

DOES CEO PAY MATTER?

An analysis of U.S. tech firms

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Yu Xuan Deng

40173189

Abstract

Currently, there is a wide range of existing literature on CEO pay and firm performance. However, no general agreement exists on whether performance-based compensation will lead to a higher-performing firm. Context-specific data and information are all factors that affect the results, such as the structure of CEO pay, culture, industry, and period. (Abowd, 1990; Benmelech et al., 2010; Frydman & Jenter, 2010). Thus, this paper provides specific context and examines whether CEO performance compensation influences U.S. tech firm performance between 2010 and 2018. Using data from Wharton Research Data Services, this paper finds no relationship between CEO performance compensation and firm performance.

Introduction

There is a consensus amongst the general population that performance compensation is an effective method of increasing productivity in the workplace because it incentivizes hard work among employees. Despite the wide range of existing literature on CEO pay and firm performance, there is no general agreement on whether performance-based compensation will lead to a higher-performing firm. A relatively weak, or even negative, correlation exists between CEO compensation and company performance (Balafas & Florackis, 2013).

The most promising research on CEO compensation and firm performance examines evidence from the London Stock Exchange. Balafas & Florackis (2013) find that "CEO incentive pay is negatively associated with subsequent short-term returns. Interestingly, firms that pay their CEOs at the bottom of the incentive-pay distribution earn positive abnormal returns and significantly outperform those at the top of the incentive-pay distribution." This paper's finding is also consistent with Cooper et al.'s research on the U.S. market (2016). However, the CEOs of Standard and Poor's (S&P) 500 companies have been rising since the late 1990s (Bereskin & Cicero, 2012). The counter-intuitive result is rather intriguing given the disincentive for shareholders to raise the CEO's compensation in the face of little added value and the high monetary costs associated. Most of a CEO's compensation package is performance-based, so shareholders must evaluate whether the common belief holds merit and whether lucrative compensation packages for CEOs are worth the investment.

According to the research of Abowd, 1990; Benmelech et al., 2010 and Frydman & Jenter, 2010, context-specific data and information are all factors that affect the results, such as

the structure of CEO pay, culture, industry, and period. Since very few studies currently evaluate the relationship between CEO performance compensation in the U.S. tech industry, this paper fills the gap in the current literature study by analyzing context-specific data and examining whether CEO performance compensation influences U.S. tech firm performance between 2010 and 2018. Given the high volatility of high-tech industries and the speculative nature of investments in high-tech, it would be interesting to see whether tech CEOs' performance compensation affects firm returns; it would be in the CEO's best interest to take advantage of the speculation in stock prices, so this paper hypothesizes there would be a relationship between tech CEO performance compensation and firm returns.

Using data from Wharton Research Data Services CRSP, this paper runs a linear regression and finds that there is a statistically significant correlation between CEO performance compensation and firm returns for public firms in the high-tech sector of the U.S. Specifically, running the univariate regression of returns in percentage and stock options in thousands, the resulting coefficient is 0.4666 with a standard error of 0.169 and a p-value of 0.006. The result is statistically at the 95% confidence level. Running the bivariate regression of returns in percentage, stock options in thousands, and base salary in hundred thousand, the resulting coefficient is 0.6103 with a standard error of 0.199 and a p-value of 0.002. This result is also statistically at the 95% confidence level.

The following data section will provide a comprehensive description of the database used and a description of the data set. Summary statistics will be provided, and a short discussion on regressors, controls and the regressor of interest will also be included. Then this paper will discuss the empirical methods used, and some manipulations are done to help make

the data more understandable. This paper will discuss the findings in more detail in the results section. Finally, the conclusion will summarize the paper and conclude this paper.

Data

The data this paper uses is from three separate sources. First, a list of U.S. public firms in the high-tech sector and industry are obtained from NASDAQ Stock Screener under Global Select with the Technology sector filter on and North America region filter on. Next, the company data, including the company name, calendar year closing price, market value, and company name, are obtained from the Wharton Research Data Services CRSP/Compustat Merged database under Fundamentals Annual. Finally, the CEO salary base compensation and CEO stock options performance compensation data are retrieved from Compustat Execucomp Annual Compensation. The panel data tracks 94 companies between 2010 and 2018 to avoid the pandemic effects of 2019. Key variables include salary, stock option, CEO name, and company name. The returns are calculated as simple future returns, where 2018 returns are calculated as $(2018 \text{ price close} - 2017 \text{ price close}) / (2017 \text{ price close})$.

In the sample, there were 95 technology companies and CEOs with their respective salaries before data cleaning. Variables include coname (company name), salary (in thousands), stock option, gvkey, year, pceo (present CEO), title, exec_lname, exec_fname, gender, ticker, PCC (price close in dollars), MV (market value in millions), sector, industry, returns (in percentage). The mean salary is \$614,484, with a standard deviation of \$357,159. The highest and lowest salaries are \$3,057,692 and \$0, respectively. In terms of market value, the mean is \$299.4 billion, with a standard deviation of \$115 billion. The highest and lowest market values

are \$58.2 million and \$1.07 trillion, respectively. The mean return is 15.88%, with a standard deviation of 43.4%. The minimum and maximum returns are -80.33% and 462%, respectively. The sample size is small; however, the variation among different variables is significant. The regressor of interest will be stock option, and the dependent variable will be returns. Market value and base salary are included as controls for the regression. This study will have a statement about correlation and not attempt to reach a causal statement.

```
df.describe()
```

	SALARY	STOCKOPT	GVKEY	YEAR	PRICECLOSE	MKVAL	RETURNS
count	638.000000	6.380000e+02	638.000000	638.000000	638.000000	6.380000e+02	638.000000
mean	614.484577	1.900203e+04	71692.579937	2014.857367	59.012555	2.994811e+04	0.158880
std	357.159859	1.614256e+05	65797.695393	2.237830	110.673731	1.148045e+05	0.433663
min	0.000000	8.523000e+00	1161.000000	2011.000000	1.330000	5.822980e+01	-0.803251
25%	400.000000	1.271606e+03	13480.000000	2013.000000	17.350000	7.476317e+02	-0.093427
50%	572.161000	3.329225e+03	31843.000000	2015.000000	34.280000	1.828749e+03	0.107036
75%	786.201500	7.642506e+03	133288.000000	2017.000000	63.927500	6.977171e+03	0.350476
max	3057.692000	3.302978e+06	264416.000000	2018.000000	1053.400000	1.073391e+06	4.617761

Table I.

The data were obtained from the above sources, then downloaded into CSV files. The sources of the data also provided documentation. For most of the data, the variables are used as is. Base salary, stock options, and returns are rescaled to make coefficients easier to read and more meaningful. Base salary is rescaled to a hundred thousand, stock options are rescaled to thousands, and returns are expressed in percentage points instead of decimals. The future returns are calculated as simple returns using the calendar year closing price of 2018 and 2017.

The data have been downloaded, then merged using Python with Pandas on gvkey and ticker. Numpy, Matplotlib, Sklearn, and Statsmodels are imported into Python as libraries for analysis. Then, the data is cleaned by dropping N.A. observations and sorting them by company name alphabetically. The outliers that are affecting the linear regression model are dropped. Specifically, observations with >\$1.5 million base salary, >200% returns, and 60000 stock option are dropped.

After dropping the observations, the stock option has the following summary statistics. Mean: 6115, std: 8657, min: 8.5, max: 5492. The tables and figures in the following sections will detail the data results before and after cleaning.

```
df.describe()
```

	SALARY	STOCKOPT	GVKEY	YEAR	PRICECLOSE	MKVAL	RETURNS
count	607.000000	607.000000	607.000000	607.000000	607.000000	607.000000	607.000000
mean	578.919870	6115.150804	71280.920923	2014.797364	45.441634	13838.325870	0.142372
std	263.361007	8657.950393	65377.818050	2.244199	46.135371	55824.860411	0.361541
min	0.000000	8.523000	1161.000000	2011.000000	1.330000	58.229800	-0.740587
25%	395.154000	1226.411000	16710.000000	2013.000000	16.690000	713.092050	-0.095132
50%	550.000000	3002.419000	31843.000000	2015.000000	32.790000	1696.196300	0.107111
75%	750.000500	6421.144500	133288.000000	2017.000000	60.345000	5489.276300	0.342385
max	1450.000000	54962.851000	264416.000000	2018.000000	532.172900	626550.352800	1.545868

Table II.

Empirical Methods

Below is the regression model that aims to establish a correlation between returns and stock options.

$$\text{Returns} = \alpha + \beta \text{Stock Options} + \gamma \text{Base Salary} + \delta \text{MarketValue} + \varepsilon$$

After running the regression, beta = 0.5773 with std = 0.202 and a p-value = 0.004, this result is statistically significant at the 95% confidence level, and on average, for every 577 increase in stock options, returns will increase by one percentage point. Below are tables with different controls. Figure I is the long regression, figure II contains only the two compensations, and figure III only contains the regressor of interest.

OLS Regression Results						
=====						
Dep. Variable:	RETURNS2	R-squared:	0.017			
Model:	OLS	Adj. R-squared:	0.013			
Method:	Least Squares	F-statistic:	3.560			
Date:	Sat, 18 Mar 2023	Prob (F-statistic):	0.0141			
Time:	20:22:42	Log-Likelihood:	-3033.3			
No. Observations:	607	AIC:	6075.			
Df Residuals:	603	BIC:	6092.			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	15.8765	3.621	4.385	0.000	8.765	22.988
SALARY_HUNDRED_THOUSANDS	-0.9635	0.659	-1.462	0.144	-2.257	0.330
STOCKOPT_THOUSANDS	0.5773	0.202	2.864	0.004	0.181	0.973
MKVAL	2.95e-05	2.71e-05	1.089	0.276	-2.37e-05	8.27e-05
=====						
Omnibus:	36.942	Durbin-Watson:	2.203			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	45.401			
Skew:	0.552	Prob(JB):	1.38e-10			
Kurtosis:	3.759	Cond. No.	1.45e+05			
=====						

Figure I

OLS Regression Results						
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Figure II

OLS Regression Results						
=====						
Dep. Variable:	RETURNS2	R-squared:		0.012		
Model:	OLS	Adj. R-squared:		0.011		
Method:	Least Squares	F-statistic:		7.648		
Date:	Sat, 18 Mar 2023	Prob (F-statistic):		0.00586		
Time:	20:23:38	Log-Likelihood:		-3034.8		
No. Observations:	607	AIC:		6074.		
Df Residuals:	605	BIC:		6082.		
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	11.3841	1.787	6.369	0.000	7.874	14.894
STOCKOPT_THOUSANDS	0.4666	0.169	2.766	0.006	0.135	0.798
=====						
Omnibus:	38.207	Durbin-Watson:		2.200		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		46.691		
Skew:	0.570	Prob(JB):		7.26e-11		
Kurtosis:	3.740	Cond. No.		13.0		
=====						

Figure III

Since the omitted variable bias is greater than 0 in this case, the short regression is likely underestimating the correlation between CEO performance compensation and firm returns.

Results

The results make intuitive sense and confirm the hypothesis at the beginning that higher CEO performance compensation may lead to higher firm stock returns in the tech industry due to the sector's highly volatile and speculative nature. CEOs may take advantage and attempt to maximize stock returns. However, it is unclear whether non-observable and intrinsic firm values are affected. It is also unclear whether the long-term consequences of maximizing stock returns are positive or negative. In contrast to previous literature, these results indicate that firm returns are positively correlated with CEO performance pay. In contrast to previous papers, this paper does not attempt to make a causal statement; hence it is difficult to make claims about both the proximal and distal causes. Nonetheless, this result follows intuition and could provide insight into whether CEO performance pay is adequate but also raises the question of whether CEOs in tech sectors are sacrificing other unobservable aspects of the firm for higher short-term stock returns.

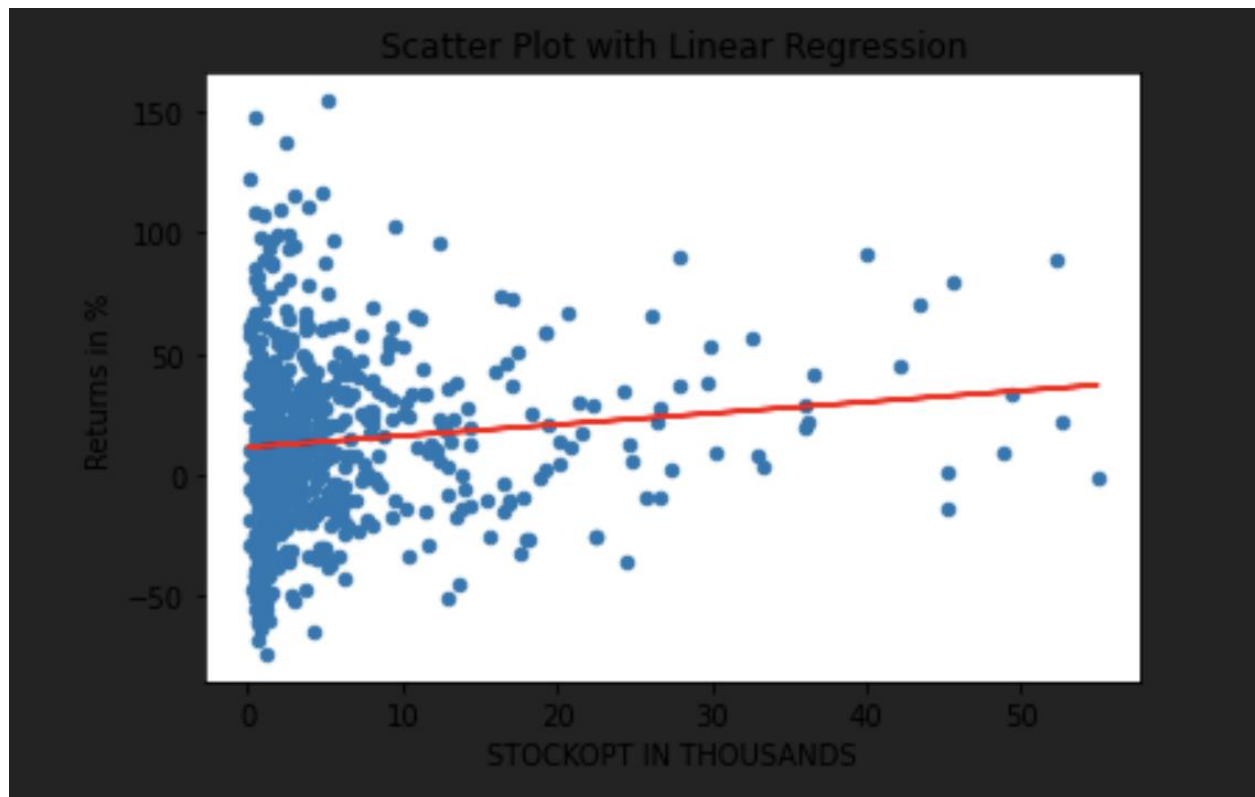


Figure IV

Conclusion

This paper provides context-specific information and analyzes whether there is a correlation between CEO performance compensation and firm returns of public U.S. firms in the tech industry. Using panel data from 2010 to 2018, this paper finds a positive correlation between CEO performance pay and firm returns. However, whether this correlation has a causal interpretation and whether firm return is an appropriate proxy for a firm's long-run performance is unclear. Furthermore, unobservable firm values that affect long-term performance are not accounted for in this paper; hence it is unclear whether positive returns are necessarily good for the firm.

Tables & Figures

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Figure III

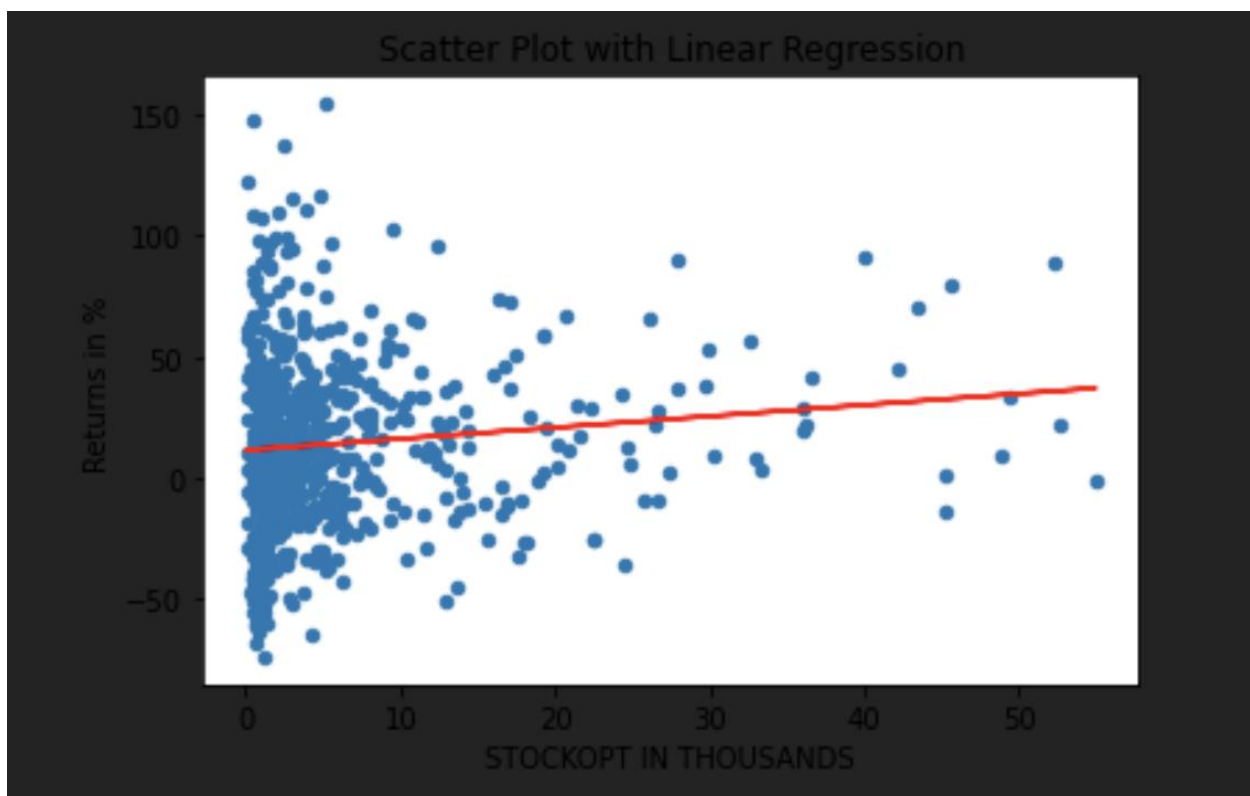


Figure IV

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