The Impact of CEO Salaries on Charitable Contributions

Rohit Ravikumar

Abstract

A frequently discussed matter of controversy is the amount of money that charitable organizations should spend on salaries relative to program expenses. This paper analyzed the effect that CEO salaries at a charity have on contributions to that charity. Using a dataset of 290 observations collected from IRS forms, this paper used 3SLS and 2SLS simultaneous equation models to control for simultaneity and isolate the effect of salaries on contributions. After taking steps to control for heteroskedasticity and autocorrelation, the model ultimately yielded relatively weak results with low significance, though questions were raised for further analysis.

I. Introduction

On January 12, 2010, an earthquake of magnitude 7.0 struck the country of Haiti, doing devastating damage and killing about 160,000 people. The destruction wrought by the natural disaster was uncommonly immense, but so too was the humanitarian response. According to the UN information portal ReliefWeb, $3.5 billion was donated to Haiti to assist with recovery, out of about $4.5 billion pledged, much of which was donated by non-profit charitable organizations.

The work done by these organizations across the world is essential, with their responses to natural disasters, disease outbreaks, refugee crises, and abject poverty often meaning the difference between life and death for thousands of people, if not millions. These charities, of course, are able to exist because of donations made by those of privilege who wish to see their money doing some good elsewhere. Money, however, can be a difficult subject to address, and is the root of some controversy with respect to many charities.

At a fundamental level, every charity has three types of expenses: as organized by the website Charity Navigator, they are as follows. The main type is program expenses, representing the amount of a charity's total expenses spent on its programs and services; that is, the money spent "properly". Next is fundraising expenses, the amount a charity spends on advertising, publicity, and solicitation. While far from glamorous, these expenses are clearly necessary to allow for program expenses. The final, and likely most controversial, type is administrative expenses, the amount spent by a charity on overhead and staff. This includes, in large part, salaries.

Administrative expenses, and in particular executive salaries, have been the root of a heated debate about charities in recent years. Certainly, seeing the salaries of some charity CEOs might raise an eyebrow: James R. Downing, CEO of St. Jude Children's Research Hospital, earned over $1 million in 2015, to name one example. Entire websites and organizations, such as the aforementioned Charity Navigator, America's Most Cost-Effective Charities (AMCEC), and others, have cropped up to provide prospective charitable contributors with the resources necessary to pick charities where as much of their money as possible goes to program expenses, at the expense of administrative expenses. Yet the argument goes the other way as well: high administrative expenses, and particularly salaries, can attract the best talent, catching the eye of visionary CEOs and experienced and capable employees, and improve the quality of the charity and the volume of contributions.

This paper hypothesizes the following: increasing the compensation of a charity's CEO will increase the charity's total annual contributions, all other things held equal. High salaries will increase the probability of hiring a talented, high-demand CEO, who will in turn establish more efficient fundraising and outreach systems, allowing the charity to raise more money.

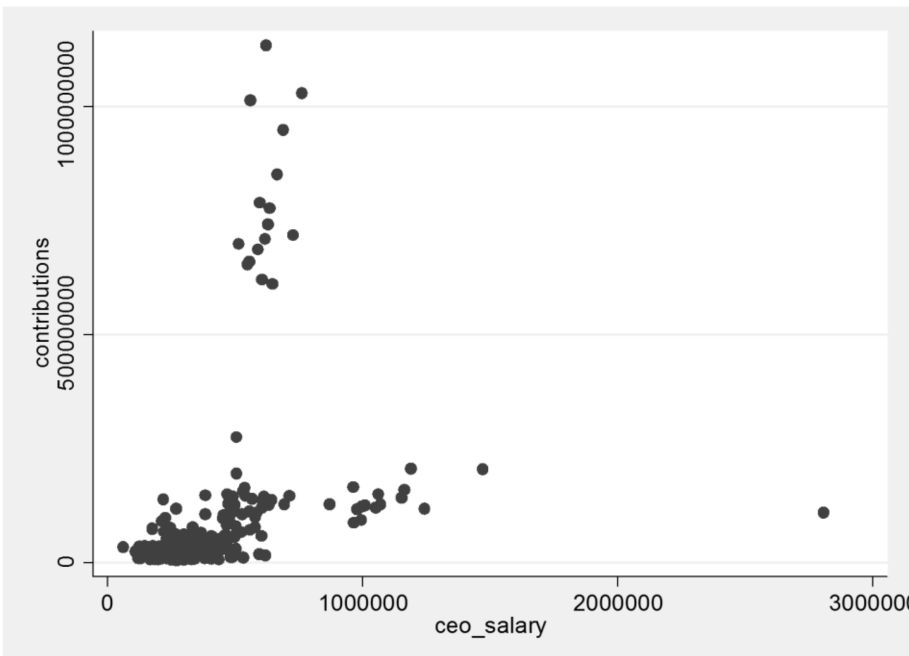
This study was performed using a dataset of 290 observations, compiled from IRS Form 990s. These are required forms for all American tax-exempt organizations with annual gross receipts of $200,000 or more or assets of $500,000 or more, excepting churches; this includes most charities, and is required for transparency purposes. Key variables in this dataset are as follows:

Table 1: Summary Statistics

	Mean	SD	Median	Min	Max
Contributions (in $)	87,400,000	180,000,000	29,800,000	3,819,022	1,130,000,000
CEO salary (in $)	390,863.80	258,314.20	317,430	62,253	2,809,674
Charity age (in yrs)	49.13448	35.50173	41	0	190

Using this data, the following relationship between CEO salary and contributions can be seen graphically in Figure 1.

Figure 1: CEO Salary on Contributions



A positive relationship between the two variables is clearly visible.

The charities used for this study were not selected by any particular method, including by a random generation process. These data include 75 different CEOs working across 9 different charity sectors: Animals, Health, Education, Community Development, Human & Civil Rights, International, Arts & Culture, Environment, and Human Services.

II. OLS Model

To begin with, I constructed a simple linear regression model to measure the effect of CEO salary on contributions to a charity:

(1) $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \epsilon$

where:

y: total annual contributions to a charity

x_1: annual CEO salary

x_2: age of the charity (in years)

x_3: series of dummy variables for the charity's sector of focus

x_4: series of dummy variables for the U.S. state in which the charity is based

The reasoning for including contributions and CEO salary in this model is obvious. The age of the charity was included to capture the effect of an older charity having greater name recognition, and therefore being more likely to raise money independent of existing funds. The charity's sector was included because charities with radically different goals operate at different necessary levels of funding; for instance, doing serious work overseas requires significantly more investment than performing the same work in one's backyard. Finally, the state in which the charity is based plays a large role in determining the incomes of those closest to the charity, who are therefore particularly likely to donate.

Key results from the regression in (1) can be seen in Table 2 below:

Table 2: OLS Model

	Coefficient	**SE**	**t**	**p**
CEO salary	266.4024	32.65855	8.16	~0.000
Charity age	935705	337662.5	2.77	0.006
				Observations: 290
				Adjusted R^2: 0.6814
				Parameters: 31

Using this model, we can see that CEO salary is quite significant, with a p-value well below 0.001. Furthermore, the adjusted R^2 of 0.6814 indicates that the model has significant explanatory power.

III. 3SLS Simultaneous Equation Model

While the results of (1) appear to be sound, they do not take into account a fundamental issue: that of simultaneity.

Multiple plausible channels of causality for total annual contributions to affect CEO salaries, rather than the causality being strictly vice versa. For instance, a charity could budget its expenses in advance, and upon raising a greater than anticipated amount of contributions, choose to allocate the excess to salaries; this could explain contributions increasing CEO salaries. Alternately, prospective donors could research charities and choose not to donate to those where CEO salaries seem excessively high to them; this could explain the opposite effect.

Regardless of which channel is dominant, the presence of a two-way causal effect is too likely to be ignored. This renders the results of (1) suspect, and indicates the need for a model to address the issue of simultaneity.

To that end, I constructed a system of simultaneous equations to explain both contributions and CEO salaries, treating both variables as endogenous:

(2) $y_1 = \alpha_0 + \alpha_1 y_2 + \alpha_2 x_1 + \alpha_3 x_2 + \alpha_4 x_3 + \varepsilon_1$

$y_2 = \beta_0 + \beta_1 y_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon_2$

where:

y_1: total annual contributions to a charity (in $)
y_2: annual CEO salary (in $)
x_1: age of the charity (in years)
x_2: series of dummy variables for the charity's sector of focus
x_3: series of dummy variables for the U.S. state in which the charity is based
x_4: time CEO has spent running charity (in years)
x_5: dummy variable for CEO's gender
x_6: dummy variable for whether CEO founded the charity
x_7: series of dummy variables for CEO's terminal degree

The first equation in this system is the same as (1), and explains total annual contributions to a charity.

The second equation, in explaining CEO salary, contains contributions for the reasons discussed above. The charity sector variable from the first equation was included because CEOs working in different sectors will have different skillsets and expectations befitting the very different work the charities do, while the state variable here captures living expenses for a CEO, which would necessarily impact compensation.

CEO duration at a charity, a new variable, was included to capture increases in compensation over time at the same organization, while founder status captures the preferential status that founders of a charity often hold. Finally, gender and terminal degree are both variables that have been known to strongly predict income in other studies.

By treating both contributions and CEO salary as endogenous, (2) should control for the simultaneity and reveal the specific effect of CEO salary on contributions.

Key results from the regression in (2) can be seen in Table 3 below:

Table 3: 3SLS Model

Contributions model:

	Coefficient	**SE**	**t**	**p**
CEO salary	423.9188	67.94048	6.24	~0.000
Charity age	161428.2	444034.4	0.36	0.716

Observations: 290
Adjusted R^2: 0.6900
Parameters: 31

CEO salary model:

	Coefficient	**SE**	**t**	**p**
Contributions	0.0021401	0.0007135	3.00	0.003
Founder	10182.34	73716.19	0.14	0.716
CEO duration	489.0188	2448.348	0.20	0.842

Observations: 290
Adjusted R^2: 0.2801
Parameters: 46

From these results, we can see that both CEO salary and total contributions are significant across the two models; in addition, the adjusted R^2 of the first equation is slightly higher, indicating good explanatory power.

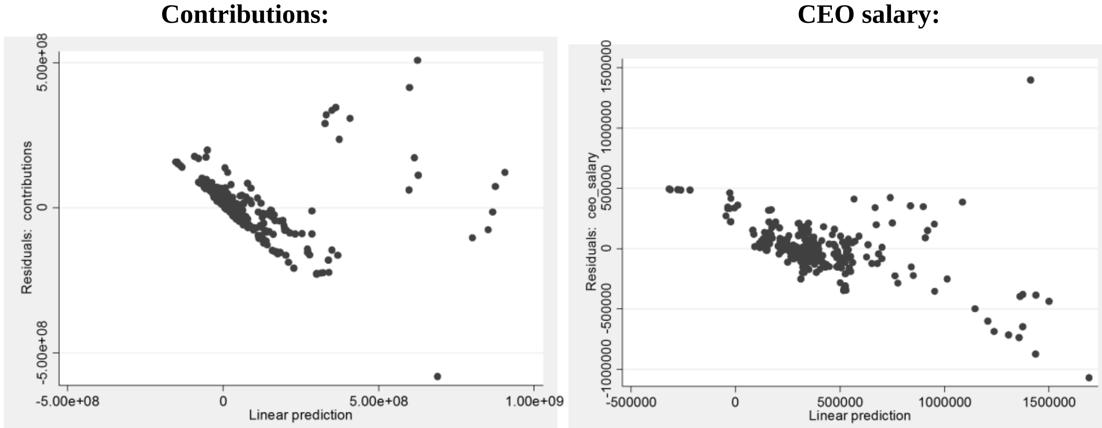
Comparing the results of (1) and (2), the most obvious difference is that the coefficient for CEO salary has increased significantly, going from 266.4024 in (1) to 423.9188 in (2). This indicates that the effect of simultaneity resulted in significantly underestimating the impact of CEO salary on contributions.

IV. Robustness Checks

A potential flaw with (2) cannot be spotted simply from observing its coefficients and standard errors, but rather can be seen in the residuals, plotted against fitted values in Figure 2:

Figure 2: Residuals of Equations in (2)

Contributions: **CEO salary:**



From these graphs, it is clear that the residuals are not evenly distributed around 0. This strongly implies that heteroskedasticity is present in the data. Performing formal tests of heteroskedasticity on (1) confirms this, as seen in Table 4:

Table 4: Test for Heteroskedasticity on (1)

	χ^2	p
White's test	210.23	~0.000

H_0: homoskedasticity

While the above estimates of (1) and (2) can be assumed to be unbiased and consistent, they are not necessarily efficient; that is, they do not necessarily provide the smallest variance among all unbiased estimators. This does not invalidate the results.

However, the significance levels reported in Tables 2 and 3 are no longer valid. Therefore, a new analysis must be performed using more accurate standard errors.

To do so, I performed another regression on (2), this time using the 2SLS method and heteroskedasticity-consistent standard errors. Key results from this regression can be seen in Table 5 below:

Table 5: 2SLS Robust Model

Contributions model:

	Coefficient	SE	t	p
CEO salary	420.2435	149.6947	2.81	0.005
Charity age	179493.1	984660.3	0.18	0.855

Observations: 290
Adjusted R^2: 0.6912
Parameters: 31

Several differences can be seen between Tables 3 and 5, attributable to the differences between the 2SLS and 3SLS methods. The coefficient of CEO salary is slightly smaller, though it is very similar to the coefficient in Table 3, particularly in proportion to the standard errors.

The main difference, though, comes from the use of robust standard errors. The standard error in Table 5 is much larger than in Table 3; accordingly, the significance level measured by the t-statistic has fallen considerably. However, it is still significant. Another issue with the data is autocorrelation, which can be seen in a test performed on (1) in Table 6:

Table 6: Test for Autocorrelation on (1)

	χ^2	p
Breusch-Godfrey	102.589	~0.000

H_0: no serial correlation

Clearly, the data is strongly autocorrelated. While the estimates of (2) are still unbiased and consistent, and while the model has already lost the assumption of efficiency, the presence of autocorrelation again leads to underestimating standard errors and overestimating t-statistics.

This is most likely because the dataset contains observations across five different years using the same CEOs, which can easily lead to correlation between values at different times. This can be checked by performing a regression on (1) separately for each of the five main years of data, ranging from 2010 to 2014, and testing each of the five models for autocorrelation. Note that dividing the data by year involves leaving out 10 of the 290 observations, belonging to 2009, 2015, and 2016. The results of this test can be seen in Table 7 below:

Table 7: Tests for Autocorrelation on (1), 2010 – 2014

	χ^2	p
2010	3.469	0.0625
2011	2.431	0.1189
2012	1.276	0.2586
2013	0.398	0.5283
2014	0.162	0.6874

H_0: no serial correlation

At a significance level of 0.05, none of the above tests are significant, indicating weak or absent autocorrelation in each. This strongly suggests that the regression suggested in (2) should be performed on observations within the same year, rather than across years.

Performing a 2SLS regression with robust standard errors on the model in (2) after dividing the data into five separate models, one for each year from 2010 to 2014, yields results summarized in Table 7:

Table 8: 2SLS Robust Model, 2010 – 2014

	CEO salary coefficient	CEO salary robust SE	t	p	Adj-R^2	Obs
2010	673.5503	1144.93	0.59	0.556	0.7268	47
2011	496.2102	2013.287	0.25	0.805	0.7509	59
2012	267.1742	249.0639	1.07	0.283	0.7689	59
2013	532.5676	312.969	1.70	0.089	0.7654	59
2014	456.6856	614.1666	0.74	0.457	0.8197	56

After both using robust standard errors and controlling for autocorrelation by dividing the sample, the result is clear: at a significance level of 0.05, there appears to be no significant impact of CEO salary on annual contributions, controlling for simultaneity and other covariates. However, in the 2013 subset, CEO salary is significant at a 0.1 significance level, and is considerably more so than every other year. This discrepancy between years is notable.

Splitting the dataset into five parts naturally decreases the size of each dataset considerably. With only 47 observations for 2010, 56 for 2014, and 59 for the other years, the 31-parameter model in (2) becomes a problem. To mitigate this problem, I constructed a new model below:

(3) $y_1 = \alpha_0 + \alpha_1 y_2 + \alpha_2 x_1 + \alpha_3 x_2 + \varepsilon_1$

$y_2 = \beta_0 + \beta_1 y_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \varepsilon_2$

where:

y_1: total annual contributions to a charity (in $)
y_2: annual CEO salary (in $)
x_1: age of the charity (in years)
x_2: series of dummy variables for the charity's sector of focus
x_3: time CEO has spent running charity (in years)
x_4: dummy variable for CEO's gender
x_5: dummy variable for whether CEO founded the charity
x_6: series of dummy variables for CEO's terminal degree

This model is almost identical to (2), but without the dummy variables representing the charity's state present in either equation. As the state dummy variables constitute 22 of the 31 parameters in the first equation, they are the logical choice to remove first.

To see the overall impact of removing the state variable, I performed a 2SLS regression with robust standard errors on (3). The results can be seen in Table 9 below:

Table 9: 2SLS Robust Model Without States

	Coefficient	**SE**	**t**	**p**
CEO salary	468.8709	116.1203	4.04	~0.000
Charity age	356365.2	461769.8	0.77	0.440
				Observations: 290
				Adjusted R^2: 0.1822
				Parameters: 10

As can be seen, removing the state variable from the model has major effects. Notably, the coefficient on CEO salary increases significantly, and the t-statistic also increases. However, the adjusted R^2 falls from 0.6912 to 0.1822, indicating that the model has much lower explanatory power.

By dividing the data into five parts as in Table 8 and performing a 2SLS regression with robust standard errors on each, the following results are obtained, shown in Table 10:

	CEO salary coefficient	CEO salary robust SE	t	p	Adj-R^2	Obs
2010	489.4451	268.3227	1.82	0.068	0.4012	47
2011	573.3338	266.692	2.15	0.032	0.2457	59
2012	312.1839	229.6661	1.36	0.174	0.1488	59
2013	461.4912	180.2222	2.56	0.010	0.2976	59
2014	443.5561	229.171	1.94	0.053	0.3270	56

Table 10: 2SLS Robust Model Without States, 2010 – 2014

The significance of the coefficients on CEO salary have increased considerably from Table 8; every year but 2012 is significant at the 0.1 level, and 2011 and 2013 are significant at the 0.05 level. However, as in Table 9, this increase in significance has come at the cost of explanatory power, with the adjusted R^2 values falling considerably.

By combining the residual sum of squares (RSS) of each of the equations in Table 10, and comparing it to the RSS of Table 9, I was able to construct an F-statistic to test for the constancy of these equations, as seen below:

$$F = \frac{(RSS_{restricted} - RSS_{unrestricted})/q}{RSS_{unrestricted}/(n-k)} = \frac{(7.618 \times 10^{18} - 6.716 \times 10^{18})/11}{(6.716 \times 10^{18})/279} = 3.40649$$

Computing this yields a p-value of 0.00019; as such, we can resoundingly reject the null hypothesis that the coefficients and constants are equal. This result could indicate significant differences in circumstances across years, though it is also possible that these findings are simply noise caused by insufficiently large data samples.

V. Conclusion

In conclusion, the effect of CEO salary on charitable contributions in (1) appears significant, and becomes larger while remaining significant after controlling for simultaneity in (2).

However, after correcting for the presence of heteroskedasticity and autocorrelation in the data, the significance of each year declines significantly, with only the 2013 data remaining significant at a significance level of 0.1, and no data remaining significant at a level of 0.05. After removing the state variable from the analysis, the significance of CEO salary has increased, but the explanatory power of the model has fallen considerably. Overall, the results of this analysis were relatively weak, and would benefit from being repeated with a larger dataset.

While the results of this particular study may have been inconclusive, the issue remains very real. Every year, Americans donate nearly $400 billion to charities, to say nothing of people throughout the rest of the world; their need for a clear heuristic to determine the best charity to donate to remains great, and the current practice of eschewing those charities with high CEO salaries is inelegant. There is room to pursue this topic further, and I plan to do so.