and got familiar with the variables. We have made suggestions regarding which variables relations will be used in the regression models for pattern identification.

Conducted analyses

What was analyzed:

- Linear regression models. We have run 20 different regressions of Budweiser revenue on marketing expenses in order to see any pattern and data correlation. We needed that number of models to see the correlation in different situations such as different lag parameters etc.
- AED. We have calculated the advertising elasticity of demand for Budweiser and the beer industry as a whole by combining our regression models and the gathered research data.

We obtained the following results:

- Budweiser has high advertising elasticity of demand
- Budweiser's market share increases after event-related campaigns
- Beer consumption is falling, consumers are switching to substitutes
- AED differs between brands
- AED of the beer industry as a whole is very close to zero and brand marketing primarily takes an existing market share instead of creating new demand.

Risk Assessment

We have identified several risks that may affect the result of the analyses and need to be addressed in the early stages of the research.

The first risk is the absence of brand-specific data. Even though many companies in the beer industry are public and have their data available, there is a certain risk that the deeper analysis of the industry or certain competitors will not be possible due to the limited data availability. In order to cope with that risk, we have used existing research regarding the industry data in order to collect quantitative and qualitative data useful for our conclusions.

The second risk we identified is that the level of data detalization may not be on par with our expectations and may affect the result. We will be looking into very specific events, and how they affect the performance of the company, however detailed data might be limited due to the periodic nature of the company's reports. In order to cope with that risk, we have used many different lag type models that made sense in the particular research in order to minimize risks of false causation.

The final risk we have identified is that certain patterns that we will see might be affected by the COVID-19 situation. Therefore, we assessed the data for relevancy and correct causation.

## Industry-wide Effects

### Advertising and US alcoholic beverage demand system-wide estimates[1]

Table 5 *Conditional elasticity estimates with advertising variables (point estimates evaluated at sample means)*

| Model | Group income | Slutsky price elasticities | | | Advertising elasticities | | | Cournot own-price elasticity |
|---|---|---|---|---|---|---|---|---|
| | | Beer | Wine | Spirit | Beer | Wine | Spirit | |
| ROT Beer | 0.689* | −0.038 | 0.008 | 0.030 | 0.007 | 0.006 | 0.014 | −0.372* |
| ROT Wine | 0.979* | 0.039 | −0.083 | 0.044 | 0.038 | 0.100* | −0.146* | −0.179 |
| ROT Spirit | 1.368* | 0.035 | 0.010 | −0.045 | −0.018 | −0.030* | 0.018 | −0.615* |
| AID Beer | 0.768* | −0.080* | 0.034 | 0.046* | 0.007 | 0.002 | 0.001 | −0.453* |
| AID Wine | 1.061 | 0.169 | −0.256* | 0.088* | 0.031 | 0.099* | −0.112* | −0.360* |
| AID Spirit | 1.257* | 0.054* | 0.021* | −0.074* | −0.015 | −0.026* | 0.025 | −0.597* |
| CBS Beer | 0.748* | −0.050 | 0.004 | 0.046 | 0.005 | 0.003 | 0.011 | −0.414* |
| CBS Wine | 1.132 | 0.022 | −0.041 | 0.018 | 0.036 | 0.089* | −0.164* | −0.152 |
| CBS Spirit | 1.263* | 0.054 | 0.004 | −0.058 | −0.015 | −0.025* | 0.026 | −0.583* |
| NBR Beer | 0.709* | −0.069* | 0.037 | 0.032* | 0.009 | 0.005 | 0.005 | −0.414* |
| NBR Wine | 0.903* | 0.185 | −0.293* | 0.108* | 0.033 | 0.110* | −0.094 | −0.382* |
| NBR Spirit | 1.363* | 0.037* | 0.025* | −0.063* | −0.018 | −0.031* | 0.016 | −0.629* |

Budget shares at the means are 0.486, 0.098, and 0.416 for beer, wine, and spirits respectively. Asterisks indicate statistically significant estimates

As we can see, the advertising elasticities of different types of drinks in the industry is very low. That means that advertising does not have a strong effect on demand. That research showed that advertising also has a minimal effect on the consumption levels of individual beverages. That implies that alcohol advertising redistributes specific brand sales and market shares. However, that research states that advertising by leading brands could affect beverage or overall demand for alcohol, but that still needs to be researched further.

### Beer Snobs Do Exist Estimation of Beer Demand by Type[2]

This study states that mass-produced beer is in high demand in the US; however, recently, people have switched out to substitutes such as craft beer. It verifies that beer is a "normal good with a considerably inelastic demand".

Further research confirms that while advertising across beer brands is primarily predatory, and its effect is gaining more market share, the category effect of advertising in beer is close to zero.

"The results indicate that beer is a normal good with a demand that is inelastic to changes in prices and almost no substitution across types of beer. Although the own-price elasticity is quite inelastic within types, the category that is the least price-responsive is mass-produced (American lager) beer."

### Demand for differentiated products Price and advertising evidence from the US beer market[3]

This research focuses on the nature of advertising in the beer industry, particularly interesting to us since we would like to know if the advertising has a predatory or cooperative nature. That will allow us to judge the difference between the advertising effect among brands and the advertising effect in the beer industry category.

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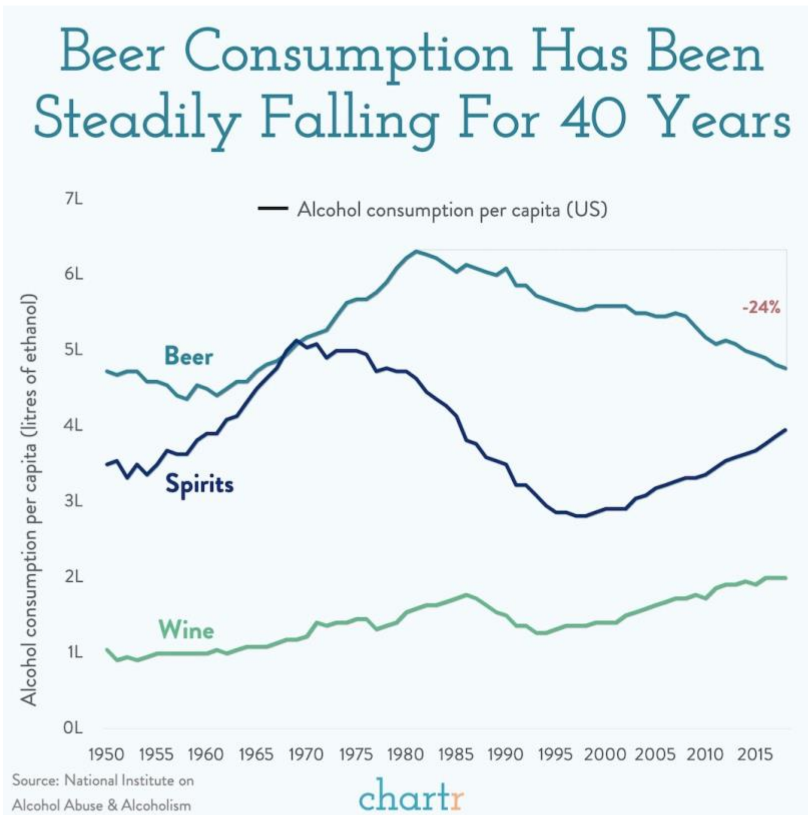
[1] Nelson, J. P., & Moran, J. R. (1995). Advertising and US alcoholic beverage demand: System-wide estimates. In Applied Economics (Vol. 27, Issue 12, pp. 1225–1236). https://doi.org/10.1080/00036849500000105

[2] Toro-González, D., McCluskey, J. J., & Mittelhammer, R. C. (2014). Beer snobs do exist: Estimation of beer demand by type. *Journal of Agricultural and Resource Economics*, *39*(2), 174–187.

[3] Rojas, C., & Peterson, E. B. (2008). Demand for differentiated products: Price and advertising evidence from the U.S. beer market. International Journal of Industrial Organization, 26(1), 288–307. https://doi.org/10.1016/j.ijindorg.2006.12.003

"The median advertising elasticities vary considerably across brands. Approximately 78% of the advertising elasticity estimates are statistically different than zero at the 5% level"
Results of that research indicate that advertising in the US brewing industry is cooperative to some extent; however, when it comes to light beer mass producers, we can see a strong predatory pattern, when brands simply rearrange the existing market share between each other by advertising.

**Modeling the demand for alcoholic beverages and advertising specifications**[4]
This research also strengthens our expected result from the research by stating that advertising effects in the beer industry are highly dependent on the dataset and that cross-brand advertising elasticity is high. In contrast, the overall category elasticity is closer to zero.
In addition to that, this research states that the advertising effect is still strong in the spirit segment and has a significant effect on the demand, unlike the advertising in the beer segment.
"In light of the level of expenditures devoted to and the effectiveness of advertising, we can conclude that industry spending on advertising is excessive, especially on the part of breweries. This suggests that advertising is effective at promoting brand-switching among beer drinkers"



[5]

[4] Larivière, É., Larue, B., & Chalfant, J. (2000). Modeling the demand for alcoholic beverages and advertising specifications. *Agricultural Economics*, *22*(2), 147–162. https://doi.org/10.1016/S0169-5150(99)00044-4
[5] Data Storytelling. (n.d.). Retrieved December 17, 2020, from https://www.chartr.co/

**AB InBev AED**

Therefore, our primary goal for the project was to establish brand-specific AED and justify Budweiser's heavy sponsorship of sports events and advertising as a whole. Approaching this analysis, we faced several data issues and were able to resolve some of them, allowing for some assumptions for the rest:

1. Issue: Brand-detailed data is not disclosed; we're only able to access AB InBev company-wide data.
   How we addressed it: We assume that the effects observed at the company-wide level are (to different extents) observed at the brand-level as well. If we can prove a non-zero elasticity of advertising on a company-wide level, this already proves that despite the industry having an AED of zero, it makes sense for AB InBev to advertise.

2. Issue: Typical figure one would come across in the financial books of a public company is Sales & Marketing expenses (or Selling, General, & Administrative expenses), rather than Advertising expenses alone.
   How we addressed it: First, we ran regressions of Sales & Marketing expenses on revenues and profits (both with or without a time lag). Sales & Marketing can be used as a close proxy for Advertising, as the former includes the latter. Another good feature of this data is that it is available for the past 43 quarters, not years so that we can time lag it by 1-2 quarters, which is more realistic.
   Later we found additional data on AB InBev advertising (via Advertising Age & Kantar Media) and were able to run additional models using those data. However, as these Advertising data are provided by third-party, not by the company itself, and thus might not be as reliable.
   As we ran multiple different configurations, we kept them to compare and pick the best model.

3. Issue: Publicly available data on Advertising expenses is only accessible with yearly figures, rather than quarterly or monthly. At the same time, we cannot assume that advertising is uniform throughout the year (in most part because a large part of AB InBev advertising is event sponsorship, which is unevenly distributed).
   How we addressed it: We only ran advertising in yearly settings and time-lagged advertising one year back. The models still show that it makes sense to make a time lag, though it would've been better to make it 1-2 quarters, not 1 year.

4. Issue: We only have Advertising data for the past 11 years. After time lagging, it's just 10 observations.
   How we addressed it: We assume that the patterns are strong not only between 2009 and 2019 but also outside that time frame. This is supported by evidence from various independent articles.

To sum up, to estimate the AED relationship, we used Revenue as the dependent variable and Sales & Marketing expenses and Advertising expenses as independent variables in different settings. We also time-lagged Sales & Marketing expenses and Advertising expenses and ran another set of models. We tried a couple of different settings and then compared them.

1. Revenue ~ Sales & Marketing expenses
2. Revenue ~ Sales & Marketing expenses lag 1 quarter
3. Revenue ~ Sales & Marketing expenses lag 2 quarters
4. Revenue ~ Advertising expenses
5. Revenue ~ Advertising expenses lag 1 year

| model № | dependent variable | independent variables | estimated b1 | $R^2$ | coefficient significance |
|---|---|---|---|---|---|
| 1 | Revenue | Sales & Marketing expenses | 2.3167 | 0.8932 | sales_mktg_other *** |
| 2 | Revenue | Sales & Marketing expenses lag 1 quarter | 1.9326 | 0.662 | sales_mktg_other_quarter_lag1 *** |
| 3 | Revenue | Sales & Marketing expenses lag 2 quarters | 1.7101 | 0.54 | sales_mktg_other_quarter_lag2 *** |
| 4 | Revenue | Advertising expenses | 13.28 | -0.01322 | advertising |
| 5 | Revenue | Advertising expenses lag 1 year | 27.97 | 0.3959 | advertising_year_lag1 * |

6. Revenue ~ Sales & Marketing expenses + year + quarter
7. Revenue ~ Sales & Marketing expenses lag 1 quarter + year + quarter
8. Revenue ~ Sales & Marketing expenses lag 2 quarters + year + quarter
9. Revenue ~ Advertising expenses + year
10. Revenue ~ Advertising expenses lag 1 year + year

| model № | dependent variable | independent variables | estimated b1 | $R^2$ | coefficient significance |
|---|---|---|---|---|---|
| 6 | Revenue | Sales & Marketing expenses + year + quarter | 2.6366 | 0.9233 | sales_mktg_other ***<br>year *<br>quarterQ2<br>quarterQ3 *<br>quarterQ4 * |
| 7 | Revenue | Sales & Marketing expenses lag 1 quarter + year + quarter | 1.9682 | 0.7307 | sales_mktg_other_quarter_lag1 ***<br>year<br>quarterQ2 **<br>quarterQ3 **<br>quarterQ4 * |
| 8 | Revenue | Sales & Marketing expenses lag 2 quarters + year + quarter | 1.8697 | 0.6556 | sales_mktg_other_quarter_lag2 ***<br>year |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | quarterQ2 *<br>quarterQ3 ***<br>quarterQ4 * |
| 9 | Revenue | Advertising expenses + year | -8.015 | 0.8719 | advertising<br>year *** |
| 10 | Revenue | Advertising expenses lag 1 year + year | 9.25 | 0.859 | advertising_year_lag1<br>year ** |

11. ln(Revenue) ~ ln(Sales & Marketing expenses)
12. ln(Revenue) ~ ln(Sales & Marketing expenses lag 1 quarter)
13. ln(Revenue) ~ ln(Sales & Marketing expenses lag 2 quarters)
14. ln(Revenue) ~ ln(Advertising expenses)
15. ln(Revenue) ~ ln(Advertising expenses lag 1 year)

| model № | dependent variable | independent variables | estimated b1 | $R^2$ | coefficient significance |
|---|---|---|---|---|---|
| 11 | ln(Revenue) | ln(Sales & Marketing expenses) | 0.6831 | 0.8825 | sales_mktg_other *** |
| 12 | ln(Revenue) | ln(Sales & Marketing expenses lag 1 quarter) | 0.57145 | 0.6725 | sales_mktg_other_quarter_lag1 *** |
| 13 | ln(Revenue) | ln(Sales & Marketing expenses lag 2 quarters) | 0.49584 | 0.5301 | sales_mktg_other_quarter_lag2 *** |
| 14 | ln(Revenue) | ln(Advertising expenses) | 0.5921 | 0.03672 | advertising |
| 15 | ln(Revenue) | ln(Advertising expenses lag 1 year) | 1.0112 | 0.403 | advertising_year_lag1 * |

16. ln(Revenue) ~ ln(Sales & Marketing expenses) + year + quarter
17. ln(Revenue) ~ ln(Sales & Marketing expenses lag 1 quarter) + year + quarter
18. ln(Revenue) ~ ln(Sales & Marketing expenses lag 2 quarters) + year + quarter
19. ln(Revenue) ~ ln(Advertising expenses) + year
20. ln(Revenue) ~ ln(Advertising expenses lag 1 year) + year

| model № | dependent variable | independent variables | estimated b1 | $R^2$ | coefficient significance |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 16 | ln(Revenue) | ln(Sales & Marketing expenses) + year + quarter | 0.789982 | 0.9162 | sales_mktg_other *** year * quarterQ2 quarterQ3 * quarterQ4 * |
| 17 | ln(Revenue) | ln(Sales & Marketing expenses lag 1 quarter) + year + quarter | 0.604330 | 0.7438 | sales_mktg_other_quarter_lag1 *** year quarterQ2 ** quarterQ3 ** quarterQ4 * |
| 18 | ln(Revenue) | ln(Sales & Marketing expenses lag 2 quarters) + year + quarter | 0.556968 | 0.6606 | sales_mktg_other_quarter_lag2 *** year quarterQ2 * quarterQ3 *** quarterQ4 * |
| 19 | ln(Revenue) | ln(Advertising expenses) + year | -0.211313 | 0.8764 | advertising year *** |
| 20 | ln(Revenue) | ln(Advertising expenses lag 1 year) + year | 0.0000000001906 | 0.8703 | advertising_year_lag1 year *** |

We made the following observations about out set of linear regression models:
If we take models with quarterly data, lag 1 always has higher adjusted $R^2$ than lag 2. Therefore, we can get rid of the models with lag 2.
Even though some models without time lags are more significant than with lags, this represents wrong time ordering: obviously, the more revenue a company makes the more it can afford to spend on advertising in the same period. But that is not a causal relationship we are looking for: advertising expense typically has some delayed effect which would last in the following period. Therefore, we can also get rid of the models without time lags.

After eliminating some inferior models, we kept the following;
2. Revenue ~ Sales & Marketing expenses lag 1 quarter
5. Revenue ~ Advertising expenses lag 1 year
7. Revenue ~ Sales & Marketing expenses lag 1 quarter + year + quarter
10. Revenue ~ Advertising expenses lag 1 year + year
12. ln(Revenue) ~ ln(Sales & Marketing expenses lag 1 quarter)
15. ln(Revenue) ~ ln(Advertising expenses lag 1 year)
17. ln(Revenue) ~ ln(Sales & Marketing expenses lag 1 quarter) + year + quarter
20. ln(Revenue) ~ ln(Advertising expenses lag 1 year) + year

| model № | dependent variable | independent variables | estimated b1 | adjusted $R^2$ | coefficient significance |
|---|---|---|---|---|---|
| 2 | Revenue | Sales & Marketing expenses lag 1 quarter | 1.9326 | 0.662 | sales_mktg_other_quarter_lag1 *** |
| 5 | Revenue | Advertising expenses lag 1 year | 27.97 | 0.3959 | advertising_year_lag1 * |
| 7 | Revenue | Sales & Marketing expenses lag 1 quarter + year + quarter | 1.9682 | 0.7307 | sales_mktg_other_quarter_lag1 ***<br>year<br>quarterQ2 **<br>quarterQ3 **<br>quarterQ4 * |
| 10 | Revenue | Advertising expenses lag 1 year + year | 9.25 | 0.859 | advertising_year_lag1<br>year ** |
| 12 | ln(Revenue) | ln(Sales & Marketing expenses lag 1 quarter) | 0.57145 | 0.6725 | sales_mktg_other_quarter_lag1 *** |
| 15 | ln(Revenue) | ln(Advertising expenses lag 1 year) | 1.0112 | 0.403 | advertising_year_lag1 * |
| 17 | ln(Revenue) | ln(Sales & Marketing expenses lag 1 quarter) + year + quarter | 0.604330 | 0.7438 | sales_mktg_other_quarter_lag1 ***<br>year<br>quarterQ2 **<br>quarterQ3 **<br>quarterQ4 * |
| 20 | ln(Revenue) | ln(Advertising expenses lag 1 year) + year | 0.0000000001906 | 0.8703 | advertising_year_lag1 |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | year *** |

The models here which best respond to our question about AED are №15 and №20 because they straightforwardly show the advertising elasticity of demand for AB InBev.
15. ln(Revenue) ~ ln(Advertising expenses lag 1 year)
20. ln(Revenue) ~ ln(Advertising expenses lag 1 year) + year

№15 shows that with every 1% increase in advertising expenses, next year's revenues increase by 1.0112%. However, the coefficient of Advertising expenses lag 1 year is only significant at 0.05 significance level and the model has very moderate $R^2$ of 0.403.

№ 20 shows that with every 1% increase in advertising expenses, next year's revenues increase by 0.0000000001906%. However, the coefficient of Advertising expenses lag 1 year is not significant so we cannot make any managerial conclusions from it. This model has a significant coefficient of yearly time trend but as our advertising expense coefficient is not, we won't consider it any further.

We are left with the following model:

**№15 ln(Revenue) ~ ln(Advertising expenses lag 1 year)**

Despite the fact that advertising expenses explain only 40.3% variability in revenue, our model proves the point that AED of beer brands is not zero (1.0112), unlike the industry AED.
It's important to note that we used only 10 observations for the model, however, our conclusions are widely supported by research so we can still count them as valid.

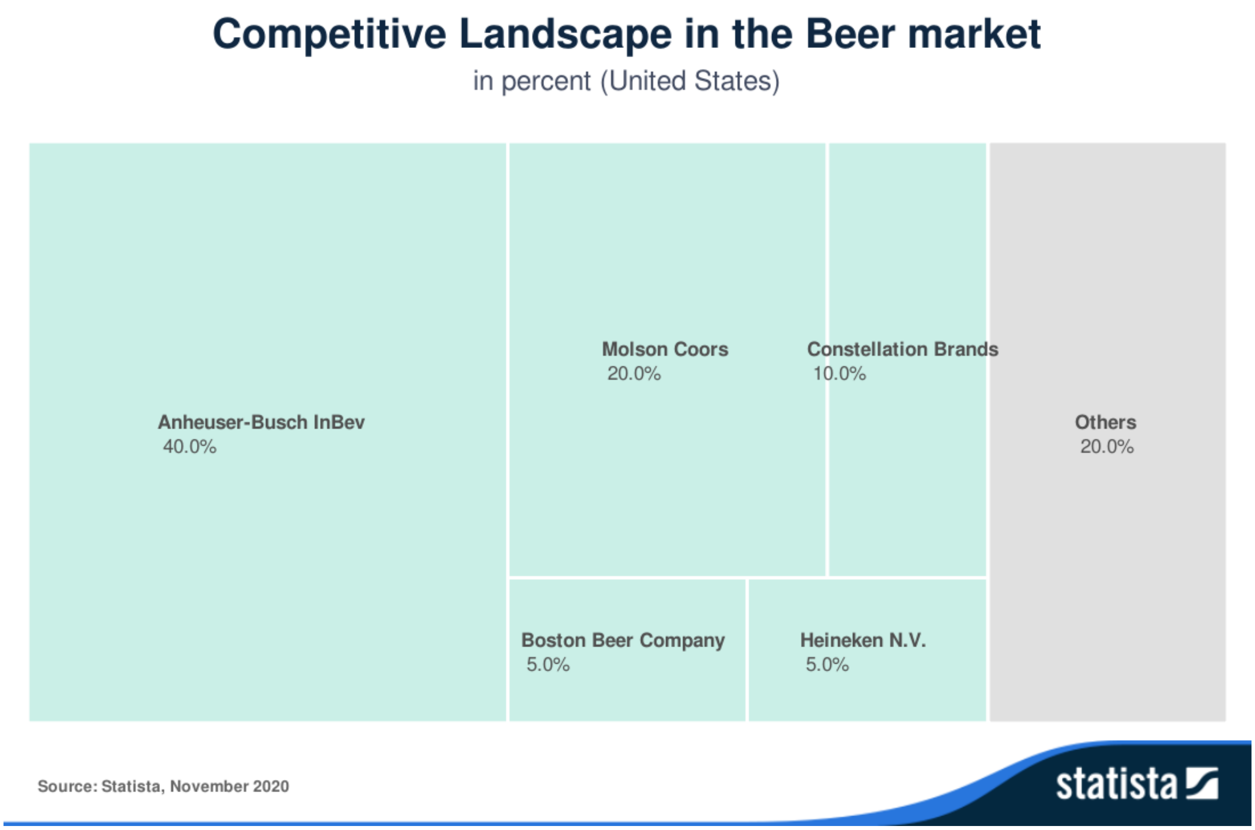
**Market Share**

Now that we've estimated this relationship, we know that the beer market is a "pie" that cannot get larger, but a brand may get a bigger "piece." We should check if the advertising efforts of Budweiser help them increase their market share or not.

Issue: We only have Market share data for the past 6 years. After time lagging, it's just 5 observations.
How we addressed it: We assume that the patterns are strong not only between 2014 and 2019 but also outside that time frame. This is supported by evidence from various independent articles.

**ln(Market Share) ~ ln(Advertising expenses lag 1 year)**
**ln(Market Share) ~ ln(Advertising expenses lag 1 year)+year**

The model for market share has a negative adjusted R2 and insignificant coefficient.
Therefore, we cannot conclude that advertising has any effect on market share.
However, if we add a yearly time trend, the adjusted R2 is 94.4%, and the year's coefficient is significant at the 0.01 significance level. Therefore, with every year market share of AB InBev decreases by -1.94092%. It's important to note that we used only 5 observations for the model and these conclusions contradict the research, so with more data, we could've potentially obtained another conclusion.



[6]

[6] Beer - United States: Statista Market Forecast. (n.d.). Retrieved December 17, 2020, from https://www.statista.com/outlook/10010000/109/beer/united-states

## Special Events

Budweiser, along with many other beer brands of the AB InBev holding, utilizes an exceptional way of advertising by creating targeted marketing campaigns for major world sports events. They become sponsors of such events as the FIFA World Cup or Super Bowl. Such marketing campaigns present a great case for us to investigate how such campaigns affected the company's future sales. Such data, along with research papers, will strengthen our assumption that individual beer brands must invest in advertising in order to stay at the top of the market.

### FIFA World Cup

Lighting up the world of football was a great marketing campaign launched by Budweiser in order to sponsor a FIFA championship of 2018 in Russia. According to the official marketing agency that was presenting Budweiser, that campaign was a great success. Such powerful marketing allowed Budweiser to become a most discussed brand around the event. In addition to that, the campaign resulted in an 8% increase in global sales since the World Cup, which indicates that marketing efforts made by a brand eventually result in a sales increase.

### SuperBowl

Budweiser and AB InBev in particular, hold exclusive advertising rights in the alcohol category to sponsor Super Bowl, and they have been successful in such marketing for many years since 1986. Every single advertiser that works with Super Bowl sees an increase in sales, and Budweiser was not an exception. That beer brand's campaign resulted in a 3.9% sales increase and a 4.7% revenue increase for Budweiser in the weeks following the game. That case supports our assumption that beer brands need to invest in advertising and that advertising elasticity for brands is significant..[7],[8]

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[7] Sweeney, E. (2018, January 09). Study: Super Bowl advertisers see sustained post-game sales boost. Retrieved December 17, 2020, from https://www.marketingdive.com/news/study-super-bowl-advertisers-see-sustained-post-game-sales-boost/514379/

[8] Szaroleta, T. (2017, January 24). A history of Budweiser Clydesdales Super Bowl commercials. Retrieved December 17, 2020, from https://www.jacksonville.com/entertainment/2017-01-24/history-budweiser-clydesdales-super-bowl-commercials

## Conclusion

Many research papers stated that industry advertising elasticity is close to zero, whereas brand advertising elasticity is significant. In our work, we analyzed several previous research papers along with the most current data from AB InBev holding in order to prove that such a statement is correct on a real-life example of Budweiser, which spends many funds on marketing.

According to our regression models, we can conclude that such statements are true and brand advertising elasticity for beer is significant in determining their revenue. We could not establish whether a market share was increasing in response to the company's marketing expenses, but we assume that this is due to the limited amount of data we could have gathered for the research. With more data regarding the company's market share, we will be able to make a more certain conclusion regarding that topic as the research states that "advertising is effective at promoting brand-switching among beer drinkers."

## Managerial Proposal

Advertising elasticity significance is vital for Budweiser and AB InBev holding since it proves that despite the elasticity of demand on the industry level being close to zero, they still benefit from advertising beer brands, and it still has an effect on brands’ sales and revenues. Therefore large marketing campaigns are essential for mass-produced beer brands to be successful.

## Appendix
## Members’ Contribution

**Zinaida Dvoskina** was an incredible partner for this project. She brought her unique experience of working closely with Budweiser during the FIFA world cup in Russia and proposed a great research topic. She was enthusiastic about it and determined to prove the elasticity theory. She showed great analytical skills in determining specific correlations and interpreting them. Zinaida was great at searching for relevant information and at its transformation for the analysis. She was a hard-working and determined partner that I was incredibly lucky and happy to work with. Her organizational skills, along with incredible R skills, determined the scope of our project and allowed us to conduct such a thorough analysis.

**Kirill Ilin** was an awesome BUDdy to work on this project with. He has discovered over 25 industry research publications and selected the most relevant to our project. Kirill guided our research according to the prior developments in the industry studies. He made sure that all the data analytics tasks we were performing were directly contributing to the project’s main goals and purposes. Kirill ensured that the regression model had the best data fit and was truly suited for the business need, choosing the right structure (y versus ln(y)) for proper interpretation. Among his strongest sides as a project partner, I would highlight his excellent understanding of real-world business issues and goal focus.