The following paper was researched and written as part of LSE GROUPS 2024.

LSE GROUPS takes place during the final fortnight of the LSE Spring Term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question and carry out every stage of a small-scale research project, in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry and developing the skills needed for knowledge creation.

The overall theme of LSE GROUPS 2024 was *Power and Politics.*

This paper was submitted on the final Thursday afternoon of the project. Students then presented their work at a conference, on the closing Friday.

More information on LSE GROUPS, and other papers.

Papers are presented as submitted by the students, without corrections.

London School of Economics and Political Science

Eden.GROUPS@lse.ac.uk

Polls and Profits: An Analysis of Share Price Performance of Companies Funding Winning US Presidential Parties

The London School of Economics - Group 8
EDEN Centre: LSE GROUPS
Flore Charbit, Hong Li, Shiqi Chen, Jessie Fung, Hassan Duffaydar, Leon Madakbas

13/06/2024

Abstract

The possibility that corporate funding for election may tilt the financial playing field in favour of such firms has been an area of significant attention within the American financial and political space. In this study, we look at the impact of corporate funding of winning candidates on stock prices during six different American presidential elections from 2000 to 2020 and ask whether political financing can be considered "good investments." Based on ROCE, ROE, debt-to-equity ratio, and EPS, we selected 8 cooperation across 4 sectors, including tech, oil, consumable, retail, and extracted their changes of stock prices after the day of election outcome. Using multiple linear regression, controlling for stock momentum and S&P500 index for market regular changes, we found no significant correlation between cooperation's funding choices and their relative changes of stock returns after the reveal of election result. That is, compared to co-operations that have funded the losing candidate, those who funded the winning candidate did not experience a greater change to their stock prices after 1 day or 1 week. Our finding is consistent with our hypothesis and previous studies on congressional election, providing additional evidence to suggest that political funding decisions by cooperation do not yield financially meaningful returns.

Keywords: ***corporate political contribution, presidential election, stock prices, fiscal campaign.***

Introduction

The 2020 US presidential election raised more than $4 billion from candidates across the country, breaking a financial record and making it the most expensive election in global history (Federal Election Commission, 2024). The massive influx of funds highlights a crucial trend: the increasing intertwining of corporate finances and political outcomes. While, surprisingly, it is widely believed by corporate investors that supporting the winning presidential or congressional candidate guarantees financial gains (Pan and Tian, 2020), recent research suggests that the relationship between corporate funding and stock performance may be more complex (Kim et al, 2018). Indeed, amongst others, current empirical evidence showed no correlation between the amount of political funding and the result of the election on cooperation's subsequent financial performance (Fowler et al., 2020), but the case of recent presidential election has not been studied yet.

Thus, we wonder to what extent do companies that fund winning political candidates at US presidential elections perform better financially in share prices after the election? Working with stock prices of publicly traded companies divided into four main sectors (retail, consumable, technology, and oil), before and after the election, we observe that funding the winning candidate is not correlated with rising stock prices. Our findings are further confirmed after controlling for adding additional financial metrics (including ROCE, ROE, debt-to-equity ratio, and EPS). Our research provides a new insight on corporate funding strategies and on investors decision-making awareness.

Literature Review

US Presidential elections have been shown to have a significant impact on stock prices. Oehler (2020) finds that, largely as a result of uncertainty over future policy, market volatility has historically been higher during election years, reflected in a 20% increase in the standard deviation of stock returns during these periods on average. It is further found that, when the incumbent party retains power (e.g. when a Democratic president is replaced by another Democratic president), the stock market consistently performs better when the new president is from the opposite party of the incumbent. This is clear from a 10.5% average annual return in the former, and a 7.1% average annual return in the latter (Oehler, 2020).

During presidential terms, evidence linking stock price performance and the party affiliation of the sitting president is mixed. Santa-Clara and Valkanov (2003) document significantly higher excess stock returns during Democratic presidencies than during Republican presidencies, which is explained only in part by unexpected returns which would reflect positively supposed investors during Democratic presidencies. In contrast, analysing across 48 industries, Stangl and Jacobson (2008) do not find any consistent differences in industry performances between Democratic and Republican presidencies. However, Sabherwal et al (2012) find that stocks in businesses related to tobacco, alcohol, and gaming stand out as performing significantly better during Republican presidencies than during Democratic presidencies, while Oehler (2020) finds that stock prices and returns associated with mining and manufacturing industries suffer disproportionately after the election of a Democratic candidate compared to a Republican candidate.

Further, it has been theorised that funding an electoral candidate that goes on to win will produce a financial payoff for the corporation that funded the candidate pre-election, observable in their stock prices. This could be the case for two reasons, which are not mutually exclusive. First, if a candidate supports policies that are beneficial to the corporation, that corporation has a clear incentive to fund that candidate, which will in turn increase the chance that this candidate will be elected, and likely produce a policy change that will create a financial payoff for the corporation (Green and Gerber, 2015). Second, corporations may fund a candidate that would have won independently of the contribution itself, but in doing so influence the policy that is supported by the candidate such that it is more likely to be beneficial for the corporation when it is enacted, resulting in a financial payoff for the corporation (see Hall and Wayman (1990), Austen-Smith (1995)). Kalla and Broockman (2016)). The latter relies on the fact that campaign contributions are systematically guided by the motive of seeking political influence, and that, in most cases, the goal of funding political candidates is to 'buy' access to politicans, rather than seeking to directly buy favourable policies from them directly (Teso, 2023).

However, at the congressional, governor, and state legislative levels, Fowler et al (2020) shows empirically that there is no connection between corporate political funding to candidates and positive financial outcomes when that candidate wins, and thus further suggests that corporate campaign contributions do not buy significant political favors or beneficial policies either directly or indirectly to induce financial payoffs. In explaining this, and in rejecting the causal chains presented above, it has been suggested that the benefits of funding may be too small to be statistically detectable, and that corporations may, on average, 'give a little and get a little' (Ansolabehere et al, 2003), that benefits that companies accrue as a resulting of candidate funding do not actually depend on who wins at the congressional, governor, and state legislative level (Gordon and Hafer (2005) and Schnakenberg and Turner (2020)), or that agency problems within companies allow its leadership to benefit from contributions at the expense of shareholders (Bonica (2016) and Aggarwal et al (2012)).

However, while researchers continue to examine the effects of elections on stock prices, no literature to date has attempted to empirically and holistically investigate the correlation between the corporate funding of presidential election candidates specifically and post-election stock prices. Based on Fowler et al (2020), we hypothesise that, in comparison to corporations that fund the losing candidate in US elections, those that fund the winning candidate would not experience greater positive stock returns, and thus that there is no financial payoff for funding a winning electoral candidate at a US presidential election.

Methodology

To establish causality, we first attempted the Difference-in-Differences (DiD) technique, motivated by its ability to control for unobservable confounding variables. Our initial approach was to compare two firms for which the trends in stock prices and fundamental financial performance before the election exhibited parallel trends, yet which have funded the winning and losing party by random assignment. However, we could not find two firms with parallel trend (see Technical Appendix for further detail), we have therefore resorted to multiple linear regression to control for as many confounding variables as possible, with a caveat for unobservable variables and reverse causality.

The companies under study include **Amazon, eBay, Pepsi, Coca-Cola, Starbucks, Home Depot, BP, and ExxonMobil**. Throughout the 6 presidential election cycles, Amazon, eBay, and Starbucks consistently funded Democrat, ExxonMobil and Home Depot consistently funded Republican, while Pepsi, Coca-Cola, and BP switched parties at least once. In each election year, a firm is considered to be in the treatment group if it had funded the winning presidential candidate. We collect these companies' stock prices 30 days before the election, 1 day before the election, 1 day after the election, and 30 days after the election using the Yahoo Finance database.

Multiple Linear Regression

We perform 2 regressions, varying the length of the examined pre-election and post-election period. In our baseline regression model, we use stock prices 1 month before and 1 month after election day. By using a 2-month time window, we can address potential lags in the market's internalisation of the effects of the election results. The baseline regression model is as follows:

Baseline Model

$$\frac{P_t - P_{t-1}}{P_{t-1}} \times 100 = \beta_0 + \beta_1 D_{tr} + \beta_2 \text{DE\_ratio} + \beta_3 \text{EPS} + \beta_4 \text{ROE} + \beta_5 \text{ROCE} + \epsilon$$

- P_t: stock price 30 days before election day
- P_{t-1}: stock price 30 days after election day
- $\frac{P_t - P_{t-1}}{P_{t-1}} \times 100$: percentage change in stock price pre- and post-election
- β_1: coefficient of interest, indicating the treatment effect
- D_{tr}: dummy variable, 1 if in the treatment group, 0 otherwise
- DE_ratio: debt to equity ratio
- EPS: normalised diluted earnings per share
- ROE: return on equity
- ROCE: return on capital employed
- ϵ: error term

The coefficient of interest β_1 can be interpreted as the average increase in the percentage change in a company's stock price associated with funding the winning presidential candidate, controlling for company fundamentals and market health. We have included 4 variables controlling for the financial health and performance of the individual companies: 2 profitability ratios (ROE and ROCE), 1 long term solvency ratio (DE ratio), and 1 investment ratio (EPS). ROE controls for the efficiency of a company in generating profits from its equity base; ROCE evaluates the overall efficiency in using capital; DE ratio controls for the impact of leverage on stock performance; normalized EPS controls for earnings differences among companies.

In addition to the baseline model, we perform a second regression examining the percentage change in stock price 1 day before and 1 day after the election. With the shorter time frame, we can eliminate non-election related shocks to stock prices and isolate the effect of the election. Apart from the change in the specification of P_t and P_{t-1}, we also control for momentum and overall US stock market performance. In technical analysis, the momentum effect refers to the tendency for an asset that performs well to continue doing so. We use the percentage change in stock price from 30 days before the election to 1 day before the election as an indicator of the momentum effect and control for this (Quantified Strategies, 2024). Additionally, we use the S&P 500 index as an indicator of the overall stock market performance of large US firms, thus eliminating the effect of different macroeconomic conditions between elections (Quantified Strategies, 2024). The second regression is as follows:

Improved Model

$$\frac{P_t - P_{t-1}}{P_{t-1}} \times 100 = \beta_0 + \beta_1 D_{tr} + \beta_2 \text{DE\_ratio} + \beta_3 \text{EPS} + \beta_4 \text{ROE} + \beta_5 \text{ROCE} + \beta_6 \text{S\&P500} + \beta_7 \text{momentum} + \epsilon$$

- P_t: stock price 1 day before election day (Monday)
- P_{t-1}: stock price 1 day after election day (Wednesday)
- S&P500: S&P500 index on election day
- momentum $= \frac{P_{t-1} - P_{t-2}}{P_{t-2}} \times 100$
- P_{t-2}: stock price 30 days before election

Regression Models

Baseline Model

```
lm(formula=D1_perc_diff ~ treatment * (ROCE +ROE +DebtEquity+ Normalised_Diluted_EPS ,
    data=reg_data)
```

Listing 1: Baseline Model

treatment is a binary variable representing whether or not a firm has backed the party that will go on to win the presidential election (treatment=1) or not (treatment=0)
D1-perc-diff represents the percentage difference in stock prices between a time period of 1 day before the presidential election and 1 day after the election. (green)
M1-perc-diff represents the percentage difference in stock prices between a time period of 1 month before the presidential election and 1 month after the election.(blue)

Improved Model

Here, we control for two additional variables: *sp500* and *momentum*. The *sp500* index is used to indicate the current market health and landscape. The *momentum* variable accounts for stock price cycles, such as when a stock price is already in the increasing section of a candlestick pattern.

```
lm(formula=D1_perc_diff ~ treatment * (ROCE +ROE +DebtEquity+ Normalised_Diluted_EPS)+
    momentum +sp500 , data=reg_data)
```

Listing 2: Improved Model

Event frame

Using data spanning 1 month and 1 day away from the treatment (election day) allows us to provide a more rigorous analysis providing a clearer picture of stock dynamics (Sigma Computing, 2024). We will later exploit this data to calculate stock momentum- a measure of the initial trend of the stock as it approaches election date. (bullish[1]/ bearish[2]/uptrend[3]/downtrend[4]).

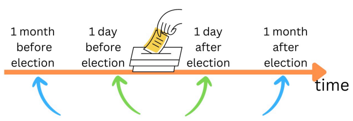


Figure 1: Scraping time of stock prices

[1]bullish:Expecting price rise
[2]bearish:Expecting price fall
[3]uptrend:Sustained price increase
[4]Sustained price decrease

Results

Overall, we observed no significant difference in stock price changes pre- and post-election when comparing cooperations that have funded the winning and losing candidate across 4 selected elections. However, sector-specific analysis revealed potential effect by policy introductions, such as tech and energy sector.

As shown in Figures 2 to 5, the temporal changes in stock prices do not correspond to cooperation's funding decision and the electoral outcomes. Red segments represents the time in which the cooperation funded Republicans and blue represents funding towards Democrats. The x-axis also shows which party won the elections using their respective party emblems. Figure 6 and 7 show the percentage difference

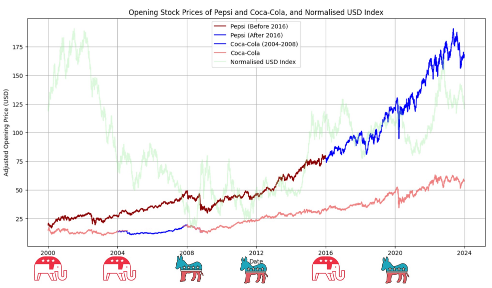


Figure 2: Pepsi and Coca-Cola

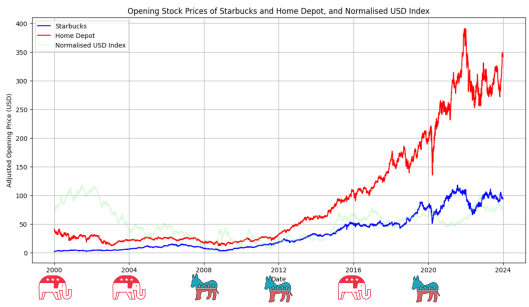


Figure 3: Starbucks and Home Depot

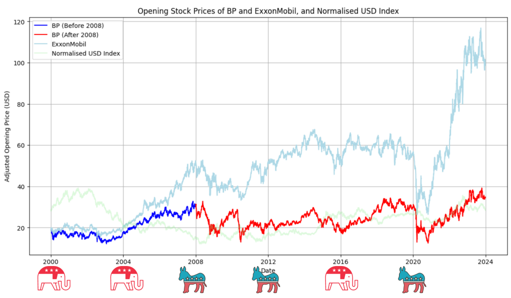


Figure 4: BP and ExxonMobil

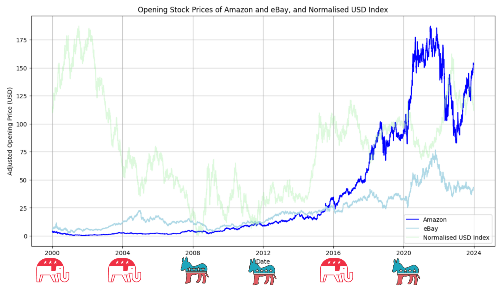


Figure 5: Amazon and eBay

in stock price for 1 month and 1 day before and 1 month and 1 day after the elections, respectively. We observe that companies in the same industry have similar long term trends but differ on a daily basis pattern.

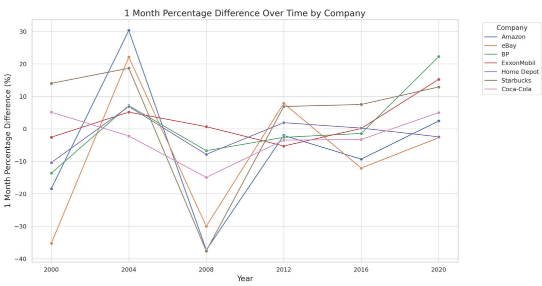


Figure 6: 1 Month Percentage Difference over time

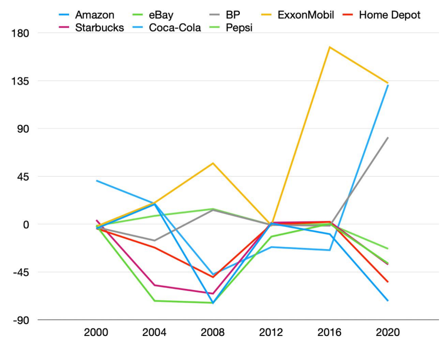


Figure 7: 1 Day Percentage Difference over time

Variables	(1)	(2)	(3)	(4)
Fund Winning Party	-13.73 (14.52)	.58(14.44)	-2.80(14.56)	.33(14.79)
Return On Capital Employed		-1.04(.54)	-.75(.58)	-1.55(.74)
Return On Equity		.01(.07)	.01(.08)	.004(.080)
Debt Equity Ratio		.77(2.08)	1.48(2.22)	1.12(2.25)
Normalised Diluted Earnings Per Share		.54(3.29)	-.84(3.60)	1.20(3.85)
Momentum		-61.67(14.17)	-62.20(15.86)	-62.21(17.36)
GDP Per Capita			.004(.005)	.003(.005)
S&P500			.006(.012)	.004(.012)
Oil Sector				-34.42(25.42)
Tech Sector				-30.45(23.81)
Consumables Sector				7.19(21.29)
Adjusted R-Squared	-0.0023	0.3068	0.3126	0.3132
N	48	48	48	48

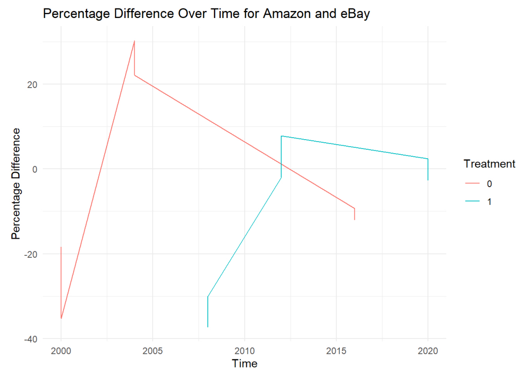
Table 1: Linear Regression: Testing the Effect of Funding Winning Party on Growth Rate in Stock Prices after 1 day of Election Outcome

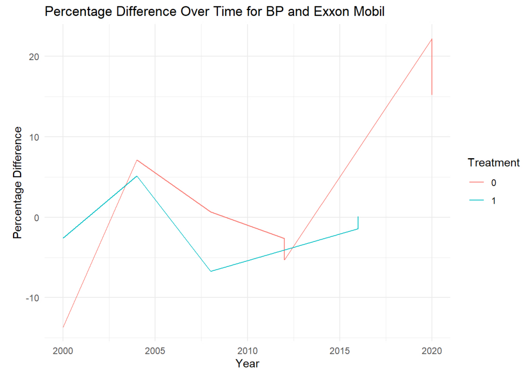
Variables	(1)	(2)	(3)	(4)
Fund Winning Party	-3.53(4.18)	-2.82(4.00)	-3.54(4.08)	-4.04(4.25)
Return On Capital Employed		-.12(.15)	-.05(.16)	-.07(.21)
Return On Equity		.04(.02)	.04(.02)	.04(.02)
Debt Equity Ratio		-.49(.58)	-.27(.62)	-.26(.65)
Normalised Diluted Earnings Per Share		-1.13(.91)	-1.27(1.01)	-1.41(1.11)
Momentum		-16.23(3.92)	-15.47(4.44)	-17.13(4.99)
GDP Per Capita			.0004(.0013)	.0006(.0013)
S&P500			.003(.003)	.002(.003)
Oil Sector				-1.14(7.30)
Tech Sector				-4.77(6.84)
Consumables Sector				-6.26(6.12)
Adjusted R-Squared	-0.0062	0.3327	0.3225	0.2871
N	48	48	48	48

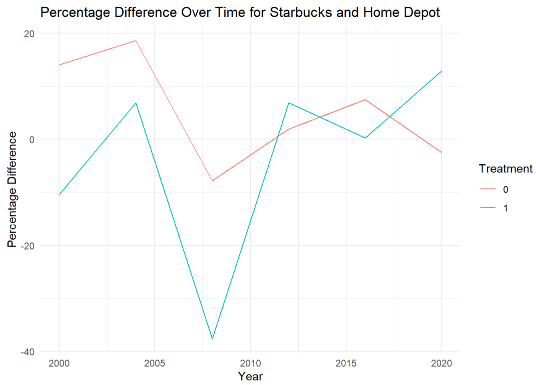
Table 2: Linear Regression: Testing the Effect of Funding Winning Party on Growth Rate in Stock Prices after 1 month of Election Outcome

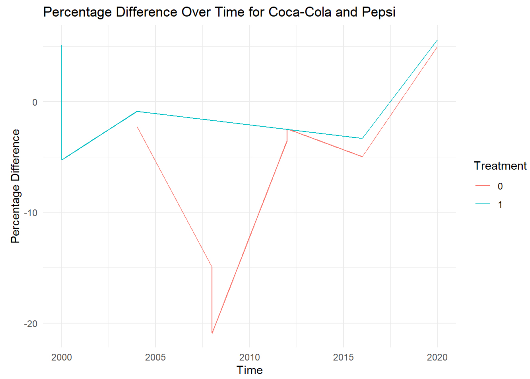
As shown in Table 1, the adjusted R squared for simple linear regression is negative, suggesting poor fit of the model in explaining the variance in changes of stock price after election outcome. In accordance of our argument to add further controls from the Method section, we added further controls for specification 2 to 4, boosting the adjusted R square to 0.31. Specifically, after controlling for firm's natural stock performances using relevant metrics detailed in the Method section, we found that funding the winning candidate would increase the firm's stock return by 0.33%, suggesting a positive correlation between funding the winning party and the financial outcome. Nevertheless, such correlation is not significant across specifications, agreeing with our hypothesis and findings of prior literature on congressional election.

We then restricted our analysis to within sectors, namely the tech, oil, retail and consumables. It is notable that certain industries, such as retail, have experienced negative impacts on both companies within a pair due to poor financial market conditions (e.g., the 2008 financial crisis), while other industries have seen either one company affected or none at all.









Discussions

Lack of Correlation Explained

Returning to the literature, the lack of a connection between corporate funding and financial payoff in terms of stock prices can be explained in a number of ways. First, significant events like the COVID-19 pandemic in 2020 and the financial crisis in 2008 have profoundly impacted share prices, overshadowing any potential effects of political contributions. These large-scale disruptions introduce substantial volatility into the market, making it challenging to isolate the influence of political contributions on share prices.

Second, the benefits of political contributions might be too minor to detect statistically. Given that many organizations and individuals contribute to political candidates, each contribution represents a small fraction of the total received by all candidates. Consequently, organizations are unlikely to be able to "buy" political favors substantial enough to result in a meaningful or detectable financial payoff. Ansolabehere et al. (2003) suggests instead that corporations 'give a little to get a little', such that relatively small campaign contributions create corresponding small payoffs that are too small to be statistically detectable.

Third, using the logic presented by Green and Gerber (2015), corporations may contribute to help a candidate win, hoping for beneficial policies if the candidate succeeds, rather than contributing to the candidate most likely to win. Although this strategy can produce a financial payoff, it does not guarantee it, as predicting electoral results and subsequent policy changes is inherently uncertain, and as a result not all corporations will fund the same candidate. As a result, in many cases, corporations within sample will inevitably fund candidates in an attempt to increase the chances of that candidate winning, but which will lose regardless, meaning that there can be no financial payoff.

Fourth, agency problems may lead to company leadership benefiting from political contributions rather than shareholders. Studies by Bonica (2016) and Aggarwal et al. (2012) indicate that executives might use corporate funds for political contributions to enhance their personal networks or future career prospects, rather than benefiting the company or its shareholders. Thus, while there may be a financial payoff, it is effectively captured by company leadership, leaving stock prices unaffected.

Reasons for Continued Corporate Donations

Having proven that funding a winning political candidate may not produce a financial payoff, and that it thus may not be a effective investment for the company, it is worth theorising as to why corporations do so at all. First, and most plainly, corporate contributions might reflect the personal convictions of executives rather than a financial strategy. Teso (2023) suggests that some corporate donations are guided by the ideological beliefs of CEO's or other leadership figures, who may direct corporate funds based on personal support for a candidate without considering financial benefits. More broadly, it is also possible that CEOs or those in leadership positions derive personal benefits that are neither financial in their nature nor accrued to the corporation associated with that individual. For example, buying access to politicians through corporations could be used by individuals in leadership positions to advance their own personal careers, without any expected benefit to the company.

Second, corporations might contribute to establish connections with elected officials to gain better insights into potential regulatory changes. Even if contributions do not directly affect elections or policy, they can create valuable connections that help companies anticipate and respond to regulatory developments. Fowler et al. (2020) highlight that corporations are willing to pay for this information, even if it indicates potential financial losses. These strategic connections provide a long-term advantage that may not be immediately reflected in share price performance.

Third, contributions might aim to influence the behavior of sitting incumbents before the next election, regardless of the candidate's chances of winning. This strategy aligns with the logic presented by Hall and Wayman (1990), Austen-Smith (1995), and Kalla and Broockman (2016), where influence occurs during the candidate's term rather than before the election. However, the timing of contributions, often late in an official's term, casts doubt on this explanation as it may be too late to enact meaningful policy changes. Nonetheless, the potential for future influence remains a motivating factor for corporate donations.

Fourth, Gordon and Hafer (2005) theorise that corporate funding may be motivated by a perceived need to signal support (or a lack of support) for particular policies that different candidates are associated with. If a particular candidate in a presidential election is known to support a particular policy which the corporations perceive as being against their interest, they could fund the opposite candidate (even on the assumption that that candidate has very little chance of winning regardless) as a way to show that they would be willing to fight regulatory changes when the former candidate is eventually elected.

Limitations

Our limited sample size presents a significant limitation to our methodology. The 8 selected companies operate in different industries and have highly differentiated products and production processes, which have enabled them to become corporate giants. Their stock prices are therefore impacted by factors unique to each company, for which we are unable to fully control due to a lack of data: in particular, market expectations of changes in cost and profitability are not reflected in the balance sheets of companies and are therefore difficult to quantify. Their important size adds another challenge: reverse causality, or the possibility that firms' change in stock prices over the election cause changes in the explanatory and control variables.

Additionally, data availability requires us to restrain our database to publicly traded companies, thus ignoring financial dark pools, which may influence stock prices. We also do not control for industry-specific trends (e.g. COVID-19 diminishing demand for oil while boosting demand for e-commerce) and among the firms that were badly affected by the 2008 financial crisis, all supported the winning party, leading to an overestimation of the treatment effect. Then, the stochastic behavior of stock prices further the difficulty to control. Finally, it is important to remind that correlation does infer causality, especially with a limited data set.

More generally, the stock market follows complex and unexpected trends, that are difficult, if not impossible, to fully assimilate into a theoretic model.

Conclusion

This study examined the relationship between corporate political funding and post-election stock performance throughout six US presidential elections. Analyzed stock prices across different sectors, there was no significant correlation between funding the winning candidate and stock price increases. Thus, the complexity of factors influencing corporate financial outcomes goes beyond the sole scope of political contributions.

Our research provides empirical evidence on corporate funding and financial results, prompting a reevaluation of investment strategies tied to political outcomes, as their efficiency is actively being challenged. It encourages a more nuanced understanding of political investments' impact on financial performance, advocating for comprehensive approaches that consider broader financial metrics and strategic objectives.

This research is relevant to a number of questions about the role of corporate funding in democratic processes, and gives some indication that corporate influence on presidential elections is smaller than has previously been estimated. Relevant to corporations themselves, it is an indication that the funding of winning political candidates may not have the expected financial payoff on average, and thus that investing in politics in such a way may not be an effective strategy.

Acknowledgements

We would like to extend deep gratitude to LSE EDEN Centre, Dr. Ellis Saxey and our beloved supervisor: Haoran Shi, Department of Psychological and Behavioural Science, LSE. We are appreciative of this research experience and the friends we made along the way.

Bibliography

- Aggarwal, R.K., Meschke, F., Wang, T.Y., 2012. Corporate Political Donations: Investment or Agency? *Business and Politics*, 14, 1–38.
- Ansolabehere, S., de Figueiredo, J.M., Snyder Jr, J.M., 2003. Why is There so Little Money in U.S. Politics? *Journal of Economic Perspectives*, 17, 105–130.
- Austen-Smith, D., 1995. Campaign Contributions and Access. *American Political Science Review*, 89, 566–581.
- Bonica, A., 2016. Avenues of influence: On the political expenditures of corporations and their directors and executives. *Business and Politics*, 18.
- Federal Election Commission (2019). Home - fec.gov. [online] FEC.gov. Available at: https://www.fec.gov/.
- Fouirnaies, A., Hall, A.B., 2018. How Do Interest Groups Seek Access to Committees? *American Journal of Political Science*, 62, 132–147.
- Fowler, A., Garro, H., Spenkuch, J.L., 2020. Quid Pro Quo? Corporate Returns to Campaign Contributions. *The Journal of Politics*, 82, 844–858.
- Gordon, S.C., Hafer, C., 2005. Flexing Muscle: Corporate Political Expenditures as Signals to the Bureaucracy. *American Political Science Review*, 99, 245–261.
- Hall, R.L., Wayman, F.W., 1990. Buying Time: Moneyed Interests and the Mobilization of Bias in Congressional Committees. *American Political Science Review*, 84, 797–820.
- Huber, J. and Kirchler, M., 2011. Corporate Campaign Contributions and Abnormal Stock Returns after Presidential Elections. *Public Choice*, 156(1-2), pp.285–307.
- Kim, C. (Francis), Kim, I., Pantzalis, C. and Park, J.C., 2018. Corporate Political Strategies and Return Predictability. *Financial Analysts Journal*, 74(4), pp.87–101.
- Krueger, A.O., 1974. The Political Economy of the Rent-Seeking Society. *The American Economic Review*, 64(3), pp.291–303.
- Oehler, A., Walker, T.J., Wendt, S., 2013. Effects of election results on stock price performance: evidence from 1980 to 2008. *Managerial Finance*, 39, 714–736.
- Powell, E., Grimmer, J., 2016. Money in Exile: Campaign Contributions and Committee Access. *The Journal of Politics*, 78, 974–988.
- Schnakenberg, K.E., Turner, I.R., 2021. Helping Friends or Influencing Foes: Electoral and Policy Effects of Campaign Finance Contributions. *American Journal of Political Science*, 65, 88–100.
- Snyder, J., Romer, T., 1994. An Empirical Investigation of the Dynamics of PAC Contributions. *American Journal of Political Science*, 38, 745–769.
- Teso, E., 2023. Influence-Seeking in U.S. Corporate Elites' Campaign Contribution Behavior. *The Review of Economics and Statistics*, 1–34.

Polls and Profits: An Analysis of Share Price Performance of Companies Funding Winning US Presidential Parties

Group 8
EDEN Centre: LSE GROUPS
Flore Charbit, Serena Li, Andreas Chen, Jessie Fung,
Hassan Duffaydar, Leon Madakbas

Technical Appendix

Parallel Trends Assumption in Difference-in-Differences

Parallel Trends Assumption

The *parallel trends assumption* is a key requirement for the validity of the Difference-in-Differences (DiD) approach. It posits that, in the absence of treatment, the difference between the treatment and control groups would have remained constant over time. Formally, let Y_{it} denote the outcome for unit i at time t, and let D_i be a binary indicator of treatment. The assumption can be expressed as:

$$E[Y_{it} \mid D_i = 1, t = T] - E[Y_{it} \mid D_i = 0, t = T] = E[Y_{it} \mid D_i = 1, t = T-1] - E[Y_{it} \mid D_i = 0, t = T-1]$$

where T denotes the post-treatment period and $T-1$ denotes the pre-treatment period. This implies that any differences in outcomes between the treatment and control groups are attributable solely to the treatment effect, under the assumption that both groups would have followed parallel paths in the absence of the treatment.

Capital Asset Pricing Model (CAPM)

Parallel Trends Assumption

The CAPM predicts the expected return of an asset based on its systematic risk, also known as beta, and the expected return of the market as a whole. This model follows the Efficient Market Hypothesis (EMH), which posits that financial markets are efficient in that prices reflect all relevant information and adjust instantaneously to new information.

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate, β_i is the beta of asset i, and $E(R_m)$ is the expected return of the market.

Critiques of CAPM: Idiosyncratic Risk: This risk is specific to an individual stock or asset and is not related to the overall market. An example is the sudden resignation of a CEO. Diversification can mitigate idiosyncratic risk, but assets typically earn a risk premium based on their exposure to common market risks, not idiosyncratic characteristics. - Momentum Effect: Assets that have performed well in the past tend to continue performing well, and those that have performed poorly tend to continue performing poorly. This effect, discovered by Clifford Asness in the late 1980s, challenges the CAPM assumption that only systematic risk should affect asset returns.

Arbitrage Pricing Theory (APT)

Parallel Trends Assumption

APT extends CAPM by considering multiple factors or sources of risk, offering a more flexible approach to asset pricing. Developed by Stephen Ross in the 1970s, APT is expressed as:

$$E(R_i) = R_f + \beta_{i1}F_1 + \beta_{i2}F_2 + \cdots + \beta_{ik}F_k + \epsilon_i$$

where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate, β_{ij} are the sensitivities of asset i to the j-th factor F_j, and ϵ_i is the error term.

Alpha Factors

Parallel Trends Assumption

Alpha factors are variables or metrics used to predict the future returns of financial assets. The results of a presidential election, for instance, can serve as an alpha factor by impacting market sentiment, policy expectations, and the macroeconomic outlook. These factors depend on each investor's strategy and can influence market reactions.

Statistical Analysis

For our statistical and exploratory analyses, we employed both R and Stata. Utilizing R allowed us to take advantage of its powerful packages for data manipulation, statistical modeling, and visualization, which were critical for our in-depth exploratory data analysis. Stata, on the other hand, provided robust tools for econometric and statistical analysis, ensuring precise and reliable results. The combination of these two software tools enabled us to leverage their respective strengths, ensuring a comprehensive and rigorous analytical process throughout our research.

Technical Appendix: R statistical analysis

24841

2024-06-04

libraries

```
library(readxl)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(reshape2)
```

```
##
## Attaching package: 'reshape2'
```

```
## The following object is masked from 'package:tidyr':
##
##     smiths
```

```
library(ggplot2)
library(plotly)
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
data <- read_xlsx("C:/Users/Hassan/Downloads/workdata.xlsx",sheet=1)
data2 <- read_xlsx("C:/Users/Hassan/Downloads/workdata.xlsx",sheet=2)
data3 <- read_xlsx("C:/Users/Hassan/Downloads/workdata.xlsx",sheet="did")
```

```
## New names:
## • `` -> `...9`
## • `` -> `...10`
## • `` -> `...11`
```

```
data3 <- data3[,1:7]
table(data3$`Party backed`)
```

```
##
## dem rep
##  41  39
```

```
table(data3$`Party won`)
```

```
##
## dem rep
##  41  39
```

identify companies that backed losing party

```
#treated=0
lose_comp <- data3 %>% filter(`Party won` != `Party backed`)
#treated=1
win_comp <- data3 %>% filter(`Party won` == `Party backed`)
nrow(lose_comp)
```

```
## [1] 38
```

```
nrow(data3)
```

```
## [1] 80
```

```
head(win_comp)
```

Ticker <chr>
AMZN
AMZN
AMZN
BP
EBAY
EBAY

6 rows | 1-1 of 7 columns

selecting only the companies that have 3 rows of data or more

```
tickers_to_keep <- data3 %>%
  group_by(Ticker) %>%
  filter(n() >= 3) %>%
  pull(Ticker) %>%
  unique()

rep_comp <- data3 %>%
  filter(Ticker %in% tickers_to_keep) %>%
  filter(`Party won` == `Party backed`, Treated == 1)
```

Calculate mean change in opening stock price , small sample size (n=4 or 3) so we use then use a t-test

```
rep_comp <- rep_comp %>%
  mutate(Difference = `1 Month After` - `1 Month Before`,
         PercentageDifference = (Difference / `1 Month Before`) * 100)

# Compute the mean percentage difference for each company
mean_percentage_diff <- rep_comp %>%
  group_by(Ticker) %>%
  summarize(MeanPercentageDifference = mean(PercentageDifference, na.rm = TRUE))

# Display the result
print(mean_percentage_diff)
```

```
## # A tibble: 14 × 2
##    Ticker MeanPercentageDifference
##    <chr>                     <dbl>
##  1 AMZN                    -12.3
##  2 BP                       -4.08
##  3 EBAY                     -8.30
##  4 F                        -0.738
##  5 GM                       42.6
##  6 GOOGL                    -4.71
##  7 HD                       -1.11
##  8 KO                        0.921
##  9 MSFT                     -6.67
## 10 PEP                      -0.160
## 11 SBUX                     -5.95
## 12 TGT                      18.0
## 13 WMT                       6.72
## 14 XOM                       0.889
```

```
#double check we have 14 companies
unique(rep_comp$Ticker)
```

```
##  [1] "AMZN"  "BP"    "EBAY"  "F"     "GM"    "GOOGL" "MSFT"  "PEP"   "SBUX"
## [10] "TGT"   "WMT"   "HD"    "KO"    "XOM"
```

repeat the above procedure with control companies , treatment=0

```
rep_comp_cont <- data3 %>%
  filter(Ticker %in% tickers_to_keep) %>%
  filter(`Party won` != `Party backed`, Treated == 0)

rep_comp_cont <- rep_comp_cont %>%
  mutate(Difference = `1 Month After` - `1 Month Before`,
         PercentageDifference = (Difference / `1 Month Before`) * 100)

# Compute the mean percentage difference for each company
mean_percentage_diff_cont <- rep_comp_cont %>%
  group_by(Ticker) %>%
  summarize(MeanPercentageDifference = mean(PercentageDifference, na.rm = TRUE))

# Display the result
print(mean_percentage_diff_cont)
```

```
## # A tibble: 14 × 2
##    Ticker MeanPercentageDifference
##    <chr>                     <dbl>
##  1 AMZN                    -10.3
##  2 BP                        3.28
##  3 EBAY                     -8.42
##  4 F                        12.5
##  5 GM                        5.61
##  6 GOOGL                    15.8
##  7 HD                       -2.82
##  8 KO                       -3.91
##  9 MSFT                     -0.806
## 10 PEP                      -9.33
## 11 SBUX                     13.4
## 12 TGT                      -6.71
## 13 WMT                      -7.25
## 14 XOM                       3.53
```

```
# Perform a paired t-test
t_test_result <- t.test(mean_percentage_diff$MeanPercentageDifference, mean_percentage_diff_cont$MeanPercentageDi
fference, paired = TRUE)

# Print the result
print(t_test_result)
```

```
##
##  Paired t-test
##
## data:  mean_percentage_diff$MeanPercentageDifference and mean_percentage_diff_cont$MeanPercentageDifference
## t = 0.34509, df = 13, p-value = 0.7355
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -7.760546 10.711115
## sample estimates:
## mean difference
##        1.475284
```

p-value: The p-value is 0.7355, which is significantly higher than the common significance levels of 0.05 or 0.01. Interpretation: A high p-value suggests that there is not enough evidence to reject the null hypothesis. The null hypothesis in this context is that the mean difference between the two sets of data is zero. simple terms: p value- how likely is the data to take this value/ more extreme values–> basically p: probability that difference in results is caused by random chance.

correlation

```
# Calculate the average stock price before and after for each company
average_prices <- data3 %>%
  group_by(Ticker) %>%
  summarize(
    AvgBefore = mean(`1 Month Before`, na.rm = TRUE),
    AvgAfter = mean(`1 Month After`, na.rm = TRUE)
  )

# Display the result
print(average_prices)
```

```
## # A tibble: 14 × 3
##    Ticker AvgBefore AvgAfter
##    <chr>      <dbl>    <dbl>
##  1 AMZN        36.5     36.2
##  2 BP          42.1     41.5
##  3 EBAY        23.0     22.3
##  4 F           12.2     12.3
##  5 GM          29.3     34.8
##  6 GOOGL       29.0     31.5
##  7 HD          97.6     96.0
##  8 KO          34.2     33.7
##  9 MSFT        62.8     62.8
## 10 PEP         80.0     77.4
## 11 SBUX        31.4     34.3
## 12 TGT         67.7     71.8
## 13 WMT         24.6     25.2
## 14 XOM         63.7     64.0
```

```
# Combine AvgBefore and AvgAfter into a single row for each company
combined_avg_prices <- average_prices %>%
  pivot_longer(cols = c(AvgBefore, AvgAfter), names_to = "TimePeriod", values_to = "AveragePrice") %>%
  pivot_wider(names_from = Ticker, values_from = AveragePrice)

# Display the combined data
print(combined_avg_prices)
```

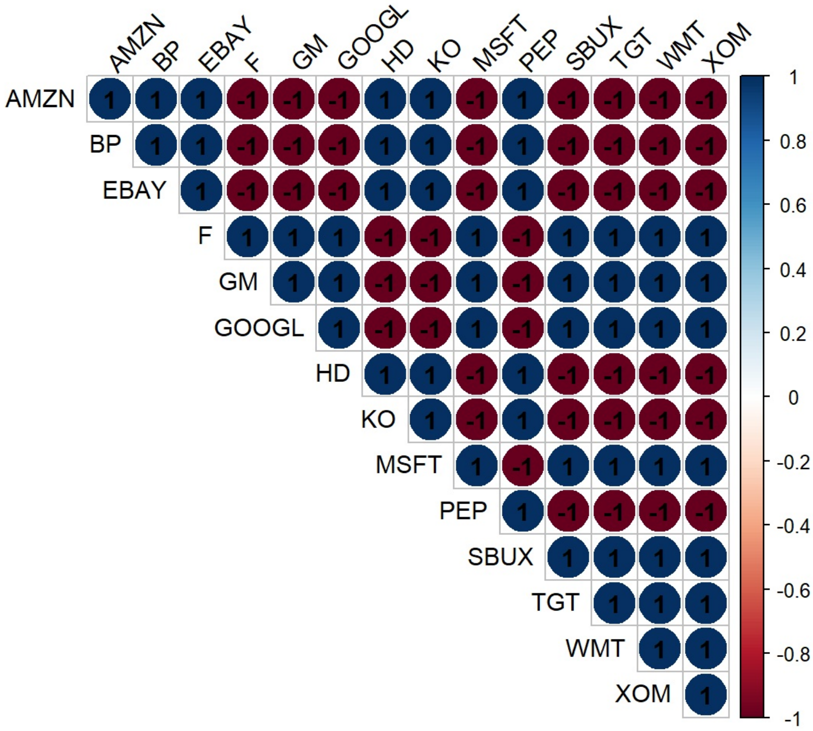
```
## # A tibble: 2 × 15
##   TimePeriod  AMZN    BP  EBAY     F    GM GOOGL    HD    KO  MSFT   PEP  SBUX
##   <chr>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 AvgBefore   36.5  42.1  23.0  12.2  29.3  29.0  97.6  34.2  62.8  80.0  31.4
## 2 AvgAfter    36.2  41.5  22.3  12.3  34.8  31.5  96.0  33.7  62.8  77.4  34.3
## # ℹ 3 more variables: TGT <dbl>, WMT <dbl>, XOM <dbl>
```

```
# Calculate the correlation matrix for the transposed data
correlation_matrix <- cor(combined_avg_prices[-1], use = "complete.obs")

# Display the correlation matrix
print(correlation_matrix)
```

```
##       AMZN BP EBAY  F GM GOOGL HD KO MSFT PEP SBUX TGT WMT XOM
## AMZN     1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## BP       1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## EBAY     1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## F       -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## GM      -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## GOOGL   -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## HD       1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## KO       1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## MSFT    -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## PEP      1  1    1 -1 -1    -1  1  1   -1   1   -1  -1  -1  -1
## SBUX    -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## TGT     -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## WMT     -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
## XOM     -1 -1   -1  1  1     1 -1 -1    1  -1    1   1   1   1
```

```r
# Create the correlation plot
corrplot(correlation_matrix, method = "circle", type = "upper",
         tl.col = "black", tl.srt = 45, addCoef.col = "black")
```



```
# Load necessary libraries



# Create the dataframe from the provided log differences
log_diff_ratio_df <- data.frame(
  Ticker = c("AMZN", "BP", "EBAY", "F", "GM", "GOOGL", "HD", "KO", "MSFT", "PEP", "SBUX", "TGT", "WMT", "XOM"),
  LogDiffRatio = c(0.0024808500, 0.0044016098, 0.0092043015, -0.0042276014, -0.0511808648, -0.0241109206,
                   0.0037213446, 0.0042251062, -0.0001394564, 0.0077461571, -0.0254836013, -0.0139361914,
                   -0.0073428861, -0.0013467369)
)
# Create a dataframe with 4 rows of the same data
log_diff_ratio_repeated <- log_diff_ratio_df[rep(1:nrow(log_diff_ratio_df), each = 6),]

# Transpose the dataframe to get companies as columns
log_diff_ratio_transposed_df <- as.data.frame(t(log_diff_ratio_repeated$LogDiffRatio))
colnames(log_diff_ratio_transposed_df) <- log_diff_ratio_df$Ticker

log_diff_ratio_transposed_df <- log_diff_ratio_transposed_df[rep(1:nrow(log_diff_ratio_df), each = 6),]

# Calculate the correlation matrix using Hmisc
#correlation_matrix <- rcorr(as.matrix(log_diff_ratio_transposed_df))

# Extract the correlation coefficients
#correlation_coeffs <- correlation_matrix$r

# Extract the p-values
#p_values <- correlation_matrix$P

# Display the correlation matrix
#print(correlation_coeffs)

# Visualize the correlation matrix
#corrplot(correlation_coeffs, method = "circle", type = "upper",
        # tl.col = "black", tl.srt = 45, addCoef.col = "black")
```

```
#k-means clustering
#library(cluster)

#k <- 5  # number of clusters
#clusters <- kmeans(as.vector(log_diff_ratio), centers = k)

# Display clusters
#print(clusters$cluster)
```

```
data4 <- read_xlsx("C:/Users/Hassan/Downloads/workdata8.xlsx",sheet="8 Companies")
```

feature enginering - adding binary variable - whether treatment /no treatment

```
data4$treatment <- ifelse(data4$`Party won`==data4$`Party backed`,1,0)
```

```
reg_data <- data4[,-c(7,8,9,10,11,12)]
names(reg_data)[5] <- "DebtEquity"
names(reg_data)[6] <- "Normalised_Diluted_EPS"
names(reg_data)[7] <- "M1_perc_diff"
names(reg_data)[8] <- "D1_perc_diff"
```

```
# Fit separate regression models for each treatment group

model_treatment_0 <- lm(M1_perc_diff ~ ROCE + ROE + DebtEquity + Normalised_Diluted_EPS, data = reg_data, subset
= (treatment == 0))
model_treatment_1 <- lm(M1_perc_diff ~ ROCE + ROE + DebtEquity + Normalised_Diluted_EPS, data = reg_data, subset
= (treatment == 1))

# Summarize the models
summary(model_treatment_0)
```

```
##
## Call:
## lm(formula = M1_perc_diff ~ ROCE + ROE + DebtEquity + Normalised_Diluted_EPS,
##     data = reg_data, subset = (treatment == 0))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.881  -6.195   1.032   8.793  19.814
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             4.57621    5.17022   0.885    0.388
## ROCE                   -0.16505    0.22974  -0.718    0.482
## ROE                     0.04403    0.02805   1.570    0.134
## DebtEquity             -0.39571    0.80975  -0.489    0.631
## Normalised_Diluted_EPS -0.64246    1.33223  -0.482    0.635
##
## Residual standard error: 14.5 on 18 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.2635, Adjusted R-squared:  0.09979
## F-statistic:  1.61 on 4 and 18 DF,  p-value: 0.215
```

```
summary(model_treatment_1)
```

```
##
## Call:
## lm(formula = M1_perc_diff ~ ROCE + ROE + DebtEquity + Normalised_Diluted_EPS,
##     data = reg_data, subset = (treatment == 1))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -30.424  -4.826   6.092   9.153  12.147
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            -9.00495    7.01310  -1.284    0.220
## ROCE                    0.13251    0.30520   0.434    0.671
## ROE                     0.04342    0.12672   0.343    0.737
## DebtEquity             -2.88228    4.31620  -0.668    0.515
## Normalised_Diluted_EPS  1.09318    2.11095   0.518    0.613
##
## Residual standard error: 16.03 on 14 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.07151,    Adjusted R-squared:  -0.1938
## F-statistic: 0.2695 on 4 and 14 DF,  p-value: 0.8927
```

#Combined

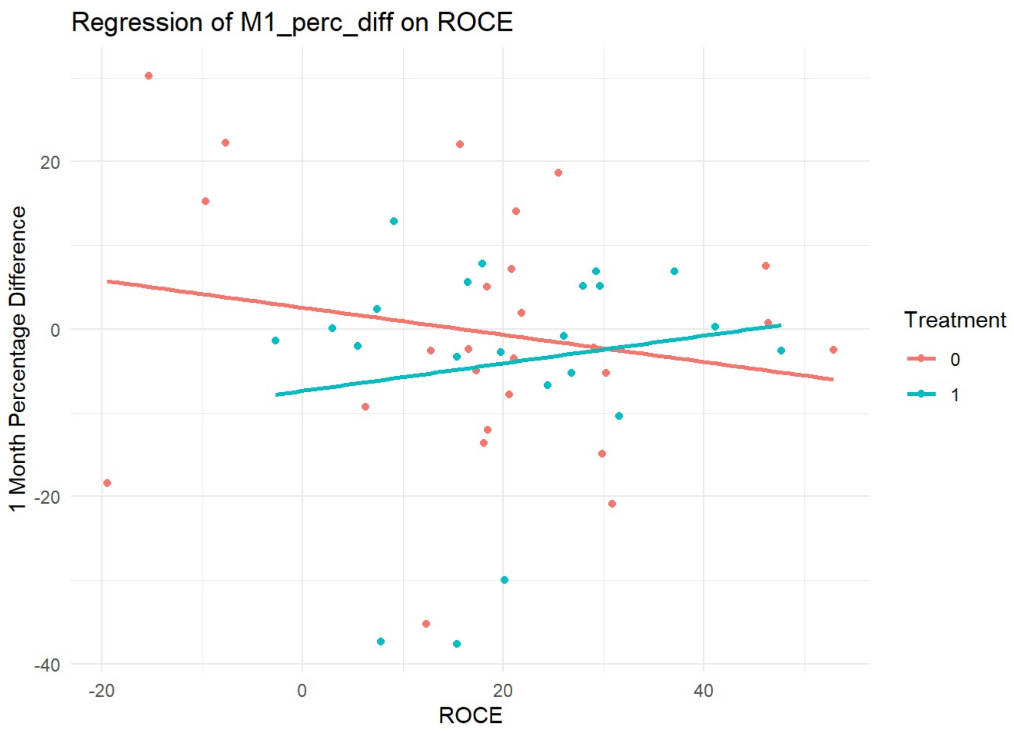
```
# Combined regression model including treatment as a binary variable
combined_model <- lm(M1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity + Normalised_Diluted_EPS), data = reg_da
ta)

# Summarize the combined model
summary(combined_model)
```

```
##
## Call:
## lm(formula = M1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity +
##     Normalised_Diluted_EPS), data = reg_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.881  -6.685   2.487   9.181  19.814
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   4.576e+00  5.415e+00   0.845    0.404
## treatment                    -1.358e+01  8.572e+00  -1.584    0.123
## ROCE                         -1.651e-01  2.406e-01  -0.686    0.498
## ROE                           4.403e-02  2.938e-02   1.498    0.144
## DebtEquity                   -3.957e-01  8.481e-01  -0.467    0.644
## Normalised_Diluted_EPS       -6.425e-01  1.395e+00  -0.460    0.648
## treatment:ROCE                2.976e-01  3.762e-01   0.791    0.435
## treatment:ROE                -6.038e-04  1.236e-01  -0.005    0.996
## treatment:DebtEquity         -2.487e+00  4.177e+00  -0.595    0.556
## treatment:Normalised_Diluted_EPS  1.736e+00  2.439e+00   0.712    0.482
##
## Residual standard error: 15.19 on 32 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.2067, Adjusted R-squared:  -0.01643
## F-statistic: 0.9264 on 9 and 32 DF,  p-value: 0.5158
```

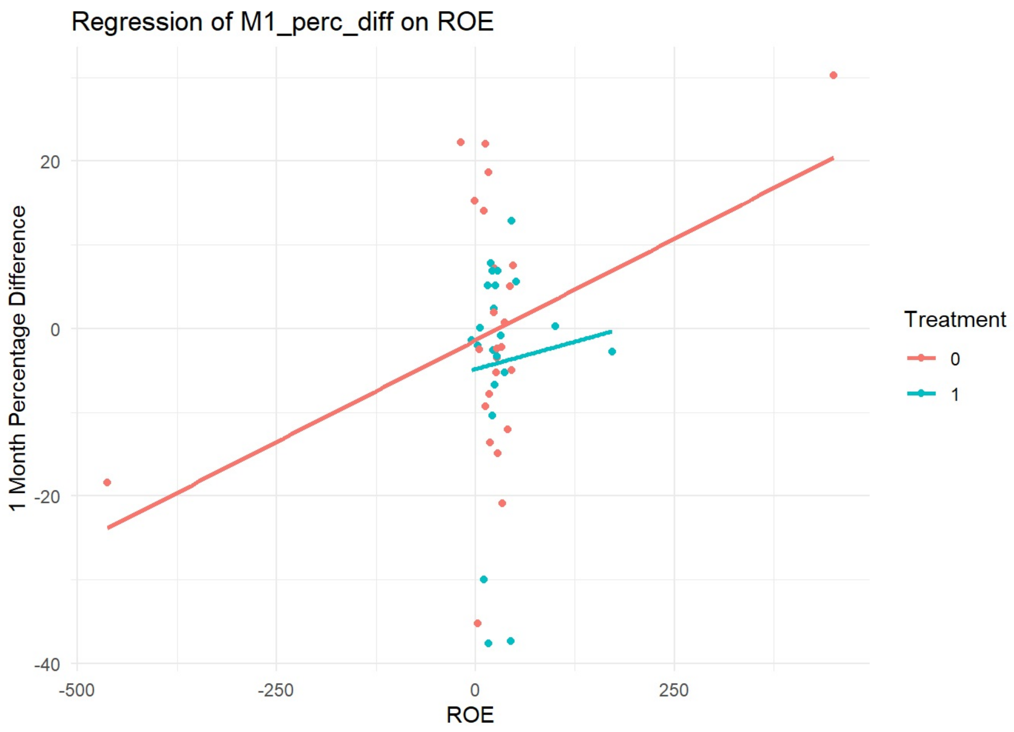
```
# Plot the data and regression lines using ggplot2
ggplot(reg_data, aes(x = ROCE, y = M1_perc_diff, color = as.factor(treatment))) +
  geom_point() +
  geom_smooth(method = "lm", aes(group = treatment), se = FALSE) +
  labs(title = "Regression of M1_perc_diff on ROCE",
       x = "ROCE",
       y = "1 Month Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



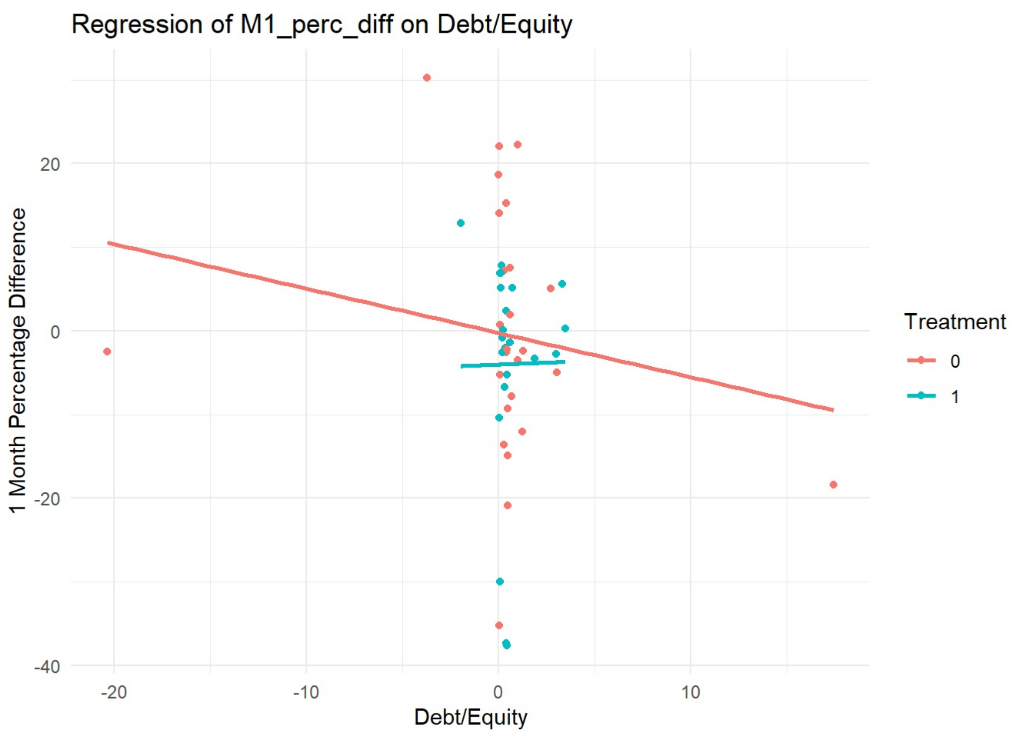

```
ggplot(reg_data, aes(x = ROE, y = M1_perc_diff, color = as.factor(treatment))) +
  geom_point() +
  geom_smooth(method = "lm", aes(group = treatment), se = FALSE) +
  labs(title = "Regression of M1_perc_diff on ROE",
       x = "ROE",
       y = "1 Month Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```
ggplot(reg_data, aes(x = DebtEquity, y = M1_perc_diff, color = as.factor(treatment))) +
  geom_point() +
  geom_smooth(method = "lm", aes(group = treatment), se = FALSE) +
  labs(title = "Regression of M1_perc_diff on Debt/Equity",
       x = "Debt/Equity",
       y = "1 Month Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

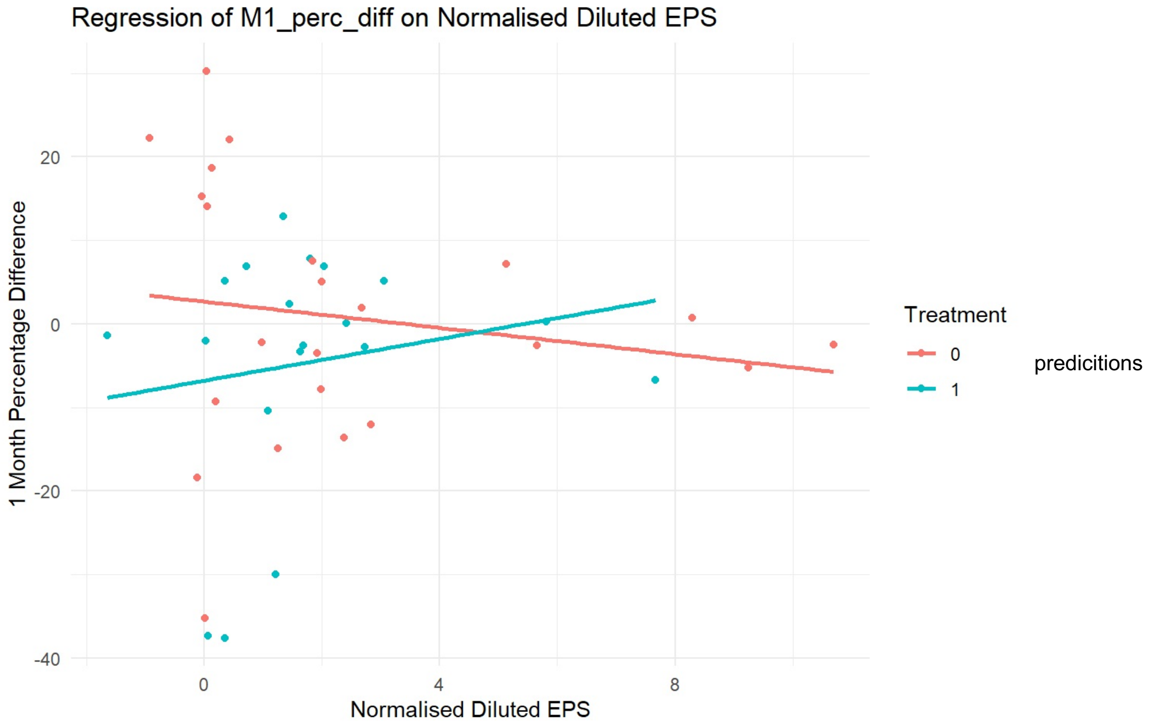



```
ggplot(reg_data, aes(x = Normalised_Diluted_EPS, y = M1_perc_diff, color = as.factor(treatment))) +
  geom_point() +
  geom_smooth(method = "lm", aes(group = treatment), se = FALSE) +
  labs(title = "Regression of M1_perc_diff on Normalised Diluted EPS",
       x = "Normalised Diluted EPS",
       y = "1 Month Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 6 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

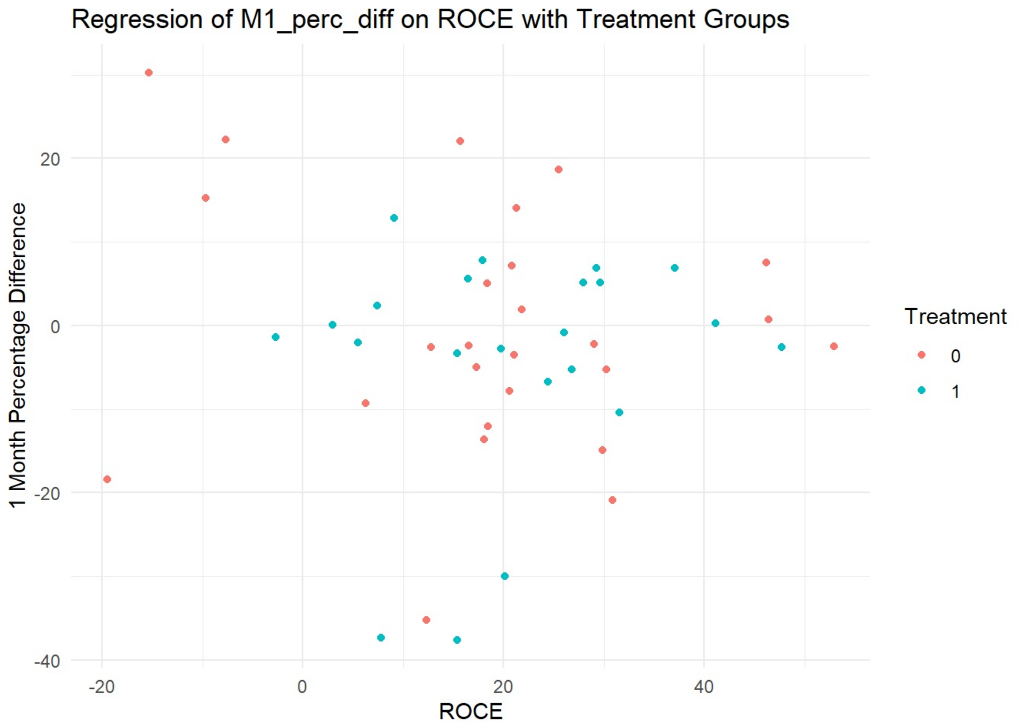
```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (`geom_point()`).
```




```
reg_data$treatment <- as.factor(reg_data$treatment)

# Predict values using the models

# Plot the regression lines
ggplot(reg_data, aes(x = ROCE, y = M1_perc_diff, color = treatment)) +
  geom_point() +
  labs(title = "Regression of M1_perc_diff on ROCE with Treatment Groups",
       x = "ROCE",
       y = "1 Month Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```



```r
plot <- plot_ly(reg_data, x = ~DebtEquity, y = ~Normalised_Diluted_EPS, z = ~M1_perc_diff, color = ~as.factor(tre
atment), colors = c('#1f77b4', '#ff7f0e')) %>%
  add_markers() %>%
  layout(scene = list(xaxis = list(title = 'Debt/Equity'),
                      yaxis = list(title = 'Normalised Diluted EPS'),
                      zaxis = list(title = '1 Month Percentage Difference')),
         title = "3D Scatter Plot of Debt/Equity, Normalised Diluted EPS, and Percentage Difference")

# Display the plot
plot
```

```
## Warning: Ignoring 6 observations
```

) Scatter Plot of Debt/Equity, Normalised Diluted EPS, and Percentage Differen

0
1

WebGL is not supported by your browser - visit https://get.webgl.org for more info

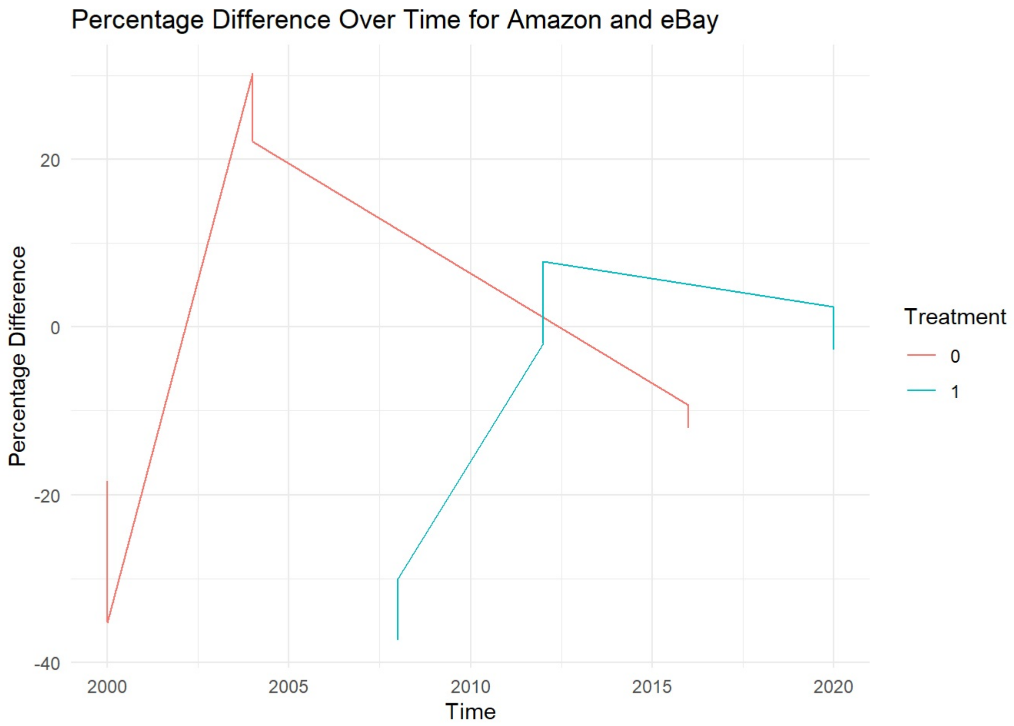
```r
# Select rows where the company is Amazon or eBay
amazon_ebay_data <- reg_data[reg_data$Company %in% c("Amazon", "eBay"), ]

# Display the first few rows of the filtered data
head(amazon_ebay_data)
```

Company <chr>
Amazon
Amazon
Amazon
Amazon
Amazon
Amazon

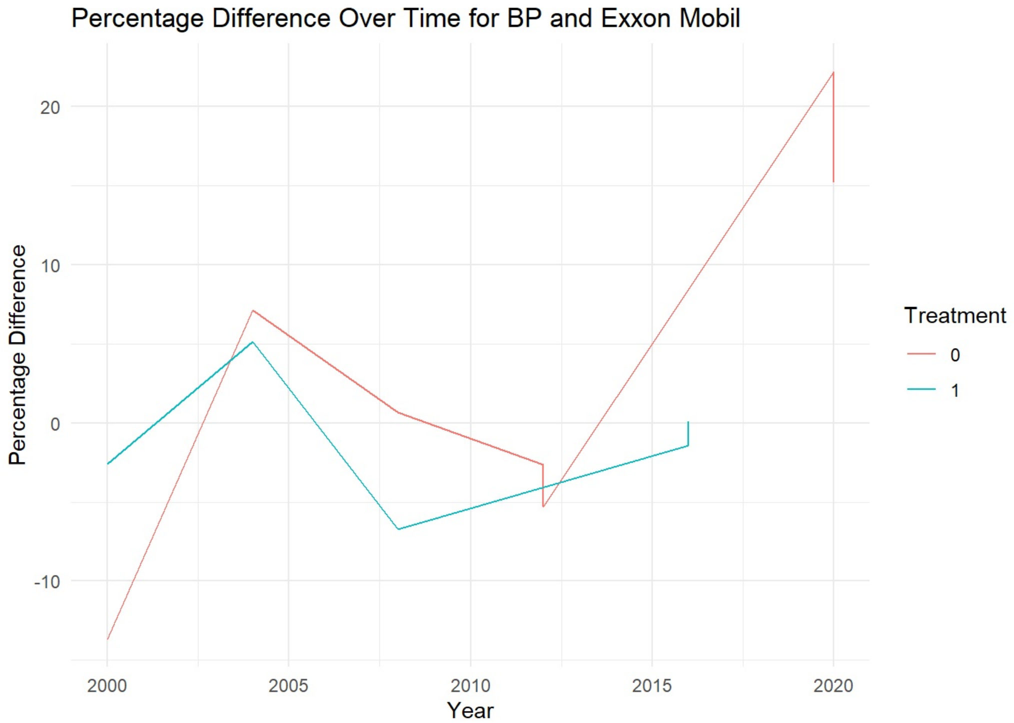
6 rows | 1-1 of 9 columns

```r
ggplot(amazon_ebay_data, aes(x = Year, y = M1_perc_diff, color = factor(treatment))) +
  geom_line() +
  labs(title = "Percentage Difference Over Time for Amazon and eBay",
       x = "Time",
       y = "Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```



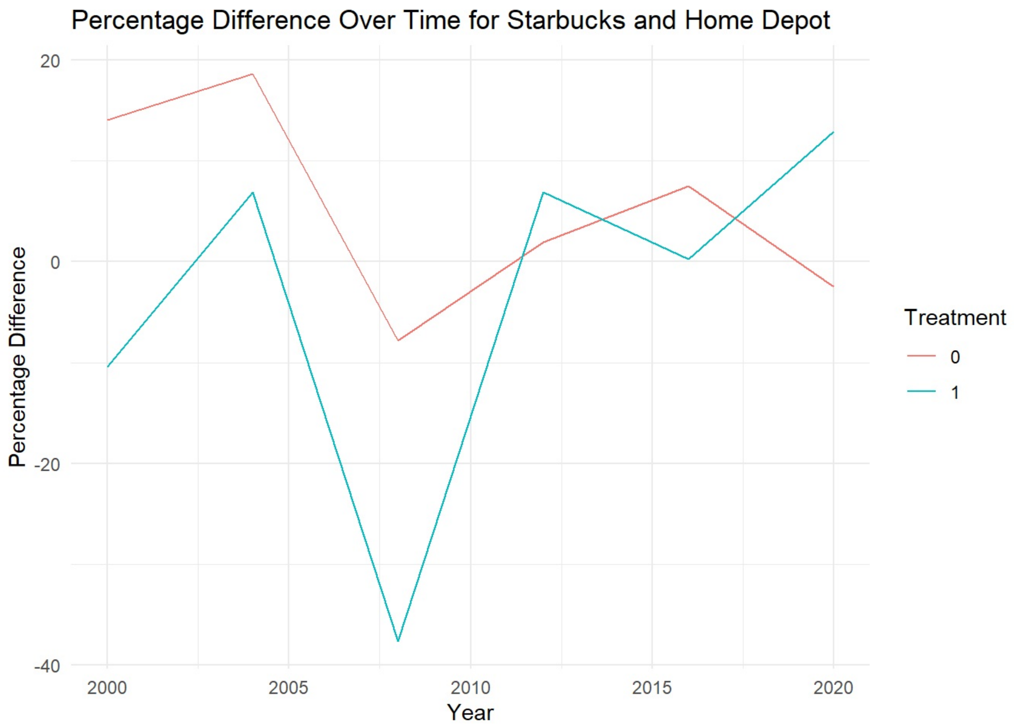

```
# Filter data for BP and Exxon Mobil
bp_exxon_data <- reg_data[reg_data$Company %in% c("BP", "ExxonMobil"), ]

# Plot percentage difference against time with separate lines for treatment groups
ggplot(bp_exxon_data, aes(x = Year, y = M1_perc_diff, color = factor(treatment))) +
  geom_line() +
  labs(title = "Percentage Difference Over Time for BP and Exxon Mobil",
       x = "Year",
       y = "Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```



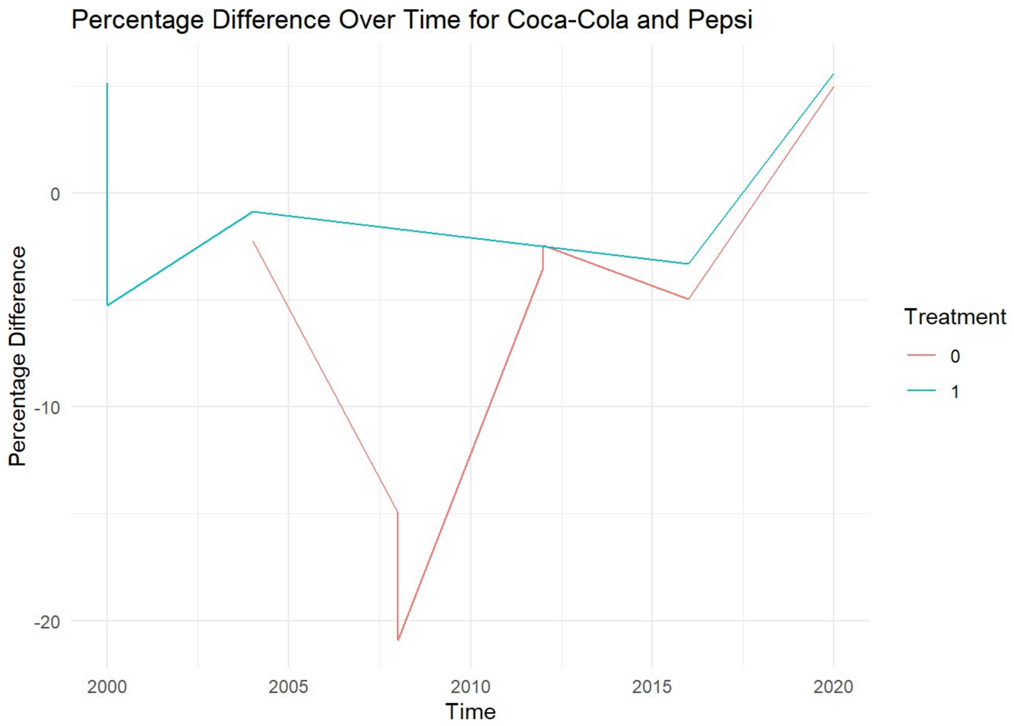
```
# Filter data for Starbucks and Home Depot
starbucks_homedepot_data <- reg_data[reg_data$Company %in% c("Starbucks", "Home Depot"), ]

# Plot percentage difference against time with separate lines for treatment groups
ggplot(starbucks_homedepot_data, aes(x = Year, y = M1_perc_diff, color = factor(treatment))) +
  geom_line() +
  labs(title = "Percentage Difference Over Time for Starbucks and Home Depot",
       x = "Year",
       y = "Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```




```
# Filter data for Coca-Cola and Pepsi
coke_pepsi_data <- reg_data[reg_data$Company %in% c("Coca-Cola", "Pepsi"), ]

# Plot percentage difference against time with separate lines for treatment groups
ggplot(coke_pepsi_data, aes(x = Year, y = M1_perc_diff, color = factor(treatment))) +
  geom_line() +
  labs(title = "Percentage Difference Over Time for Coca-Cola and Pepsi",
       x = "Time",
       y = "Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```



adding momentum 1-d regression

```
View(data4)

momentum <- (data4$int_stock_price_1D-data4$int_stock_price_1M)/data4$int_stock_price_1M

data4$momentum <- momentum
reg_data$momentum <- momentum
```

```
# Combined regression model including treatment as a binary variable
combined_model2 <- lm(D1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity + Normalised_Diluted_EPS+ momentum), da
ta = reg_data)

# Summarize the combined model
summary(combined_model2)
```

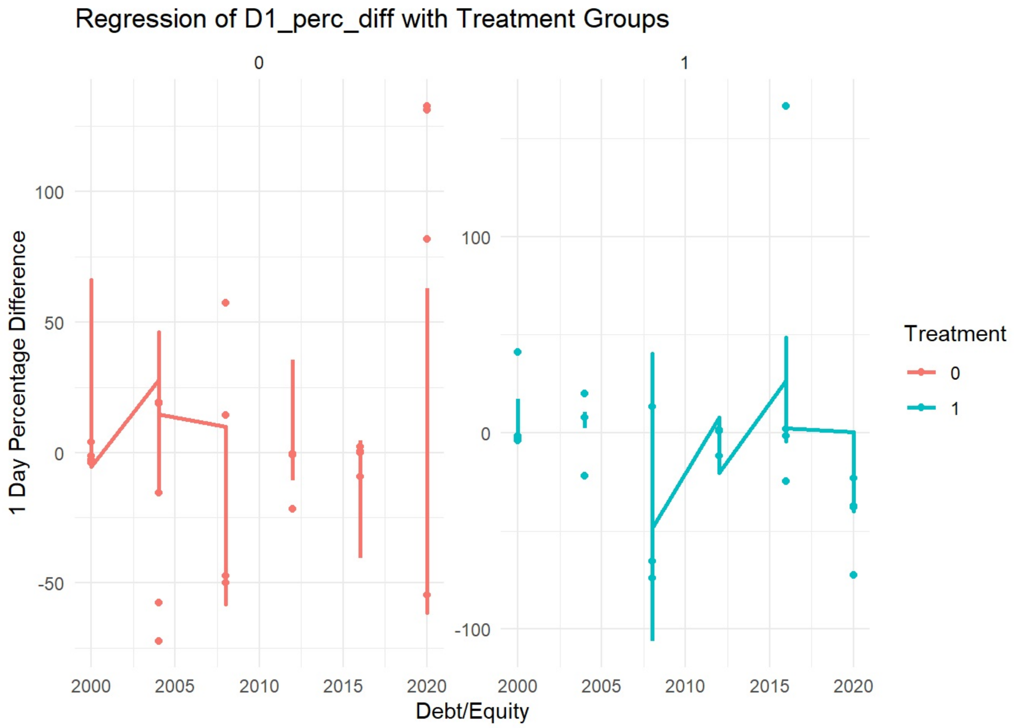
```
##
## Call:
## lm(formula = D1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity +
##     Normalised_Diluted_EPS + momentum), data = reg_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -72.778 -16.232  -3.088   9.386 117.749
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     4.86317   16.19516   0.300  0.76603
## treatment1                      0.63528   25.64076   0.025  0.98040
## ROCE                           -1.30099    0.71247  -1.826  0.07782 .
## ROE                            -0.04106    0.09587  -0.428  0.67148
## DebtEquity                     -0.71589    2.66336  -0.269  0.78993
## Normalised_Diluted_EPS         -2.63725    4.56463  -0.578  0.56774
## momentum                     -133.33269   44.70210  -2.983  0.00563 **
## treatment1:ROCE                 0.61523    1.11790   0.550  0.58616
## treatment1:ROE                 -0.38082    0.36961  -1.030  0.31109
## treatment1:DebtEquity           8.65191   12.32325   0.702  0.48804
## treatment1:Normalised_Diluted_EPS    6.50556    7.60807   0.855  0.39928
## treatment1:momentum            84.71686   47.33570   1.790  0.08360 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 44.66 on 30 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.4883, Adjusted R-squared:  0.3007
## F-statistic: 2.603 on 11 and 30 DF,  p-value: 0.01853
```

```
new_data <- reg_data
new_data$predicted <- predict(combined_model2, newdata = new_data)

# Plot the regression lines
ggplot(new_data, aes(x = Year, y = D1_perc_diff, color = as.factor(treatment))) +
  geom_point() +
  geom_line(aes(y = predicted), size = 1) +
  facet_wrap(~ treatment, scales = "free") +
  labs(title = "Regression of D1_perc_diff with Treatment Groups",
       x = "Debt/Equity",
       y = "1 Day Percentage Difference",
       color = "Treatment") +
  theme_minimal()
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_line()`).
```




```
# Fit the combined regression model
combined_model2 <- lm(D1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity + Normalised_Diluted_EPS) + momentum, d
ata = reg_data)

# Summarize the combined model
summary(combined_model2)
```

```
##
## Call:
## lm(formula = D1_perc_diff ~ treatment * (ROCE + ROE + DebtEquity +
##     Normalised_Diluted_EPS) + momentum, data = reg_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -73.846 -25.977  -7.283  16.271 111.096
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       9.85261   16.51055   0.597  0.55501
## treatment1                       -2.20666   26.48528  -0.083  0.93414
## ROCE                             -1.16026    0.73285  -1.583  0.12352
## ROE                               0.02916    0.09052   0.322  0.74950
## DebtEquity                        0.86384    2.60059   0.332  0.74200
## Normalised_Diluted_EPS            0.74301    4.30067   0.173  0.86396
## momentum                        -57.78031   15.21616  -3.797  0.00064 ***
## treatment1:ROCE                   0.39362    1.14982   0.342  0.73441
## treatment1:ROE                   -0.42017    0.38185  -1.100  0.27964
## treatment1:DebtEquity             6.85906   12.71140   0.540  0.59333
## treatment1:Normalised_Diluted_EPS   2.20390    7.47051   0.295  0.76995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46.22 on 31 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.4337, Adjusted R-squared:  0.251
## F-statistic: 2.374 on 10 and 31 DF,  p-value: 0.03192
```

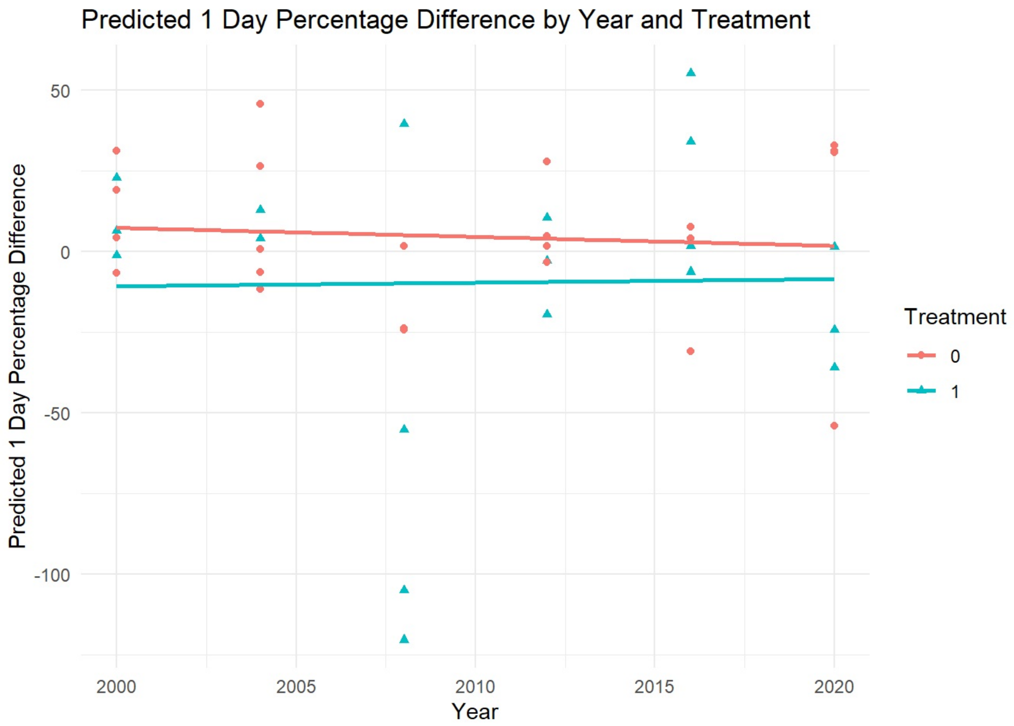
```
# Create a new dataframe for predictions
new_data <- reg_data
new_data$predicted <- predict(combined_model2, newdata = new_data)

# Plot the regression lines
ggplot(new_data, aes(x = Year, y = predicted, color = as.factor(treatment), group = treatment)) +
  geom_point(aes(shape = as.factor(treatment)))  +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Predicted 1 Day Percentage Difference by Year and Treatment",
       x = "Year",
       y = "Predicted 1 Day Percentage Difference",
       color = "Treatment",
       shape = "Treatment") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 6 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (`geom_point()`).
```




```
# Calculate mean percentage difference for treatment = 0
mean_treatment_0 <- mean(reg_data$M1_perc_diff[reg_data$treatment == 0], na.rm = TRUE)
var_treatment_0 <- var(reg_data$M1_perc_diff[reg_data$treatment == 0], na.rm = TRUE)

# Calculate mean percentage difference for treatment = 1
mean_treatment_1 <- mean(reg_data$M1_perc_diff[reg_data$treatment == 1], na.rm = TRUE)
var_treatment_1 <- var(reg_data$M1_perc_diff[reg_data$treatment == 1], na.rm = TRUE)

# Print the results
mean_treatment_0
```

```
## [1] -0.4337596
```

```
mean_treatment_1
```

```
## [1] -3.960501
```

```
var_treatment_0
```

```
## [1] 224.5619
```

```
var_treatment_1
```

```
## [1] 189.7046
```

```
# Calculate mean percentage difference for treatment = 0
mean_treatment_0 <- mean(reg_data$D1_perc_diff[reg_data$treatment == 0], na.rm = TRUE)
var_treatment_0 <- var(reg_data$D1_perc_diff[reg_data$treatment == 0], na.rm = TRUE)

# Calculate mean percentage difference for treatment = 1
mean_treatment_1 <- mean(reg_data$D1_perc_diff[reg_data$treatment == 1], na.rm = TRUE)
var_treatment_1 <- var(reg_data$D1_perc_diff[reg_data$treatment == 1], na.rm = TRUE)

# Print the results
mean_treatment_0
```

```
## [1] 4.720571
```

```
mean_treatment_1
```

```
## [1] -9.007129
```

```
var_treatment_0
```

```
## [1] 2487.109
```

```
var_treatment_1
```

```
## [1] 2539.894
```

```
clear all
import delimited "/Users/apple/Downloads/workdata(8 Companies) (1).csv", clear
//generate var and clean data
generate right_party_dummy = .
replace right_party_dummy = 1 if partywon == partybacked
replace right_party_dummy = 0 if partywon != partybacked
generate dummy_2000 = (year == 2000)
generate dummy_2004 = (year == 2004)
generate dummy_2008 = (year == 2008)
generate dummy_2016 = (year == 2016)
generate dummy_2020 = (year == 2020)
generate GDP_per_capita = 0
replace GDP_per_capita = 5517.1 if year == 2000
replace GDP_per_capita = 6829.8 if year == 2004
replace GDP_per_capita = 9443.2 if year == 2008
replace GDP_per_capita = 10584.4 if year == 2012
replace GDP_per_capita = 10207.5 if year == 2016
replace GDP_per_capita = 10904.1 if year == 2020
drop if company == ""
drop v16 v17
generate oil_dummy = (company == "Amazon" OR "eBay")
generate tech_dummy = (company == "BP" OR "ExxonMobile")
generate beverage_dummy = (company == "Coca-Cola" OR "Pepsi")
generate momentum = (int_stock_price_1d - int_stock_price_1m)/ int_stock_price
> _1m

// simple linear regression, growth rate in stock prices on funding winning pa
> rty
regress d_perc_diff right_party_dummy
// Multiple linear regression, growth rate in stock prices on funding winning
> party, control for roce, roe, debtequity, normaliseddilutedeps, momentum
regress d_perc_diff right_party_dummy roce roe debtequity normaliseddilutedeps
>  momentum
// Multiple linear regression, growth rate in stock prices on funding winning
> party, control for roce, roe, debtequity, normaliseddilutedeps, momentum, GD
> P_per_capita, sp500
regress d_perc_diff right_party_dummy roce roe debtequity normaliseddilutedeps
>  momentum GDP_per_capita sp500
// Multiple linear regression, growth rate in stock prices on funding winning
> party, control for roce, roe, debtequity, normaliseddilutedeps, momentum, GD
> P_per_capita, sp500, oil_dummy, tech_dummy, beverage_dummy
regress d_perc_diff right_party_dummy roce roe debtequity normaliseddilutedeps
>  momentum GDP_per_capita sp500 oil_dummy tech_dummy beverage_dummy

translate "Untitled 7.do" "Stata.pdf", translator(txt2pdf)
```