**Donations: Past and Present**

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**Introduction**

The purpose of our study is to assess if previous donation history or different donor characteristics of donors to Yeshiva University (YU) can predict whether or not a particular donor will donate in an upcoming year. To determine this objective, we observed when a particular donor gave a donation in two or more consecutive years and, based off of several variables, ran a regression to determine the likelihood that they would donate in the year following the consecutive years.

This is an important assessment to make, as it would deeply affect YU’s marketing strategies and their donation request strategies. Marketing frequency (among other factors) is crucial to convincing donors to give.[[1]](#footnote-1) The results of our research could give insight into which donors YU should target more or less frequently and how they should target them.

**Literature Review**

There have been previous studies about what leads people to donate to different causes. A study was published by Abila which analyzes different aspects of donor behaviors and donor attitudes. They found that Millennials (1981-1997) and Gen Xers (1965-1980) tend to donate less and to fewer nonprofits than Boomers (1946-1964) and Matures (1945 or earlier). They have found that Millennials are much less likely to donate to religious causes than their older counterparts. They also preferred to be contacted less frequently than their older counterparts. They also analyzed the behavior of high-wealth donors specifically, and found that 45% of these donors prefer to give to places of worship and 31% prefer to give to educational causes. Furthermore, their median annual donation was $2,252 and 38% restrict their donations to specific funds. Amongst donors in general, however, 37% donated to both restricted and unrestricted funds equally.[[2]](#footnote-2)

Another study was performed by M. Linda Wastyn about why university alumni don’t donate to their alma mater. She quoted a study which found that, “Nationally, 11.9 percent of alumni contributed to their alma mater in 2006, down from 13.4 percent 4 years earlier, leaving nearly 90 percent of all alumni as non-donors in a given year. Nearly, 75 percent of all alumni have never given”.[[3]](#footnote-3) Furthermore, with regard to demographic information, Wastyn quoted multiple studies which have found, “[...] a direct positive relationship between age and giving that peaks in the donor’s early fifties before decreasing again and rebounding a few years later” and, “A similarly robust positive relationship also exists between income and giving, although an interaction effect likely exists between income, age, and giving, because people tend to accumulate wealth as they age”.[[4]](#footnote-4)

Literature such as these studies have helped expand the general understanding of what donor qualities motivate donors to give to various causes. With our study, we seek to determine whether or not these findings apply to the YU donor community and to understand which donors are more or less likely to donate to YU than others.

**Theoretical Model**

According to the literature quoted above, the older one gets, the more likely they are to give. Therefore, we can recommend to YU that they would want to target their older alumni as opposed to their recent graduates.

Based on the aforementioned literature and our own intuition, we hypothesize that a donor who donates in the previous two consecutive fiscal years will donate in the following fiscal year. In other words, if a donor donates to YU in the fiscal year of 2013 and the fiscal year of 2014, we hypothesize that they will also donate to YU in the fiscal year of 2015.

**Data**

We received our data from the Office of Institutional Advancement (IA office) at YU. The original dataset consisted of two tables: a Biographical table and a Donations table. All the data we were given was from fiscal year 2009 to fiscal year 2019.

The Biographical table, containing 233,116 entries, consisted of biographical information, such as birth date, age, city, and state, for all of the donors. Certain sensitive information, such as name and street address, was removed so as to protect the donors’ privacy.

The Donations table, containing 191,045 entries, consisted of important information about every donation given. Examples of such information include the identification number of the gift, whether the gift was restricted or unrestricted, the date of the gift, and the amount of the gift. Again, certain sensitive information was removed to protect the donors’ privacy.

In the following process, we used a combination of Microsoft Excel, RStudio, and SQLiteStudio to sort, calculate, and analyze the data.

Given these two tables, our first step was to merge them and to ensure that they only included what we deemed was relevant information. This merged table contained eight columns, including the donor’s identification number (Entity\_UID), the fiscal year, and the donor’s birth date. All other information that was not in the merged table was not used.

Our next step was to sort the data by the Entity\_UID and the fiscal year, so that each row in our dataset was a unique combination of Entity\_UID and fiscal year. When we sorted the data as such, every Entity\_UID had eleven rows, one for each fiscal year from 2009 to 2019. For example, Entity\_UID 103 had eleven rows in our dataset, one for each fiscal year.

The next step was to perform some important calculations. One variable we wanted to calculate was age. To do this, we subtracted the donor’s birth date from the current date (the date that we were calculating the age). Another variable we wanted to calculate was the amount that each donor donated in every fiscal year. If the donor did not donated in a given fiscal year, we put a zero in this variable. We still kept all eleven years in the dataset, however, because knowing when someone did not donate would later be helpful to figure out who donated in two or more consecutive fiscal years.

Next, we created a “y” variable. This variable is what we are trying to calculate, namely, whether a donor donated in a given year. This is a binary variable, meaning y would be one if the donor donated in a given fiscal year and zero if the donor did not donate in a given fiscal year.

Then, we determined who donated in two or more consecutive fiscal years. To do this, we created multiple empty indicator variables titled Indicator20092010, Indicator20102011, etc., all the way to Indicator20182019. Each of these indicator variables were binary variables. For example, if Entity\_UID 103 donated in both 2009 and 2010, the combination of Entity\_UID 103 and fiscal year 2009 would get a one in the Indicator20092010 variable. Similarly, if Entity\_UID 103 donated in both 2015 and 2016, the combination of Entity\_UID 103 and fiscal year 2015 would get a one in the Indicator20152016 variable. However, if Entity\_UID 103 donated in 2013 but not in 2014, the combination of Entity\_UID 103 and fiscal year 2013 would get a zero in the Indicator 20132014 variable. We ran multiple loops in RStudio that went through the entire dataset and determined when donors donated in two or more consecutive fiscal years, and we had these loops fill in the binary indicator variables appropriately.

We then created a Dummy variable which combined all of the indicator variables into one variable. This Dummy variable was also a binary variable, meaning it received a one when someone donated in two consecutive fiscal years and a zero when someone did not donate in two consecutive fiscal years.

Our next step was to get rid of any donations from fiscal year 2009 and fiscal year 2010, as we did not have data from fiscal year 2007 or fiscal year 2008, so we could not use these years to make predictions.

Next, we grouped certain qualitative variables into fewer categories in order to lessen the amount of variables in our model. We grouped preferred\_college, which was the variable telling us which of YU’s colleges the donor was most associated with, into four different groups, namely, high school, undergraduate, graduate, and other. We placed these groups into a new qualitative variable called College. We also grouped prim\_donor\_category\_desc, which was the variable telling us what the donor’s primary relation to YU was, into four different groups, namely, alumni, friend, parent, and other. We placed these groups into a new qualitative variable called Relationship.

Thus, after all of our data manipulation and data cleaning, we were left with 377,091 entries in our final dataset, consisting of the variables displayed in the table below.

|  |  |  |
| --- | --- | --- |
| Name | Description | Additional Information |
| Entity\_UID | The donor’s identification number | Numeric variable repeated nine times for each fiscal year from 2011 to 2019 |
| Fiscal\_Year | The fiscal year in which the donation was made | Numeric variable ranging from 2011 to 2019 |
| Amt\_Actual | The amount that was donated by a particular donor in a particular fiscal year | Numeric variable |
| Birth\_Date | The date the donor was born | Date variable used to calculate age |
| Preferred\_Class | Year of donor’s graduation | Numeric variable |
| Preferred\_College | The YU college that the donor most associated with | Character variable that was condensed into College variable |
| College | The YU college that the donor most associated with | Character variable with four possible outputs: High School, Undergraduate, Graduate, and Other |
| Prim\_Donor\_Category\_Desc | The donor’s primary relation to YU | Character variable that was condensed into Relationship variable |
| Relationship | The donor’s primary relation to YU | Character variable with four possible outputs: Alumni, Friend, Parent, and Other |
| Age | The donor’s age | Numeric variable, calculated from Birth\_Date |
| Y | Whether or not the donor donates in a given fiscal year | Binary variable |
| Indicator20092010 - Indicator20182019 | A series of variables telling whether or not a donor donated in two consecutive fiscal years | Binary variables, used to create the dummy variable |
| Dummy | Whether or not a donor donated in two consecutive fiscal years | Binary variable, created from the indicator variables |

In our dataset, the dependent variable is the y variable. We are trying to determine whether a person will donate in a given year, and this is exactly what the y variable tells us. The independent variables are the dummy variable, age, fiscal year, the college variable, the relationship variable, and the total amount donated per person per year. Each of these variables has the potential to affect the y variable, and we will be including each of these variables in our model.

Finally, we will list descriptive statistics about some of the variables in our dataset. For our age variable, the minimum age is 1, the mean age is 77.51, and the maximum age is 97. The minimum age being 1 can be explained in one of two ways. The first is as a data entry error. The second is due to the format the dates were originally listed in. Originally, the years for the dates were listed as two digit values (i.e. “1963” was listed as “63”). Therefore, some of the years may have been misinterpreted (i.e. “18” may have been interpreted as “2018” instead of “1918”). We have tried to account for most cases of this. The few cases left are insignificant amongst the greater dataset. The standard deviation for the age variable is 28.56303. For our amt\_actual variable, the minimum amount is 0, the mean amount is 1,055, and the maximum amount is 5,949,550. The standard deviation for the amt\_actual variable is 31,202.57.

**Empirical Model**

In order to create a model, we will run a logistic regression model in RStudio. This model measures the likelihood that a given event will occur. In our case, it will measure the likelihood that a donor will give in a given fiscal year after having donated in the two previous fiscal years.

There are other models which we could have run, but we felt that this one was the most appropriate.

**Results and Discussion**

The technical output from this model is as follows:

The regression equation is y = -847.47999 + 11.36320 \* Dummy - 0.04147 \* Age + 0.41669 \* Fiscal\_Year - 1.57310 \* College High School - 3.32423 \* College Other + 1.30076 \* College Undergraduate + 3.16173 \* Relationship Friend + 3.63456 \* Relationship Other - 2.19575 \* Relationship Parent + 15.83406 \* Amt\_Actual.

Before we interpret this result, we must make a note of the significance of all of these coefficients. In our model, we will consider any coefficients that have a p-value that is less than 0.5 to be significant. Consequently, the intercept (-847.47999), age (-0.04147), fiscal\_year (0.41669), college other (-3.32423), relationship friend (3.16173), relationship other (3.63456), and amt\_actual (15.83406) variables are significant. The other variables all have p-values above 0.5, so they are insignificant for our model. Therefore, we will remove all other variables from our model.

So, our new regression equation is y = -847.47999 - 0.04147 \* Age + 0.41669 \* Fiscal\_Year - 3.32423 \* College Other + 3.16173 \* Relationship Friend + 3.63456 \* Relationship Other + 15.83406 \* Amt\_Actual.

Next, in order to determine the accuracy of our model, we have to calculate the misclassification rate based off of testing and training data. We split our model into two datasets, the training one consisting of 300,000 observations and the testing one consisting of 77,091 observations. We calculated that the misclassification rate is 0.00001297168, or 0.0013%. This is an extremely good misclassification rate, as this means that our model classifies 99.9987% of its observations correctly.

So, for the future, if the IA office wanted to predict which donors would donate in a given donation year, they would simply plug the appropriate values into the regression equation.

In terms of our hypothesis, we originally hypothesized that someone who donates in two or more consecutive fiscal years would be more likely to donate in the following fiscal year. However, our regression tells us that the dummy variable, the variable which tells us whether or not a donor donated in two consecutive fiscal years, is statistically insignificant. Therefore, our hypothesis is wrong. Seeing whether or not someone donated in the previous two or more consecutive fiscal years is not a good indicator for whether or not they will donate in the next fiscal year.

**Limitations and Future Works**

There are various limitations we faced within our project. One of the issues we encountered when we were trying to calculate the age variable. As explained above, the birth dates that we were given had two digit years (i.e. 05/07/88). Therefore, when we tried calculating age for a donor who had a year of “18”, Microsoft Excel was unsure whether to consider the year as 1918 or 2018. Often, Excel considered it as 2018, which is obviously incorrect. We got rid of any obvious mistakes (such as negative ages) and tried to control for this error as much as possible. In the end, we believe that the number of ages that are incorrect is insignificant to the entire dataset. We would need a better method in the future to make sure that the ages are reflected properly.

Another issue is relating to the scope of the data. We only have data from 2009 and on. A more representative sample and a more accurate model would come from access to data from before 2009. However, we understand that the IA office can only give students a certain amount of data.

Additionally, a very obvious limitation is despite everything we have discovered, there is always an uncertainty as to how a person will behave in the future. Humans are not always rational beings, and their decisions are extremely hard to predict. A donor may donate to YU for ten consecutive years and then never give again because of some external factor. These factors are hard to account for, and can always impact our model.

**Appendix**

It is important to note that some of the code listed below is from SQLStudio and some is from RStudio. Additionally, there were some calculations that were done in Microsoft Excel which we did not include.

-- Merges tables into separate dataset with relevant biographical information

create table Merged\_New\_Data as select Don.Entity\_UID, Don.Gift\_ID, Don.Fiscal\_Year, Don.Amt\_Actual, Bio.Birth\_Date, Bio.Preferred\_Class, Bio.Preferred\_College,

Bio.Prim\_Donor\_Category\_Desc from Donations Don

join Biographical Bio on Don.Entity\_UID = Bio.Entity\_UID;

# Order the data by Entity\_UID and Fiscal\_Year

library(sqldf)

Merged\_New\_Data <- sqldf("select \* from Merged\_New\_Data order by Entity\_UID, Fiscal\_Year asc")

# Creating the y variable (at some point during the process, the dataset was renamed to Updated\_Data)

Updated\_Data$y <- NA

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$amt\_actual[i] == 0) {

Updated\_Data$y[i] = 0

} else {

Updated\_Data$y[i] = 1

}

} #Y variable

#Creating the indicator variable columns

Updated\_Data$indicator20092010<- 0

Updated\_Data$indicator20102011<- 0

Updated\_Data$indicator20112012<- 0

Updated\_Data$indicator20122013<- 0

Updated\_Data$indicator20132014<- 0

Updated\_Data$indicator20142015<- 0

Updated\_Data$indicator20152016<- 0

Updated\_Data$indicator20162017<- 0

Updated\_Data$indicator20172018<- 0

Updated\_Data$indicator20182019<- 0

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2009 && Updated\_Data$Fiscal\_Year[i+1] == 2010) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20092010[i] <- 1

} else {

Updated\_Data$indicator20092010[i] <- 0

}

}

}

} # Indicator variable 2009 - 2010

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2010 && Updated\_Data$Fiscal\_Year[i+1] == 2011) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20102011[i] <- 1

} else {

Updated\_Data$indicator20102011[i] <- 0

}

}

}

} # Indicator variable 2010 - 2011

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2011 && Updated\_Data$Fiscal\_Year[i+1] == 2012) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20112012[i] <- 1

} else {

Updated\_Data$indicator20112012[i] <- 0

}

}

}

} # Indicator variable 2011 - 2012

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2012 && Updated\_Data$Fiscal\_Year[i+1] == 2013) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20122013[i] <- 1

} else {

Updated\_Data$indicator20122013[i] <- 0

}

}

}

} # Indicator variable 2012 - 2013

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2013 && Updated\_Data$Fiscal\_Year[i+1] == 2014) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20132014[i] <- 1

} else {

Updated\_Data$indicator20132014[i] <- 0

}

}

}

} # Indicator variable 2013 - 2014

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2014 && Updated\_Data$Fiscal\_Year[i+1] == 2015) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20142015[i] <- 1

} else {

Updated\_Data$indicator20142015[i] <- 0

}

}

}

} # Indicator variable 2014 - 2015

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2015 && Updated\_Data$Fiscal\_Year[i+1] == 2016) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20152016[i] <- 1

} else {

Updated\_Data$indicator20152016[i] <- 0

}

}

}

} # Indicator variable 2015 - 2016

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2016 && Updated\_Data$Fiscal\_Year[i+1] == 2017) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20162017[i] <- 1

} else {

Updated\_Data$indicator20162017[i] <- 0

}

}

}

} # Indicator variable 2016 - 2017

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2017 && Updated\_Data$Fiscal\_Year[i+1] == 2018) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20172018[i] <- 1

} else {

Updated\_Data$indicator20172018[i] <- 0

}

}

}

} # Indicator variable 2017 - 2018

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] == 2018 && Updated\_Data$Fiscal\_Year[i+1] == 2019) {

if(Updated\_Data$amt\_actual[i] != 0 && Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$indicator20182019[i] <- 1

} else {

Updated\_Data$indicator20182019[i] <- 0

}

}

}

} # Indicator variable 2018 - 2019

# Creating Dummy variable

Updated\_Data$Dummy <- 0

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Entity\_UID[i] == Updated\_Data$Entity\_UID[i+1]) {

if(Updated\_Data$Fiscal\_Year[i] < Updated\_Data$Fiscal\_Year[i+1]) {

if(Updated\_Data$amt\_actual[i] != 0) {

if(Updated\_Data$amt\_actual[i+1] != 0) {

Updated\_Data$Dummy[i] <- 1

} else {

Updated\_Data$Dummy[i] <- 0

}

}

}

}

}

# Getting rid of Fiscal Years 2009 & 2010

for(i in 1:nrow(Updated\_Data)) {

if(Updated\_Data$Fiscal\_Year[i] == 2009 | Updated\_Data$Fiscal\_Year[i] == 2010) {

Updated\_Data <- Updated\_Data[-i,]

}

}

# Getting the descriptive statistics

summary(Updated\_Data4$Age)

Min. 1st Qu. Median Mean 3rd Qu. Max.

1.00 48.00 97.00 77.51 97.00 97.00

> sd(Updated\_Data4$Age)

[1] 28.56303

> summary(Updated\_Data4$amt\_actual)

Min. 1st Qu. Median Mean 3rd Qu. Max.

0 0 0 1055 0 5949550

> sd(Updated\_Data4$amt\_actual)

[1] 31202.57

> # Model

> model <- glm(y~Dummy+Age+Fiscal\_Year+College+Relationship+amt\_actual, family = binomial(), data = Updated\_Data4)

> model

Call: glm(formula = y ~ Dummy + Age + Fiscal\_Year + College + Relationship +

amt\_actual, family = binomial(), data = Updated\_Data4)

Coefficients:

(Intercept) Dummy Age Fiscal\_Year

-847.47999 11.36320 -0.04147 0.41669

CollegeHigh School CollegeOther CollegeUndergraduate RelationshipFriend

-1.57310 -3.32423 1.30076 3.16173

RelationshipOther RelationshipParent amt\_actual

3.63456 -2.19575 15.83406

Degrees of Freedom: 377090 Total (i.e. Null); 377080 Residual

Null Deviance: 357200

Residual Deviance: 91.65 AIC: 113.6

> summary(model)

Call:

glm(formula = y ~ Dummy + Age + Fiscal\_Year + College + Relationship +

amt\_actual, family = binomial(), data = Updated\_Data4)

Deviance Residuals:

Min 1Q Median 3Q Max

-0.4690 -0.0043 -0.0019 -0.0004 4.2141

Coefficients:

Estimate Std. Error z value Pr(>|z|)

(Intercept) -847.47999 240.98374 -3.517 0.000437 \*\*\*

Dummy 11.36320 450.40862 0.025 0.979873

Age -0.04147 0.01011 -4.102 4.09e-05 \*\*\*

Fiscal\_Year 0.41669 0.11951 3.487 0.000489 \*\*\*

CollegeHigh School -1.57310 4.31483 -0.365 0.715425

CollegeOther -3.32423 1.54793 -2.148 0.031750 \*

CollegeUndergraduate 1.30076 1.39526 0.932 0.351197

RelationshipFriend 3.16173 1.04294 3.032 0.002433 \*\*

RelationshipOther 3.63456 0.90871 4.000 6.34e-05 \*\*\*

RelationshipParent -2.19575 13.49795 -0.163 0.870776

amt\_actual 15.83406 0.88225 17.947 < 2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 357232.125 on 377090 degrees of freedom

Residual deviance: 91.649 on 377080 degrees of freedom

AIC: 113.65

Number of Fisher Scoring iterations: 25

# Training and testing data

x = sample(1:377091, replace = FALSE)

data\_train <- Updated\_Data4[x[1:300000],]

data\_test <- Updated\_Data4[x[300001:377091],]

logit\_model <- glm(y~Dummy+Age+Fiscal\_Year+College+Relationship+amt\_actual, family = binomial("logit"), data = data\_train)

pred <- (predict(logit\_model, newdata = data\_test) > 0.5) \* 1

misclassrate <- sum(data\_test$y != pred) / 77091

misclassrate

[1] 1.297168e-05

1. Dietz, Rich, and Brandy Keller. “Donor Loyalty Study - A Deep Dive into Donor Behaviors and Attitudes.” *Abila*, Abila, 2016, yu.instructure.com/courses/36385/files/folder/IA%20project?preview=1123262. This article is a research study that was posted on Canvas by our course instructor. [↑](#footnote-ref-1)
2. Ibid [↑](#footnote-ref-2)
3. Wastyn, M. Linda. “Why Alumni Don't Give: A Qualitative Study of What Motivates Non-Donors to Higher Education.” *Palgrave Journals*, Palgrave Macmillan, 31 May 2009, yu.instructure.com/courses/36385/files/folder/IA%20project?preview=1123263. This article is a research study that was posted on Canvas by our course instructor. [↑](#footnote-ref-3)
4. Ibid [↑](#footnote-ref-4)