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MULTI-CLASS STOCK AND FIRM VALUE

Does Multi-Class Stock Enhance Firm Performance? A Regression Analysis

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Abstract

In this report we analyze data on 1,762 U.S.-incorporated Russell 3000 companies and design two regression models to study the relationship between multi-class common equity structures and long-term company performance from 2007 to 2015. We conclude that a multi-class common equity structure with unequal voting rights neither increases nor decreases a company's annualized return on invested capital (ROIC).

We measure multi-class status as the percentage of outstanding votes that holders of superior class shares control, creating a **PercSuperiorVote** variable that ranges from zero for single-class companies to one for fully controlled companies. We measure long-term company performance with average annual ROIC. Our first regression model—a single-stage ordinary least squares (OLS)—finds that **PercSuperiorVote** is a statistically insignificant variable at the 10% level. This remains true when we controlled for certain other variables. We then apply three model selection techniques to aid interpretation: best subset selection, forward selection and backward selection. All three techniques omit **PercSuperiorVote**, further indicating that it is not a strong predictor of ROIC. Our second regression is an instrumental variable regression (IV) designed to overcome the endogeneity problem that arises in regressions of corporate governance.[1] This model also finds that the **PercSuperiorVote** is statistically insignificant at the 10% level, which supports skepticism that multi-class common equity structures are necessary for managers to deliver long-term performance.

[1] In this case, "endogeneity" means that there is a strong chance that ROIC is not just determined by dual-class status, but that a firm's choice to go dual-class is partly determined by ROIC.

Introduction

Consider this scenario: A growing company in a cutting-edge industry files an initial public offering (IPO) that is expected to raise a significant amount of capital. The founders and early investors of the company now face a dilemma: The more common stock they issue, the more they will dilute their voting power. To keep control while accessing public capital, they decide to issue non-voting common stock to public investors and retain voting common stock for themselves.

The company in question is not Snap Inc. in 2017; instead it is Dodge Brothers, which went public in 1925 with owners who controlled 100% of the vote despite owning only 1.7% of the equity. The Dodge IPO, and others like it, caused such an uproar that the New York Stock Exchange (NYSE) launched an investigation into nonvoting stock and warned that it would "give careful thought to the matter of voting control" in the future.[2] That "careful thought" eventually led to a 1940 NYSE rule that barred listed companies from issuing nonvoting classes of common stock and also prevented any superior-voting stock from constituting more than 18.5% of all outstanding votes.[3] While this rule was not a complete ban on multi-class common equity, it did successfully limit the number of such companies in the United States. As of 1985 there were just 10 multi-class firms on the NYSE,[4] most of which were either media companies that sought to protect their journalistic independence from market forces or family-run companies such as Ford Motor, which went public in 1956 with multi-class common shares.[5]

[2] Stephen M. Bainbridge, "The Scope of the SEC's Authority over Shareholder Voting Rights", US Securities and Exchange Commission, May 2007, pp. 6, https://www.sec.gov/comments/4-537/4537-17.pdf.
[3] Robert A.G. Monks and Nell Minnow, *Corporate Governance* (Chichester, UK: John Wiley and Sons, 2015), p. 241, note 74.
[4] Joel Seligman, "Equal Protection in Shareholder Voting Rights: The One Common Share, One Common Vote Controversy", *George Washington Law Review*, Vol. 54, p. 6, available through LexisNexis at https://www.lexisnexis.com/en-us/gateway.page
[5] Bentel, Katie and Walter, Gabriel, "Dual Class Shares", *Comparative Corporate Governance and Financial Regulation*, Paper 2, 2016, p. 18. http://scholarship.law.upenn.edu/fisch_2016/2

Other major exchanges such as NASDAQ and AMEX never adopted such restrictions. The lack of restrictions by these exchanges did not pose a threat to the NYSE until the 1980s, when the NASDAQ did pose real competition, and when a wave of hostile takeover bids led companies to try various protective tactics including recapitalizing with multi-class stock. Companies threatened the NYSE with listing on another exchange if they could not adopt multi-class structures. In 1986, the NYSE relented, allowing companies to go public or recapitalize (if already listed) with multi-class shares.[6]

Seeking to level the playing field among the exchanges it regulates, the SEC responded in 1988 by passing Rule 19C-4, which required that listing standards prevent companies from issuing new common shares with per-share voting rights greater than those of current outstanding shares. The Business Roundtable challenged the rule on the basis that voting rights are a matter of state law, and in 1990 the D.C. Circuit Court of Appeals agreed unanimously and struck down the rule. By 1994, the three major U.S. exchanges had adopted a uniform policy assuring multi-class companies' ability to list and placing no restriction on voting rights assigned to new public offerings. [7]

Since 2004, the tech sector has led a new wave of multi-class equity, with companies like Google, Facebook, Zynga, Box, GoPro and Snap adopting multi-class equity structures. While nearly 90% of the companies in the Russell 3000 only have one class of voting shares, the recent spate of multi-class IPOs is causing consternation among investors and other market participants.[8]

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[6] See Ronald Gilson, "Evaluating Dual Class Common Stock: The Relevance of Substitutes", *Virginia Law Review*, Vol. 73, p. 807, n.1 (1987), accessed through *Jstor*, www.jstor.org; James Sterngold, "Big Board Ends Equal Vote Rule", *New York Times*, July 4, 1986, http://www.nytimes.com/1986/07/04/business/big-board-ends-equal-vote-rule.html?pagewanted=all

[7] Jason Howell, "Essays on the US Dual Class Share Structure", (Ph.D Dissertation, University of Georgia, 2009) p. 7, http://media.terry.uga.edu/documents/finance/howell_dual_class_share.pdf.

[8] CII analysis of FactSet data

Multi-class structures come in many varieties, but some approaches are more prevalent than others. In a typical multi-class arrangement, owners of the class of common stock with superior voting rights—the superior class— receive 10 votes per share, while the owners of the class of common stock with reduced voting rights—the inferior class— receive one vote per share. Superior-class stockowners remain in control of the company without shouldering a proportionate share of financial risk, while inferior-class stockowners get little to no say in how their capital is used. This effect is even more pronounced at companies that issue common stock with no voting rights. Some companies do allow inferior-class stockholders to elect a certain number of directors to the board, but even then, the superior-class owners remain in control. In this paper we refer to all multi-class common equity arrangements—even those with three or more classes—interchangeably as "multi-class" or "dual-class."

Dual-class companies often justify their capital structures by claiming that the public markets are too impatient, and that visionary founders need the protection of superior-class common shares to innovate and create value for the long-term. However, evidence has been mixed as to whether dual-class equity structures create higher, lower or equivalent returns for shareholders compared to single-class companies. Previous studies have returned a variety of conclusions, most of which depend on the measure of firm performance used and the time period studied.[9]

To determine whether dual-class equity affects performance, we collected data from FactSet on 1,762 Russell 3000 companies, and then designed two regression models.[10] Here, we measure multi-class

[9] See: Edward Kamonjoh, "Controlled Companies in the Standard and Poor's 1500", *IRRC Institute and ISS*, March 2016; Renée Adams and Daniel Ferreira, "One Share, One, Vote: The Empirical Evidence", *European Corporate Governance Institute*, 2007; Paul Gompers, Joy Ishii, Andrew Metrick, "Extreme Governance: An Analysis of Dual-Class Firms in the United States", *The Review of Financial Studies*, May 2008, accessed through the *Social Sciences Research Network*, http://ssrn.com/abstract=562511

[10] FactSet is a financial and corporate governance data provider, comparable to Compustat.

equity as the percentage of voting rights controlled by superior-class stock, creating a **PercSuperiorVote** variable that ranges from zero to one. Performance is measured by return on invested capital (ROIC), a metric that shows how efficiently companies use capital to produce returns.[11] The first regression is a single stage least squares that tests the effect of multi-class voting over average ROIC. The second regression is an instrumental variable (IV) regression (also on ROIC) designed to overcome the endogeneity problem that tends to plague tests on corporate governance. This IV regression is a modification of one created by Gompers et al. in their 2008 paper *Extreme Governance: An Analysis of Dual Class Firms in the United States*.[12]

Note that in both regression models we hypothesize that **PercSuperiorVote** has an impact on ROIC without making any hypothesis about the direction of that relationship. In statistical parlance, our hypothesis is H_1: $X \neq 0$, making the null hypothesis—which we hope to disprove—H_0: $X=0$. In both our regressions we found that **PercSuperiorVote** is a statistically insignificant variable, meaning that we fail to reject the null hypothesis and conclude that having multi-class equity neither helps nor hinders company's a ROIC.

We conducted the analysis in RStudio running R.3.3.1. All data, except where otherwise indicated, came from FactSet.

A note about measuring model performance

Every regression must balance predictive accuracy with interpretative ability. Since we hope to isolate the effect that multi-class equity has on ROIC, we are primarily interested in variable

[11] For a discussion on the benefits and drawbacks of ROIC, see David Benoit, "The Hottest Metric in Finance: ROIC", *The Wall Street Journal*, May 3, 2016. https://www.wsj.com/articles/the-hottest-metric-in-finance-roic-1462267809

[12] Gompers, et. al. See *supra* note 8.

interpretation. However, the model must be able to predict a company's ROIC to an acceptable degree of accuracy for us to trust the estimated coefficients of the variables.

We use several different metrics to examine the predictive accuracy of our model. Adjusted R^2 measures the percentage of the variation in ROIC that can be explained by the model. We also use the model F-Stat, a significance test for whether or not the model's predictions produce better estimates than simply using the mean of the data to gauge performance. These two measurements are common, but unfortunately are based off of the training dataset. A better measurement is the test error, which is the difference between ROIC values that our model predicts when fitted on a new dataset and the actual values of that dataset. We get an approximate calculation of the test error from the cross-validated mean squared error (MSE) of each fitted model which is:

$$MSE = \frac{\sum(Y_i - \hat{Y}_i)^2}{n}$$

Where Y_i is the measured ROIC for an observation, $\hat{Y}_i$ the value predicted by the regression, and n the number of observations collected. Cross-validation is a method of dividing a dataset into training and testing sections, which allows us to approximate the test MSE using the training data. To cross-validate, the dataset is broken into 10 sections, or folds. We then fit a regression model using data from 9 of the folds, and use that model to calculate the MSE on the "left out" fold. We repeat this process 10 times, each time holding a different fold out. We finish by averaging MSE's from each fold to approximate the test mean square error for the model. [13]

[13] Cross-validation can use any number of folds, but the standard for econometrics is K=10 folds. We chose to remain with this standard K=10 because doing so gave each fold about 200 observations and 160 degrees of freedom.

Lastly, we use scatter plots to examine data structure and fit. Particularly useful are: (1) residual plots, which plot the fitted values to the residuals; (2) Q-Q plots that line up the quantiles of the residuals with the quantiles of the fitted values; and (3) leverage plots, which show the pull that each data point exerts upon the regression equation.

Building the dataset

We began with a dataset consisting of 2,600 US-incorporated Russell 3000 companies (universe as of July 2016), the maximum number of companies that FactSet had in its SharkRepellent database as of mid-2016. We selected a study period of 2007 to 2015 because it provided an adequate balance of data availability and length of time, as we sought data that was both up-to-date and comprehensive. Our study commenced in the third quarter of 2016, precluding us from collecting data from that year.

The Russell 3000 is an index of the largest 3,000 publicly-traded companies by market cap in the United States. We chose this index because it encompasses a broad market swath ranging from the very largest companies like Apple and Google to small-cap companies with only a regional presence.

A simple pooled regression would produce time dependence between data points, with each year's ROIC being determined not just by the regression equation but also by the previous year's ROIC. While many techniques exist for removing this time dependence (often by clustering observations), those methods were out of the scope of this study. Instead, we took simple averages across all of our data points. While this technique is not perfect, it follows the tradition in finance of looking at average returns to measure performance.

We narrowed the study group from the initial sample of 2,600 companies. To start, 582 of companies in the initial sample went public after Dec. 31, 2006, the cutoff we put in place to ensure that companies were in our dataset for the entire study period. We cut an additional 256 companies from the data set for various reasons: 181 had errors for their ROIC measures, usually because they carried both negative debt and negative net income; 45 companies repeatedly returned errors in FactSet data pulls, leading to measurement error; and 27 companies went through major reorganizations during the study period that made it impossible to compare the company across years.[14] Finally, three companies were removed because they used time-based voting, a system in which shareholders accumulate more voting rights the longer they hold shares.[15] Unfortunately, companies are not required to provide the number of votes each shareholder receives, making it impossible to determine the percentage of superior-class votes or even the total number of outstanding votes.

We ended up with nine years of data on 1,762 U.S.-incorporated Russell 3000 companies. A total of 133 companies out of the 1,762 companies had some multi-class shares issued and outstanding.[16] This represents about 7.5% of the total sample, a number that is generally in line with the proportion of multi-class firms in the broader U.S. market. [17]

The dependent variable: measurement of firm performance through ROIC

Many studies on corporate governance use Tobin's Q as their measure of firm performance. Tobin's Q is the ratio of the market value of assets (tangible and intangible) to the replacement cost of those assets, approximated by the book value of assets. Although a decent measure of performance, Q

[14] For instance, Charter Communications went private between 2009 and 2011.
[15] Two more companies in the dataset used time based voting but weren't cut because they disclosed the number of shares with superior votes in their proxy statements.
[16] A list of the 133 companies with multi-class shares outstanding for at least some of the study period, as well as the average **PercSuperiorVote** over the study period, is available in Appendix C.
[17] According to a March 2016 story in the *Baltimore Sun*, approximately 7% of the S&P 500 and 8.8% of non-S&P 500 companies in the Russell 3000 use multi-class equity, based on data from Institutional Shareholder Services (ISS). Lorraine Mirabella, "T. Rowe Price takes stand against stock structures that create unequal shareholder rights", *The Baltimore Sun*, March 19, 2016. Accessible at: http://www.baltimoresun.com/business/bs-bz-t-rowe-price-oppose-dual-class-stock-20160319-story.html.

contains drawbacks, namely that it depends on the valuation of intangible assets such as human capital, goodwill and institutional knowledge.

To avoid the pitfalls of Q, we decided to use ROIC as our valuation metric. ROIC is, at its most basic level, a firm's net income divided by its total average invested capital:

$$\frac{Net\ Income}{Total\ Average\ Invested\ Capital}$$

Since these measurements are themselves calculations, the precise definition of ROIC is:

$$\frac{[(Sales - (COGS + Depreciation + SG\&A + Interest + Taxes) - Discontinued\ Operations)]}{[(Total\ Shareholder\ Equity + Prefered\ Stock\ Equity) + (Long\ Term\ Debt + Capitalized\ Leases)]}$$

Where COGS is cost of goods sold and SG&A is general, selling, and administrative expenses.

To measure multi-class status, we initially created a dummy variable for whether or not a company was authorized to issue multiple classes of common stock, information that we took directly from FactSet. However, many companies never issue authorized multi-vote shares, making this dummy variable a poor predictor. In response, we hypothesized that the degree to which a company is controlled by superior class votes might be a better variable, with higher degrees of control affecting ROIC more than lower degrees. To calculate that variable, we crafted a **percent superior vote (PercSuperiorVote)** variable, defined as:

$$\frac{(Superior\ Shares\ Outstanding * Votes\ Per\ Superior\ Share)}{[(Superior\ Shares\ Outstanding * Votes\ Per\ Share) + (Inferior\ Shares\ Outstanding * Votes\ Per\ Share)]}$$

This calculation is similar, but not identical, to the one used by Gompers et al., which calculates the difference between the voting rights and economic rights of superior shareholders. **PercSuperiorVote** is also not necessarily a measure of company control. Instead, it is a measurement of the degree to which the vote is controlled by superior-class shareholders.

We employed a couple of techniques to collect the information needed for this variable. First, we used FactSet to download bylaw provisions authorizing multi-class common stock. We then sorted companies based on the number of classes they can issue. We also recorded the votes per share for each class. For companies with more than two classes, we looked up each class's number of shares outstanding using 10-K annual reports.[18]

Second, for companies with only two classes of common stock we used a FactSet workaround that let us download: (1) the average number of outstanding common shares per year; and (2) the number of outstanding common shares eligible for public trading per year. The difference between the total number of outstanding common shares and the trade-eligible common shares gave us the number of superior-class shares for each year, since at many dual-class companies superior-class shares are common shares but cannot be traded without losing their unequal voting rights. However, the workaround didn't always produce correct results, as not every company issues its authorized multi-vote shares and others allow their superior-vote shares to be traded publically. Therefore, we used 10-K reports to look up the number of outstanding shares per class whenever the workaround indicated that no superior-vote shares were outstanding.

[18] Although these numbers are taken from a single point in time, they offer an accurate picture of the company's equity on a yearly basis, and ultimately should not cause measurement error since the final variable is an average across all nine years of the study.

Third, some companies have two one-vote-per-common-share classes, but the “superior” class elects a larger percentage of the board. For these companies, we based **PercSuperiorVote** off of the percentage of the board the superior class is privileged to elect, as disclosed in proxy statements. For the handful of companies with both unequal voting rights and unequal board elections, we reverted to basing **PercSuperiorVote** off of the original calculation based on votes-per-share.

<u>Control variables</u>

We included multiple control variables into the model. Some of these variables are transformations, meaning they have been changed using a logarithmic, quadratic, or square root formula. Others have been combined into interaction terms, meaning they have been multiplied together. Following the advice of Gareth James et al. in *Introduction to Statistical Learning with Applications in R,* when applying quadratic transformations and interactions we always left the original variable in as well, satisfying the hierarchical principle. [19]

Transformations were first reasoned *a priori*, using existing literature on financial performance to seek out relationships and by examining scatter plots to visualize the correlation between suspected non-linear variables and ROIC. We then added transformations to the model one at a time, comparing the new model’s mean squared error with the MSE of the old model. Transformations that improved the model’s predictive accuracy were kept; those that didn’t were not added.

- **Age:** The firm’s age in years as of Dec. 31, 2016.
    - We applied a natural logarithm to **Age**, as recommended by Gompers et al. The reasoning is that new firms will experience rapid growth in the first several years of

[19] Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, *An Introduction to Statistical Learning with Applications in R*, (New York: Springer, 2013), p. 89.

their existence as they gain market prominence. However, after a certain age, an additional year of existence creates diminishing returns.

- **Index:** A series of dummy variables for whether the firm belongs to the S&P 500, S&P 400, or S&P 600 as of July 2016. If all of these variables are zero, then the firm is in the small-cap Russell 2000. We predict that firms in the larger-cap indices will perform better than firms outside of the larger cap indices. In this way, the S&P 500, 400, and 600 dummy variables act as measures for market cap. We do not anticipate endogeneity between these variables and the dependent variable, ROIC.
- **Dividend:** Average dividend yield. We predict that firms with higher dividend yields will exhibit superior ROIC.
  - We applied a square root to this variable, predicting that increasing dividend yields will increase ROIC but are subject to diminishing returns, with unusually large dividend yields causing uncertainly about a firm's capital allocation. We chose to transform with a square root instead of by the natural logarithm because the minimum value for the variable is zero.
- **Share Buybacks to Equity Ratio:** We examined the ratio of share buybacks to shareholder's equity to determine how "aggressive" the firm is at returning money to shareholders instead of investing it in itself. We hypothesize that firms with high buyback ratios will have higher ROIC. We did not transform this variable because, unlike dividends per share, the ratio of share buybacks to shareholders equity ranged from -2.89 to 8, making it impossible to apply a logarithmic or square root transformation without adding to it a large and arbitrary value of at least 2.9 to all data points.
- **Sales Growth:** The percentage change in sales from the year before.
- **Debt:** The ratio of debt to assets, which calculates how leveraged a company is.

    - We transformed this variable from a linear function to a quadratic function, hypothesizing that debt becomes more of a problem in large amounts, i.e. a change from 30 to 31% leveraged is less of a risk than a change from 70 to 71% leveraged.
- **Capital Expenditures:** The ratio of capital expenditures to assets.
    - **Capital Expenditures** was transformed to the square root of capital expenditures, as we predict that capital expenditures will be subject to diminishing returns. Here we used a square root instead of another function, such as the natural logarithm, because the smallest possible value for this variable was zero.
- **R&D to Assets:** The ratio of research and development spending to assets.
    - **R&D to Assets** was transformed using a square root, with a hypothesis that early increases in R&D expenditures lead to increased return on invested capital, but are subject to diminishing returns. We also transformed this with a square root because the minimum value for this variable was zero.
- **Industry Group:** Dummy variables for 23 of the 24 Global Industry Classification Standard (GICS) industry groups, with "Utilities" dropped to avoid the "dummy variable trap." The groups are listed in Appendix A. [20]
- **R&D times Pharmaceuticals**: Multiplied the R&D to assets ratio by the dummy variable for pharmaceuticals. Pharmaceutical companies depend on R&D to create new drugs, with some companies existing for years with no products on the market. Including this variable significantly reduced the influence of high-leverage points in the model, all of which were from pharmaceutical development companies.
- **R&D times Health Equipment Manufacturing:** Multiplied the R&D to assets ratio by the dummy variable for health equipment manufacturing. Similar to pharmaceutical companies,

[20] Source: Global Industry Classification Standard, *MSCI*, effective August 31, 2016. https://www.msci.com/gics

medical device manufacturers spend a significantly higher portion of their assets on R&D than do companies in other industries.

- **R&D times Household Products:** Multiplied the R&D to assets ratio by the dummy variable for household and personal products. Household personal products also depend on new R&D for sales increases, since consumer non-durables are especially prone to market whims.
- **Sales times Pharmaceuticals:** Multiplied the percent change in sales times the dummy variable for pharmaceuticals. Pharmaceutical companies—because of their long pipelines for new drugs—are inherently more risky than other companies, and the measurement of their sales must reflect that unique status.

Data analysis: single stage least squares

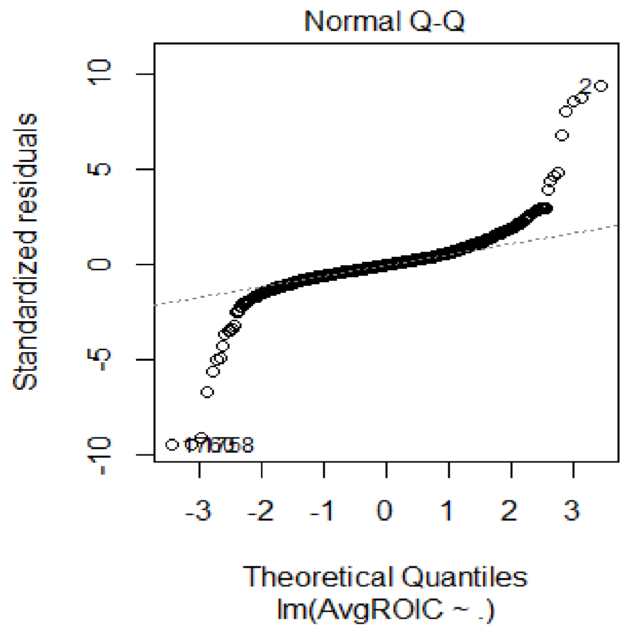
We first fit a simple linear model that included no data transformations. The model fit terribly, with a MSE of 6,337.35. Since ROIC was measured as an actual percentage—i.e. 0 to 100%—this MSE means that, on average, predictions were off by +/- 79 percentage points from the actual value. Similarly, the Adjusted R^2 was only .03001, meaning that the model fitted only explained about 3% of the variation in ROIC. Lastly, the model scored a very low F-Stat of 2.6, a figure made even worse by the fairly large 1727 degrees of freedom.

Studying the residual plots revealed several potential outliers. To test if these observations were outliers, we calculated studentized residuals for all observations. Residuals are the differences between the actual value and the predicted value of ROIC; studenitized means that the residuals were put on the same scale with a mean of zero and a standard deviation of one. Three observations had studentized residuals above or below 3, the cutoff that indicates a potential outlier.

- Westmoreland Coal, which had an average ROIC of -3,210.17%.
- Plug Power, a manufacturer of hydrogen fuel cells with an average ROIC of -419%.
- VeriSign, a web domain registration company with an average ROIC of 327%.

With these observations removed, we refitted the model. Performance improved dramatically, with MSE falling to 154 (i.e.: on average, predictions were off by +/- 12.41 percentage points), adjusted R^2 rising to 44.16, and the model F-stat rising to 41.38. The Q-Q chart for this fit (see Graph 1) reveals that the underlying data is heavy-tailed, meaning it produces outliers more frequently than would normally distributed data.

Graph 1: Q-Q Plot of Model without Extreme Outliers



Since the removed points had been such extreme results, we calculated the studentized residuals for the new fit, finding an additional 22 possible outliers. However, simply because an observation has a studentized residual of +/- 3 does not mean that is an outlier; instead, it could point to an underlying distribution issue (such as shown in the Q-Q plot) that could be resolved by either transforming the data with a function like a root or logarithm, or, alternatively, adding additional explanatory variables. It is possible that the 22 points with high residuals are not in fact outliers but real, useful data. We note that none of these potential outliers were dual-class companies.

To test, we ran the full regression on two sets of data: one with these new possible outliers removed, and another with these observations included. Interestingly, the dataset with the outliers included did not show improvement when the non-linear terms and interactions were added in. In fact, MSE worsened after those variables were added. This lowest MSE this model scored was 142, meaning that on average, predicted values were +/- 11.95 percentage points off of their observed values.

Unsurprisingly, model performance improved when we removed the 22 potential outliers, with MSE falling to 74.78, meaning that the average error was only +/- 8.64 percentage points. This model, unlike the one with the outliers kept in, responded well to inclusion of the log of dividends and the interaction terms between sales and GICs groups. When ROIC was regressed on all explanatory variables, the linear model scored an MSE of 61.34, meaning that the average error was only +/- 7.83 percentage points. Ultimately, we chose to remove these outliers because the dramatic increase in predictive ability gave us greater confidence in the model.

Looking at residuals versus leverage showed that five observations were also high-leverage points, meaning they had unusually high independent variable measurements. Removing these points led to a marginally better MSE of 60.02 in the final model, compared to an MSE of 61.34 with only one point removed (Western Union, which exhibited an unusually large **Share Buybacks to Equity** value). Although removing the remaining four data points led to a somewhat lower MSE and higher adjusted R^2, we decided to keep them in the model. Our reasoning was as follows: removing the potential high-leverage points could improve model prediction slightly but would cost interpretability, since cutting the dataset might also skew standard error measurements on variables. Furthermore, the points' leverage scores shrunk after we added our interaction terms, signifying that their high leverage was caused more by an omitted variable (the interaction between sales and pharmaceuticals) than it was by poor measurement. [21]

Interpreting the Model

The final single-stage model is summarized on the following page. Variables in a regression analysis have two types of significance: economic significance and statistical significance. The economic significance is the coefficient on the variable in the first column, which indicates the magnitude of the effect that *X* has on *Y*. The statistical significance, shown by the p-value, is listed in the last column. For **PercSuperiorVote**, the regression equation estimates that a 1% increase in the superior-class voting power will lead to a 1.06% increase in ROIC. Recall that our hypothesis is that multi-class equity affects firm performance. The null hypothesis—i.e. the counter-hypothesis that we are trying to disprove—is that multi-class voting has no effect on performance. Our fitted coefficient seems to indicate that multi-class shares do improve ROIC. However, the p-value associated with this coefficient is .345, meaning that there is a nearly 35% chance that our result is a false positive. [22] Typically researchers do not accept results unless they are below 10, 5, or even 1% chances of being false. Following that rule, we fail to reject the null hypothesis that higher levels of superior class control affect performance.

[21] Two of the five points examined for leverage were from pharmaceutical companies.
[22] In true statistical parlance, the p-value indicates that there is a 35% chance that we could have gotten a coefficient of a greater or equal value even if the null hypothesis is true.

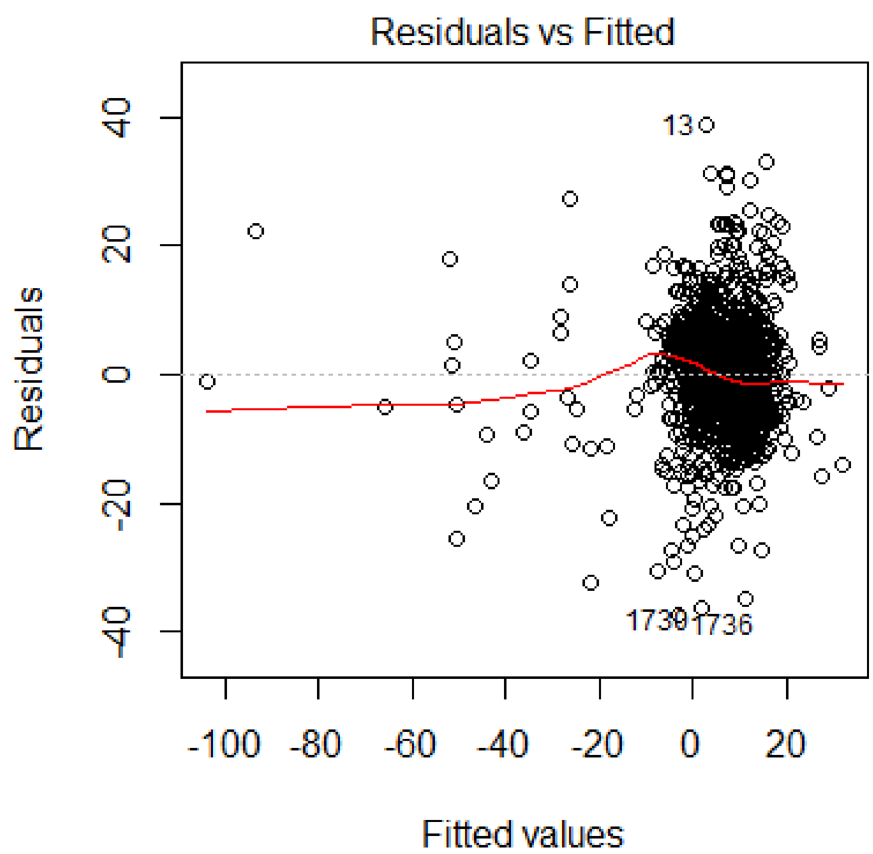
Final Single Stage Regression with Robust Standard Errors

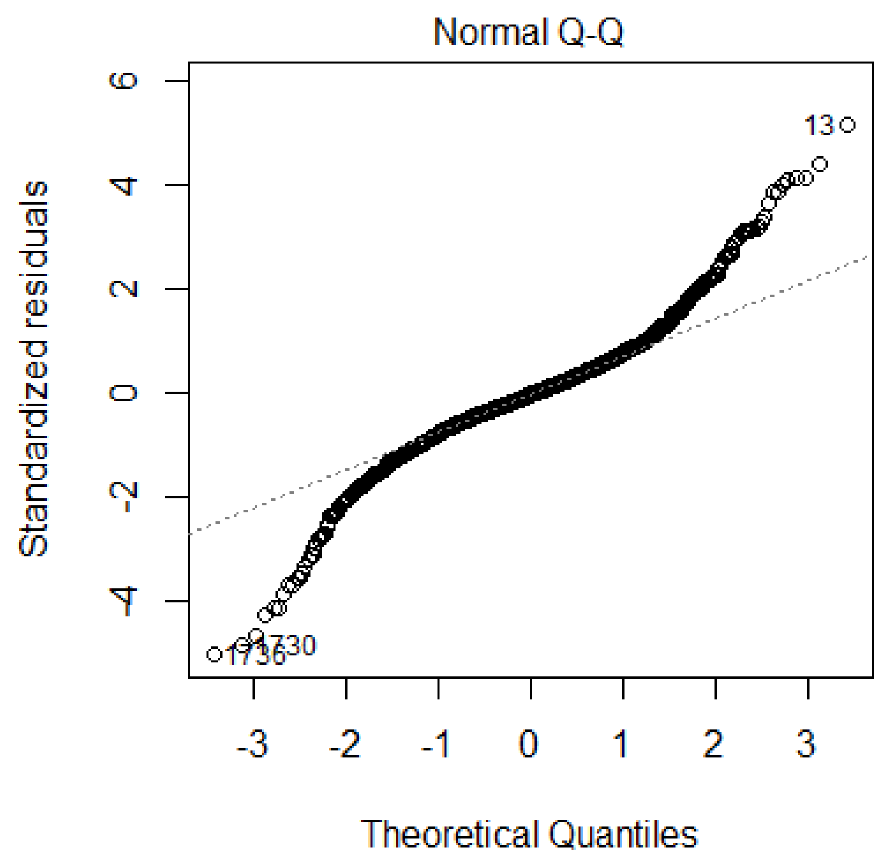
MSE: 61.34

```
Residuals:
    Min      1Q  Median      3Q     Max 
-37.291  -3.738  -0.149   3.544  38.798 

Coefficients:
                                             Estimate  Std. Error  t value  Pr(>|t|)    
(Intercept)                                 -9.162000    2.335394  -3.9231 9.091e-05 ***
PercSuperiorVote                             1.060159    1.123930   0.9433 0.3456820    
SP500                                        7.197953    0.590933  12.1807 < 2.2e-16 ***
SP400                                        5.055374    0.586708   8.6165 < 2.2e-16 ***
SP600                                        2.431115    0.542803   4.4788 8.008e-06 ***
FirmAgeYears                                -0.030269    0.010384  -2.9150 0.0036035 ** 
AvgBuybackShEquityRatio                      3.474476    1.078301   3.2222 0.0012964 ** 
AvgDivYield                                 -0.325372    0.229892  -1.4153 0.1571560    
AvgPercChangeSales                           0.420038    1.303782   0.3222 0.7473645    
AvgDebtToAssets                            -31.235636    2.875912 -10.8611 < 2.2e-16 ***
AvgCapExToAssets                           -64.922390   17.650763  -3.6782 0.0002423 ***
RDtoAssetsAvg                             -114.783846   19.164537  -5.9894 2.567e-09 ***
Energy                                       0.406372    1.078230   0.3769 0.7063039    
Materials                                    2.602112    0.934810   2.7836 0.0054362 ** 
CapitalGoods                                 4.696688    0.923720   5.0845 4.094e-07 ***
CommercialAndProfessionalServices            5.519543    1.212699   4.5515 5.708e-06 ***
Transportation                               5.182682    1.343995   3.8562 0.0001195 ***
AutomobilesAndComponents                     2.681816    1.574152   1.7037 0.0886287 .  
Consumer.DurablesAndApparel                  3.953871    1.227378   3.2214 0.0012999 ** 
ConsumerServices                             5.779114    1.534491   3.7661 0.0001715 ***
Media                                        0.484455    1.869000   0.2592 0.7955083    
Retailing                                    6.515578    1.224483   5.3211 1.169e-07 ***
FoodStaplesRetailing                         3.765005    1.142189   3.2963 0.0009999 ***
FoodBeverageTobacco                          6.551806    1.227416   5.3379 1.068e-07 ***
HouseholdPersonalProducts                    4.705750    2.357018   1.9965 0.0460412 *  
HealthCareEquipmentServices                  6.444043    1.097629   5.8709 5.206e-09 ***
PharmaceuticalsBiotechnologyLife.Sciences   12.441082    2.637578   4.7169 2.592e-06 ***
Banks                                        4.836988    1.168405   4.1398 3.647e-05 ***
DiversifiedFinancial                         7.388813    1.400992   5.2740 1.507e-07 ***
Insurance                                    4.689408    1.433690   3.2709 0.0010938 ** 
Real.Estate                                 -1.259473    0.595424  -2.1153 0.0345541 *  
SoftwareServices                             6.428574    1.435881   4.4771 8.072e-06 ***
TechnologyHardwareEquipment                  3.469179    1.293066   2.6829 0.0073696 ** 
SemiconductorsSemiconductorEquipment         3.597735    1.743607   2.0634 0.0392281 *  
TelecommunicationServices                   -2.002642    1.665215  -1.2026 0.2292868    
RDxPharma                                  -62.474311   19.024764  -3.2838 0.0010449 ** 
RDxHouseholdProducts                       449.901586  219.682099   2.0480 0.0407173 *  
RdxHealthEquip                             -41.371348   26.639059  -1.5530 0.1206022    
LogFirmAgeYears                              1.628390    0.548876   2.9668 0.0030516 ** 
SqrtRDtoAssets                              29.076060    6.448335   4.5091 6.958e-06 ***
SqrtDivYield                                 3.045055    0.668861   4.5526 5.677e-06 ***
DeltaSalesPharma                            -3.157523    1.786275  -1.7677 0.0772982 .  
AvgDebtAssetsSq                             28.495367    3.261169   8.7378 < 2.2e-16 ***
AvgCapExAssetsSq                            46.990039    8.729585   5.3828 8.358e-08 ***
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 7.636 on 1692 degrees of freedom
Multiple R-squared:  0.5477,   Adjusted R-squared:  0.5362 
F-statistic: 47.64 on 43 and 1692 DF,  p-value: < 2.2e-16
```

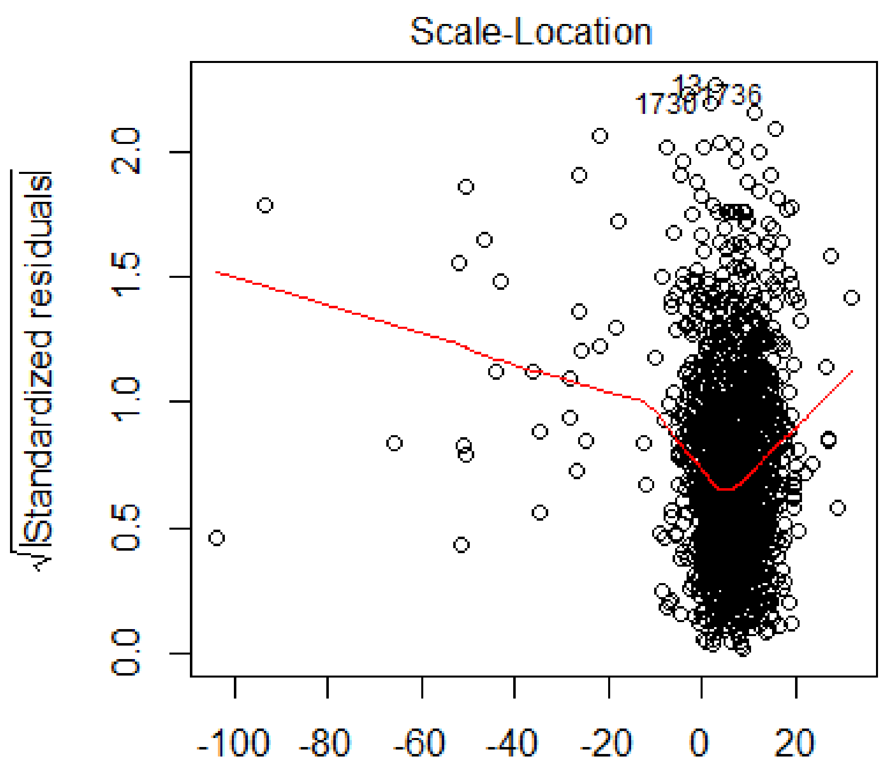
Diagnostic Plots: Final Single Stage Model with no Subset Selection



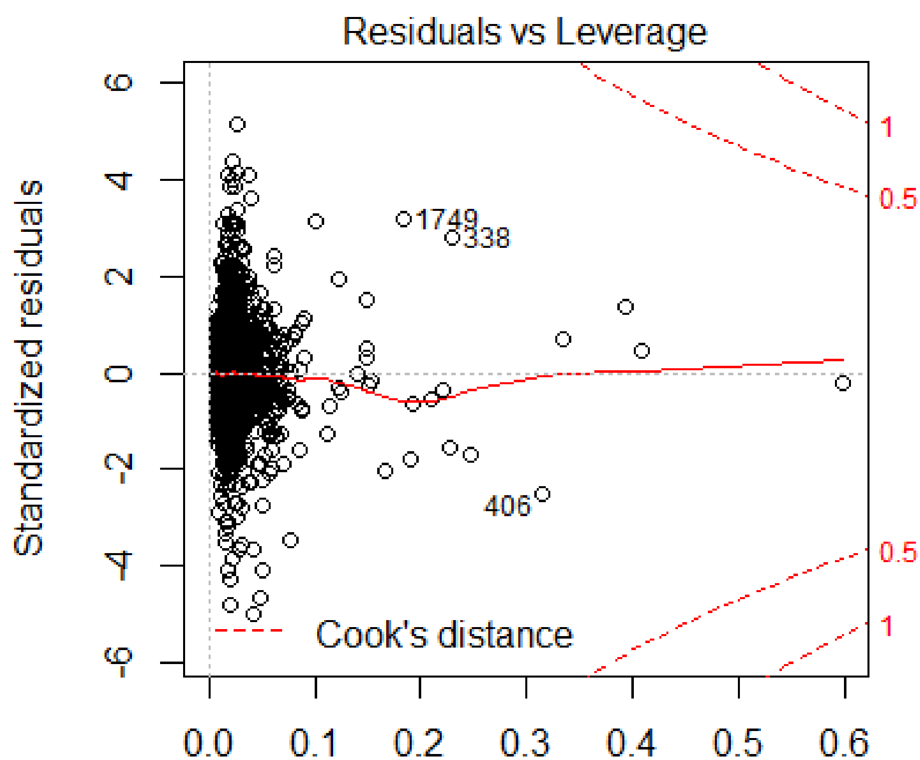


Optimally, the residuals would be spread evenly about the dashed line and not fan in either direction. Here, most of the residuals obey that requirement, although there is a slight fan outward on the left side of the plot. This indicates a small amount of heteroskedasticity, a phenomena where the residuals are correlated with the fitted values. Heteroskedasticity can result in artificially low standard errors on variables, leading us to use robust standard errors in our model.

The Q-Q chart plots the quantiles of the residuals against the quantiles of the fitted values. If the underlying data had a true normal distribution, all off the points would line up perfectly on the line, which represents the function Y=X. The distribution showed by this Q-Q plot is "heavy-tailed," meaning that more of the data lies in the extremes than we would expect under a true normal distribution.



This graph is similar to the first, but here the residuals have been studentized (transformed to have a mean of zero and standard deviation of one). It also shows slight heteroskedasticity in the model.



Leverage is a measurement of the influence that any single observation has on the model. High leverage points are more dangerous than outliers, as they can significantly alter results. The closer that the solid red line is to the horizontal dashed line, the better, since large deviations from the center line indicate high leverage points. Additionally, the curved lines in the right corners of the graph are measurements of Cook's Distance. Points lying outside of those lines (none showed here) would be high-leverage points.

Further single-stage tests: subset selection

None of the original 35 predictors in our model were subject to the testing that the interaction terms and non-linear terms were. Instead, they were included based off of recommendations from other research and *a priori* reasoning. Including insignificant variables doesn't lead to the same bias issue that failing to include a significant variable does (omitted variable bias), but it does hinder model interpretation. To ease interpretation, we applied three different model selection techniques that pick the strongest predictors of ROIC: best subset, forward selection and backward selection. All three methods work by fitting multiple versions of the model, each with a different number of variables up to a cap. The cross-validated MSE is calculated for each specified model, and the model with the lowest MSE is chosen. For our study, we capped the number of variables in our subset selections at 25, removing at least the 18 weakest variables from the model.

Best subset selection

Best subset selection is a factorial method, fitting every possible model up to the cap of variables. It first selects the best model as measured by the residual sum of squares (RSS) with only one predictor, then the best model with two predictors, then the best model with three predictors, and so on until the cap is reached. Since our model has 43 explanatory variables and a cap set at 25, there are a possible 608,359,048,206 potential models that could be fit![23] The resulting output is 25 potential models, each one minimizing RSS given the number of variables it is allowed to use (here ranging from 1 to 25). To determine which of these models is best, we calculate the cross-validated MSE of each and select the model with the lowest. The output is summarized on page 24 and features robust standard errors.

[23] Calculated by formula: C $\binom{n}{r} = \frac{n!}{r!*(n-r)!}$, where *n* is the total number of choices (43) and *r* is the subset.

Best subset selection determined that a 25-variable model returned the lowest MSE. The cross-validated MSE of this model is 60.81, which is actually slightly lower than that of the un-shrunk model. Here, the most economically significant variables (that is, those with the largest effect on ROIC) are highlighted. Every variable in this model is statistically significant at the 5% level, meaning that we have a high level of confidence that our results are accurate and not false positives. Keeping in line with previous results, the interaction of R&D spending and status as a household products manufacturer continues to have the largest economic significance, followed by the ratio of R&D to assets. The debt to assets ratio—as measured by the linear and quadratic functions—also exhibits a strong effect on ROIC. However, **PercSuperiorVote** is not included in the model, meaning that the best subset selection process found that multi-class stock does not exert a strong influence on ROIC. This finding is in line with the results of the un-shrunk model, where we determined that **PercSuperiorVote** was statistically insignificant. Again, we conclude that multi-class stock neither helps nor hinders performance.

Best Subset Selection Results (Robust Standard Errors)

```
MSE: 60.81

Residuals:
    Min      1Q  Median      3Q     Max 
-36.166  -3.814  -0.015   3.579  39.129 

Coefficients:
                                           Estimate  Std. Error  t value  Pr(>|t|)    
(Intercept)                               -3.748600    1.736275  -2.1590 0.0309897 *  
SP500                                      7.276013    0.564493  12.8895 < 2.2e-16 ***
SP400                                      5.027630    0.569401   8.8297 < 2.2e-16 ***
SP600                                      2.510320    0.530387   4.7330 2.394e-06 ***
FirmAgeYears                              -0.033739    0.010440  -3.2316 0.0012543 ** 
AvgBuybackShEquityRatio                    3.634296    1.187313   3.0609 0.0022408 ** 
AvgDebtToAssets                          -33.176022    2.776417 -11.9492 < 2.2e-16 ***
AvgCapExToAssets                         -56.766794   14.048056  -4.0409 5.561e-05 ***
RDtoAssetsAvg                           -122.213749   16.633830  -7.3473 3.118e-13 ***
Energy                                    -3.552225    0.966785  -3.6743 0.0002459 ***
Media                                     -2.987553    1.644760  -1.8164 0.0694830 .  
Retailing                                  2.365384    1.108115   2.1346 0.0329355 *  
FoodBeverageTobacco                        2.667929    1.052247   2.5355 0.0113184 *  
PharmaceuticalsBiotechnologyLife.Sciences  7.854987    2.514798   3.1235 0.0018171 ** 
DiversifiedFinancial                       2.854964    1.087082   2.6263 0.0087098 ** 
Real.Estate                               -4.946008    0.627997  -7.8759 5.966e-15 ***
SoftwareServices                           2.304885    1.115231   2.0667 0.0389094 *  
TelecommunicationServices                 -5.897804    1.647573  -3.5797 0.0003536 ***
RDxPharma                                -55.876493   17.476138  -3.1973 0.0014126 ** 
RDxHouseholdProducts                     501.025656  153.092200   3.2727 0.0010865 ** 
LogFirmAgeYears                            1.847834    0.549004   3.3658 0.0007801 ***
SqrtRDtoAssets                            28.766039    5.495036   5.2349 1.855e-07 ***
SqrtDivYield                               1.914885    0.260622   7.3474 3.116e-13 ***
DeltaSalesPharma                          -2.744181    1.198728  -2.2892 0.0221865 *  
AvgDebtAssetsSq                           30.231574    3.239229   9.3330 < 2.2e-16 ***
AvgCapExAssetsSq                          40.475217    5.967177   6.7830 1.617e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.681 on 1710 degrees of freedom
Multiple R-squared:  0.5375,	Adjusted R-squared:  0.5307 
F-statistic:  79.5 on 25 and 1710 DF,  p-value: < 2.2e-16
```

Forward and backward selection

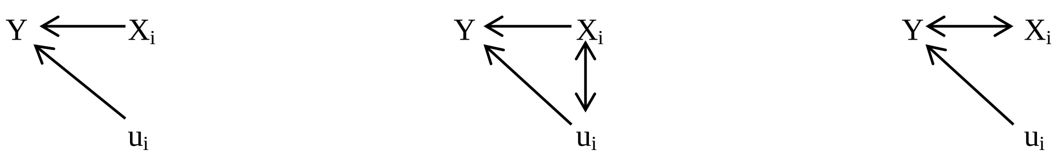
We also ran forward and backward subset selections. Forward selection begins with a model containing no predictors, and adds variables one at a time, each time choosing the variable that minimizes RSS. The best model as measured by cross-validated MSE is then selected. Backward selection works in reverse, beginning with the fully specified model and iteratively removing the least impactful variables as determined by RSS. The best model is again measured using cross-validated MSE. For brevity, the outputs from the forward and backward selections are included in Appendix A. In both selections, the best model was the 25-variable model, and each one scored an MSE of 60.96. Importantly, neither the forward nor backward model included **PercSuperiorVote** as one of the selected variables.

Two-stage least squares: overcoming the endogeneity problem

Classic regression analysis assumes that all variables are exogenous, meaning that: (1) the variables X_i effect ROIC and the errors u_i also effect ROIC, but the errors and the variables are not correlated; and (2) that causality only flows in one direction—i.e. that the variables determine ROIC, but ROIC doesn't in turn determine the variables. An *endogenous variable* is one that violates one of these two assumptions. Graphically, endogeneity can be shown as in Fig. 1:

Figure 1: The Endogeneity Problem

Exogenous (desired) | Endogenous: Feedback | Endogenous: Simultaneous Causality



Endogeneity leads to inconsistent estimates, meaning that as the sample size approaches the actual population, the estimates for our variable **do not converge on the true population mean** as we assume. This inconsistency leads to inflated standard errors that artificially raise the p-values associated with our variables, leading us to erroneously conclude that certain predictors are statistically insignificant. Unfortunately, evidence suggests that regressions with corporate governance variables like multi-class equity suffer from serious endogeneity problems. The main effect that we are concerned with is simultaneous causality, meaning that we hypothesize that ROIC is both a result and determinate of **PercSuperiorVote**.[24]

One of the most popular methods for overcoming endogeneity is instrumental variable regression (IV), also known as a two-stage least squares. This common technique was used by Gompers et al. to overcome endogeneity in their analysis of multi-class equity. We use a two-stage least squares partially because such previous literature did, but also because it is a relatively intuitive method.

Two stage least squares finds a variable Z, called the instrument, that is highly correlated with the endogenous variable X (a condition called instrumental relevance) but not correlated with the error terms (a condition called instrumental exogeneity). The instrument Z can be found using several methods. Here, we determine our instrument by regressing on **PercSuperiorVote**. Once Z is determined to meet the relevance and exogeneity requirements, we begin the two-stage least squares by again regressing X_i, the endogenous variable, on Z_i. The first regression creates a series of predicted values for the endogenous variable X_i that, hypothetically, do not suffer from endogeneity. We then regress Y (here ROIC) on these predicted values of X_i. Essentially, the instrument allows us to isolate the exogenous effect that X has on Y. Graphically, two-stage least squares act like Figure 2:

Figure 2: Instrumental Variable (IV) Regression

$$\begin{tikzcd}
Y_i & Z_i \arrow[l] & X_i \arrow[l] \\
& u_i \arrow[ul] &
\end{tikzcd}$$

[24] This effect is analogous to supply and demand, where supply partially dictates demand and in turn, demand partially dictates supply.

Determining the instrument

We used the final dataset from the single stage model to determine instrument *Z*. The only change we made to the dataset was to scale **PercSuperiorVote** by a factor of 100, making it take values of zero to 100 instead of zero to one. Doing this allowed us to accurately calculate the root of the MSE.

Regressing on **PercSuperiorVote** returned a model with an MSE of 339.25, which translates to an average error of +/- 18.41 percentage points. While this error rate is large, it is satisfactory for our needs since we really only care about the contributions of individual variables, not the model's overall ability. The regression did yield several potential instruments, all of which had fairly large coefficients (i.e. they correlated with **PercSuperiorVote**) and were statistically significant. The best option for an instrument, however, was the dummy variable for status as a media company (**Media**), which had a coefficient of 54.25. This coefficient indicates that, on average, media companies are about 55% more controlled by superior shares than the average of all companies. **Media** had a robust standard error of 7.67, giving it a p-value of 2.215^{-12} and indicating that there is a less than .00001% chance that the large coefficient is a false positive. The model's F-stat was 8.426, which is lower than the value of 10 preferred for IV regression. However, an F-test between **PercSuperiorVote** and **Media** returned an F-stat of 23633 on 1735 and 1735 DF, with a p-value less than 2.2^{-16}, indicating a high degree of correlation. The results of the first-stage regression are presented in Appendix B.

We note that Gompers et al. considered using a media dummy variable as their instrument, as their first-stage regression found Media to be significant at the 5% level with effect on their measure of performance, Tobin's Q.[25] However, they reasoned that **Media** might also suffer endogeneity, as media companies might have more value in intangible assets, an important determinant of Q.[26] We

[25] Gompers, et al, p. 20-21. See *supra* note 8.
[26] Ibid, p. 30.

do not think this concern applies to our study, since ROIC—unlike Q—is not determined in part by intangible assets, but instead by net income and average invested capital, measurements that we do not think will correlate with media companies.

We also note that Gompers et al. applied their instrument to a dataset that only included dual-class companies, arguing that an IV regression on the full dataset would not meet the instrumental exogeniety requirement. However, their dataset was a true pooled regression and therefore was larger than ours, giving them more ability to regress only on dual-class companies. When we tried a similar tactic, summarized in Appendix B, we did get an estimate for **PercSuperiorVote** that was significant at the 10% level. However, we only had 133 observations to regress upon, and the model displayed both weak instruments and poor model fit, both of which are expected results for such a high-dimension model. It also returned an MSE of 2,716.93, meaning that on average, predictions were off by nearly +/-52 percentage points. For these reasons we determined that regressing on the full dataset of single-class and multi-class companies was appropriate, and so we performed the second stage regression, the results of which are presented on the following page.

Instrumental Variable Regression with Robust Standard Errors

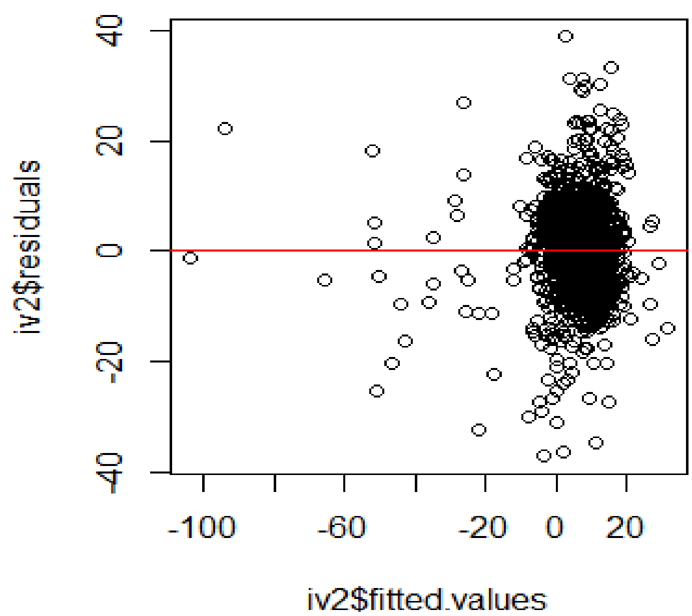
MSE: 61.30

```
Residuals:
     Min       1Q   Median       3Q      Max
-37.1959  -3.7612  -0.1207   3.5556  38.8597

                                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -9.14859    2.19076  -4.176 3.12e-05 ***
PercSuperiorVote                          0.01952    0.02936   0.665 0.506240
SP500                                     7.24616    0.58697  12.345  < 2e-16 ***
SP400                                     5.08193    0.57414   8.851  < 2e-16 ***
SP600                                     2.45312    0.53349   4.598 4.58e-06 ***
FirmAgeYears                             -0.03046    0.01001  -3.044 0.002368 **
AvgBuybackShEquityRatio                   3.48134    0.82781   4.205 2.74e-05 ***
AvgDivYield                              -0.31095    0.22275  -1.396 0.162898
AvgPercChangeSales                        0.45767    1.16259   0.394 0.693875
AvgDebtToAssets                         -31.23934    2.69943 -11.573  < 2e-16 ***
AvgCapExToAssets                        -64.56124   13.88916  -4.648 3.61e-06 ***
RDtoAssetsAvg                          -114.94230   18.12137  -6.343 2.89e-10 ***
Energy                                    0.39046    0.98183   0.398 0.690910
Materials                                 2.60959    0.91380   2.856 0.004346 **
CapitalGoods                              4.67020    0.87832   5.317 1.19e-07 ***
CommercialAndProfessionalServices         5.46924    1.15526   4.734 2.38e-06 ***
Transportation                            5.15104    1.29639   3.973 7.38e-05 ***
AutomobilesAndComponents                  2.68934    1.50012   1.793 0.073192 .
Consumer.DurablesAndApparel               3.87626    1.16045   3.340 0.000855 ***
ConsumerServices                          5.73550    1.47175   3.897 0.000101 ***
Retailing                                 6.47234    1.17775   5.496 4.49e-08 ***
FoodStaplesRetailing                      3.67921    1.06816   3.444 0.000586 ***
FoodBeverageTobacco                       6.39115    1.20612   5.299 1.32e-07 ***
HouseholdPersonalProducts                 4.63174    2.07675   2.230 0.025859 *
HealthCareEquipmentServices               6.42409    1.04084   6.172 8.42e-10 ***
PharmaceuticalsBiotechnologyLife.Sciences 12.41795   2.47587   5.016 5.84e-07 ***
Banks                                     4.83548    1.11122   4.351 1.43e-05 ***
DiversifiedFinancial                      7.23191    1.32226   5.469 5.19e-08 ***
Insurance                                 4.63103    1.33759   3.462 0.000549 ***
Real.Estate                              -1.28071    0.56914  -2.250 0.024560 *
SoftwareServices                          6.39306    1.38184   4.626 4.00e-06 ***
TechnologyHardwareEquipment               3.45235    1.25066   2.760 0.005835 **
SemiconductorsSemiconductorEquipment      3.62002    1.69971   2.130 0.033334 *
TelecommunicationServices                -2.11917    1.56403  -1.355 0.175617
RDxPharma                               -62.23357   17.62086  -3.532 0.000424 ***
RDxHouseholdProducts                    449.23544  194.44663   2.310 0.020990 *
RdxHealthEquip                          -40.96279   23.67668  -1.730 0.083796 .
LogFirmAgeYears                           1.62848    0.52445   3.105 0.001934 **
SqrtRDtoAssets                           29.05877    6.05876   4.796 1.76e-06 ***
SqrtDivYield                              3.00935    0.64560   4.661 3.39e-06 ***
DeltaSalesPharma                         -3.19422    1.52973  -2.088 0.036938 *
AvgDebtAssetsSq                          28.49619    2.92113   9.755  < 2e-16 ***
AvgCapExAssetsSq                         46.78595    7.27728   6.429 1.67e-10 ***

                  df1  df2 statistic  p-value
Weak instruments    1 1693    54.456 2.48e-13 ***
Wu-Hausman          1 1692     0.074    0.786
Sargan              0   NA        NA       NA

Residual standard error: 7.636 on 1693 degrees of freedom
Multiple R-Squared: 0.5474,   Adjusted R-squared: 0.5362
Wald test:  33.4 on 42 and 1693 DF,  p-value: < 2.2e-16
```

The bottom line: controlling for endogeneity through the two-stage process did not lead to a statistically significant prediction for **PercSuperiorVote**, with its p-value rising to .506, indicating a 50% chance of a false positive. Other results remain consistent with previous single-stage models: inclusion into the S&P 500,400, and 600 are good predictors for ROIC, as are various GICS industry sectors and basic corporate financial measures.

The two tests at the bottom of the output are also important. The weak instruments test is essentially an F-test that tests against the null hypothesis that our instruments are weak and should not be used. Since the test statistic is large and the p-value is well below 1%, we can reject the null hypothesis and conclude that our instruments are strong, satisfying the first condition of IV regression that the instruments be strongly correlated with the endogenous variable. The Wu-Hausman test measures consistency in the ordinary least squares (OLS) model, with the null hypothesis being that the OLS model is consistent. Interestingly, we fail to reject the null of the Wu-Hausman test, seeming to indicate that endogeneity is not present in the OLS model.

Graph 2: Residuals of the IV Model



Looking at Graph 2 we see that the residuals of the IV are very similar from those from the single-stage regression, with a slight degree of heteroskedasticity on the left. Our use of robust standard errors in both the single and IV regressions will partially, but not completely, remove the issue of heteroskedastic errors.

Promisingly, the cross-validated test MSE of our IV model is similar to the MSE's of our best single stage regressions, with a value of 61.30. This MSE indicates that our predictions from the instrumental variable regression were off by an average of +/- 7.82 percentage points. While this MSE would still be too high for a model that would value predictive capability over coefficient interpretation, it is within the range of expectation for our purposes, especially given the heavy-tailed data and its proclivity for returning outliers.

Conclusion

Multi-class stock is not a new phenomenon, but recent cases have made it controversial once again. However, previous research has provided mixed evidence on whether multi-class equity affects company performance. Building on this research, we collected data on 1,762 U.S.-incorporated Russell 3000 companies and designed two regression models to study the relationship between multi-class common equity and annualized ROIC from 2007 to 2015. Our first regression model, a single-stage least squares, found that **PercSuperiorVote**—even after controlling for confounding factors—is a statistically insignificant variable. We applied three model-selection techniques, all of which omitted **PercSuperiorVote** from the model. Our second regression, an instrumental variable regression (IV) designed to overcome endogeneity, also found that the **PercSuperiorVote** variable is statistically insignificant at the 10% level. We conclude multi-class equity, measured by the percentage of the company's vote controlled by holders of superior-voting shares, does not affect ROIC, positively or negatively. Our conclusion supports skepticism that multi-class equity structures are necessary for managers to deliver long-term performance.

Appendix One: Single Stage Regression

GICS Industry Groups Used

- Energy
- Materials
- Capital Goods
- Commercial & Professional Services
- Transportation
- Automobiles & Components
- Consumer Durables & Apparel
- Consumer Services
- Media
- Retailing
- Food & Staples Retailing
- Food, Beverage & Tobacco
- Household & Personal Products
- Health Care Equipment & Services
- Pharmaceuticals, Biotechnology & Life Sciences
- Banks
- Diversified Financials
- Insurance
- Software & Services
- Technology Hardware & Equipment
- Semiconductors & Semiconductor Equipment
- Telecommunication Services
- Real Estate
- *Utilities (dropped to avoid the dummy variable trap)*

Forward Selection (Robust Standard Errors)

MSE: 60.96

```
Residuals:
    Min      1Q  Median      3Q     Max 
-36.278  -3.872  -0.095   3.687  39.393 

                                            Estimate Std. Error  t value  Pr(>|t|)    
(Intercept)                                  1.14608    0.68534   1.6723 0.0946536 .  
SP500                                        7.29839    0.55517  13.1461 < 2.2e-16 ***
SP400                                        5.13637    0.57600   8.9173 < 2.2e-16 ***
SP600                                        2.63396    0.53365   4.9357 8.763e-07 ***
AvgBuybackShEquityRatio                      3.59848    1.13956   3.1578 0.0016175 ** 
AvgDebtToAssets                            -33.32424    2.71699 -12.2651 < 2.2e-16 ***
AvgCapExToAssets                           -58.09833   13.61979  -4.2657 2.102e-05 ***
RDtoAssetsAvg                             -125.48899   16.74297  -7.4950 1.058e-13 ***
Energy                                      -3.46940    0.94956  -3.6537 0.0002663 ***
Materials                                   -1.43170    0.79668  -1.7971 0.0724991 .  
ConsumerServices                             1.86060    1.50152   1.2391 0.2154627    
Media                                       -3.13156    1.64178  -1.9074 0.0566341 .  
Retailing                                    2.46532    1.10581   2.2294 0.0259152 *  
FoodBeverageTobacco                          2.55038    1.06826   2.3874 0.0170750 *  
PharmaceuticalsBiotechnologyLife.Sciences    7.54582    2.52481   2.9887 0.0028419 ** 
DiversifiedFinancial                         2.92155    1.10249   2.6499 0.0081246 ** 
Real.Estate                                 -4.83958    0.63288  -7.6469 3.414e-14 ***
SoftwareServices                             2.12942    1.11215   1.9147 0.0556989 .  
TelecommunicationServices                   -6.01105    1.64852  -3.6463 0.0002740 ***
RDxPharma                                  -54.60110   17.59148  -3.1038 0.0019416 ** 
RDxHouseholdProducts                       479.71130  148.76013   3.2247 0.0012847 ** 
SqrtRDtoAssets                              30.53674    5.55351   5.4986 4.406e-08 ***
SqrtDivYield                                 1.95147    0.25742   7.5810 5.591e-14 ***
DeltaSalesPharma                            -2.69333    1.18958  -2.2641 0.0236926 *  
AvgDebtAssetsSq                             30.01024    3.11196   9.6435 < 2.2e-16 ***
AvgCapExAssetsSq                            41.19411    5.79179   7.1125 1.669e-12 ***
```

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

Residual standard error: 7.688 on 1710 degrees of freedom
Multiple R-squared:  0.5366,   Adjusted R-squared:  0.5298 
F-statistic: 79.21 on 25 and 1710 DF,  p-value: < 2.2e-16
```

Backward Selection (Robust Standard Errors)

MSE: 60.96

```
Residuals:
    Min      1Q  Median      3Q     Max 
-36.278  -3.872  -0.095   3.687  39.393 

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)                               1.14608    0.68534  1.6723 0.0946536 .  
SP500                                     7.29839    0.55517 13.1461 < 2.2e-16 ***
SP400                                     5.13637    0.57600  8.9173 < 2.2e-16 ***
SP600                                     2.63396    0.53365  4.9357 8.763e-07 ***
AvgBuybackShEquityRatio                   3.59848    1.13956  3.1578 0.0016175 ** 
AvgDebtToAssets                         -33.32424    2.71699 -12.2651 < 2.2e-16 ***
AvgCapExToAssets                        -58.09833   13.61979 -4.2657 2.102e-05 ***
RDtoAssetsAvg                          -125.48899   16.74297 -7.4950 1.058e-13 ***
Energy                                   -3.46940    0.94956 -3.6537 0.0002663 ***
Materials                                -1.43170    0.79668 -1.7971 0.0724991 .  
ConsumerServices                          1.86060    1.50152  1.2391 0.2154627    
Media                                    -3.13156    1.64178 -1.9074 0.0566341 .  
Retailing                                 2.46532    1.10581  2.2294 0.0259152 *  
FoodBeverageTobacco                       2.55038    1.06826  2.3874 0.0170750 *  
PharmaceuticalsBiotechnologyLife.Sciences 7.54582    2.52481  2.9887 0.0028419 ** 
DiversifiedFinancial                      2.92155    1.10249  2.6499 0.0081246 ** 
Real.Estate                              -4.83958    0.63288 -7.6469 3.414e-14 ***
SoftwareServices                          2.12942    1.11215  1.9147 0.0556989 .  
TelecommunicationServices                -6.01105    1.64852 -3.6463 0.0002740 ***
RDxPharma                               -54.60110   17.59148 -3.1038 0.0019416 ** 
RDxHouseholdProducts                    479.71130  148.76013  3.2247 0.0012847 ** 
SqrtRDtoAssets                           30.53674    5.55351  5.4986 4.406e-08 ***
SqrtDivYield                              1.95147    0.25742  7.5810 5.591e-14 ***
DeltaSalesPharma                         -2.69333    1.18958 -2.2641 0.0236926 *  
AvgDebtAssetsSq                          30.01024    3.11196  9.6435 < 2.2e-16 ***
AvgCapExAssetsSq                         41.19411    5.79179  7.1125 1.669e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.688 on 1710 degrees of freedom
Multiple R-squared:  0.5366,	Adjusted R-squared:  0.5298 
F-statistic: 79.21 on 25 and 1710 DF,  p-value: < 2.2e-16
```

Appendix B: Two-Stage Least Squares

First Stage Regression (Robust Standard Errors)

MSE: 339.2546

Residuals:

Min	1Q	Median	3Q	Max
-58.831	-6.049	-2.865	-0.494	97.461

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.956553	6.281124	-0.1523	0.878976	
SP500	-5.831406	1.588465	-3.6711	0.000249	***
SP400	-3.277037	1.482160	-2.2110	0.027170	*
SP600	-2.610703	1.340303	-1.9478	0.051599	.
FirmAgeYears	0.023497	0.036929	0.6363	0.524690	
AvgBuybackShEquityRatio	-0.976248	0.483693	-2.0183	0.043715	*
AvgDivYield	-1.596175	0.624713	-2.5551	0.010704	*
AvgPercChangeSales	-4.242418	1.794479	-2.3641	0.018184	*
AvgDebtToAssets	2.278322	6.814895	0.3343	0.738183	
AvgCapExToAssets	-36.597081	30.650501	-1.1940	0.232640	
RDtoAssetsAvg	24.601212	36.460062	0.6747	0.499931	
Energy	1.758278	2.424731	0.7251	0.468464	
Materials	-0.992871	2.188948	-0.4536	0.650187	
CapitalGoods	2.688306	2.571348	1.0455	0.295948	
CommercialAndProfessionalServices	5.306932	3.645912	1.4556	0.145693	
Transportation	3.236656	2.927537	1.1056	0.269061	
AutomobilesAndComponents	-1.002936	3.043399	-0.3295	0.741785	
Consumer.DurablesAndApparel	8.460514	3.903914	2.1672	0.030360	*
ConsumerServices	4.542058	3.270850	1.3886	0.165123	
Media	54.256841	7.671257	7.0727	2.215e-12	***
Retailing	4.456002	2.804297	1.5890	0.112249	
FoodStaplesRetailing	9.389282	7.662031	1.2254	0.220584	
FoodBeverageTobacco	17.611508	5.386976	3.2693	0.001100	**
HouseholdPersonalProducts	8.012307	9.435619	0.8492	0.395915	
HealthCareEquipmentServices	1.851065	2.569436	0.7204	0.471368	
PharmaceuticalsBiotechnologyLife.Sciences	1.850311	3.845589	0.4812	0.630471	
Banks	-0.119597	3.076839	-0.0389	0.968999	
DiversifiedFinancial	17.140665	5.254635	3.2620	0.001128	**
Insurance	6.262173	4.465718	1.4023	0.161016	
Real.Estate	2.455281	2.136263	1.1493	0.250581	
SoftwareServices	3.595793	2.878414	1.2492	0.211755	
TechnologyHardwareEquipment	1.679085	3.267880	0.5138	0.607449	
SemiconductorsSemiconductorEquipment	-2.711275	3.066425	-0.8842	0.376724	
TelecommunicationServices	13.177533	6.437525	2.0470	0.040814	*
AvgROIC	0.059640	0.062973	0.9471	0.343737	
RDxPharma	-23.250724	23.290834	-0.9983	0.318287	
RDxHouseholdProducts	47.813144	600.799117	0.0796	0.936579	
RdxHealthEquip	-43.313890	24.902881	-1.7393	0.082162	.
LogFirmAgeYears	-0.107397	1.967139	-0.0546	0.956467	
SqrtRDtoAssets	0.203697	14.139195	0.0144	0.988507	
SqrtDivYield	3.819148	1.762824	2.1665	0.030413	*
DeltaSalesPharma	4.300468	1.826303	2.3547	0.018649	*
AvgDebtAssetsSq	-1.792254	8.594421	-0.2085	0.834835	
AvgCapExAssetsSq	20.066558	19.174453	1.0465	0.295468	

Residual standard error: 18.11 on 1692 degrees of freedom
Multiple R-squared: 0.1764, Adjusted R-squared: 0.1554
F-statistic: 8.426 on 43 and 1692 DF, p-value: < 2.2e-16

Attempted IV Regression on Only Dual Class Companies (Robust Standard Errors)

MSE: 2,716.93

```
Residuals:
    Min      1Q  Median      3Q     Max 
-17.586  -2.561  -0.529   2.366  17.882 

Coefficients:
                                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -4.872e+00  5.961e+00  -0.817 0.415810
PercSuperiorVote                          4.747e+00  2.752e+00   1.725 0.087886 .
SP500                                     8.103e-01  2.067e+00   0.392 0.695955
SP400                                     4.412e-01  2.003e+00   0.220 0.826094
SP600                                    -5.567e-01  1.618e+00  -0.344 0.731483
FirmAgeYears                             -4.892e-04  3.113e-02  -0.016 0.987497
AvgBuybackShEquityRatio                   3.878e+01  7.368e+00   5.263 9.21e-07 ***
AvgDivYield                              -5.323e-01  8.802e-01  -0.605 0.546784
AvgPercChangeSales                        3.078e+01  7.273e+00   4.232 5.48e-05 ***
AvgDebtToAssets                          -3.347e+01  8.285e+00  -4.039 0.000111 ***
AvgCapExToAssets                          6.777e+00  5.634e+01   0.120 0.904518
RDtoAssetsAvg                            -3.510e+01  5.305e+01  -0.662 0.509877
Energy                                   -2.766e+00  6.406e+00  -0.432 0.666924
Materials                                 5.471e+00  4.722e+00   1.159 0.249580
CapitalGoods                              4.388e+00  2.696e+00   1.627 0.107102
CommercialAndProfessionalServices        -1.921e+00  3.074e+00  -0.625 0.533636
Transportation                            3.767e-01  3.754e+00   0.100 0.920281
AutomobilesAndComponents                  6.848e+00  6.810e+00   1.006 0.317284
Consumer.DurablesAndApparel               4.333e-01  2.724e+00   0.159 0.873973
ConsumerServices                          2.668e+00  3.145e+00   0.848 0.398490
Retailing                                 1.498e+00  2.615e+00   0.573 0.568104
FoodStaplesRetailing                      1.678e+00  4.595e+00   0.365 0.715741
FoodBeverageTobacco                       4.707e+00  2.376e+00   1.981 0.050578 .
HouseholdPersonalProducts                 2.731e+00  6.254e+00   0.437 0.663355
HealthCareEquipmentServices               8.833e+00  4.667e+00   1.893 0.061530 .
PharmaceuticalsBiotechnologyLife.Sciences 7.967e+00  9.010e+00   0.884 0.378882
Banks                                     4.961e+00  4.906e+00   1.011 0.314482
DiversifiedFinancial                      2.926e+00  2.503e+00   1.169 0.245395
Insurance                                 3.525e-01  3.525e+00   0.100 0.920559
Real.Estate                               3.812e+00  3.845e+00   0.992 0.323998
SoftwareServices                          1.784e+00  3.360e+00   0.531 0.596723
TechnologyHardwareEquipment              -3.102e+00  3.960e+00  -0.783 0.435535
TelecommunicationServices                -1.574e+00  3.508e+00  -0.449 0.654752
RDxPharma                                -5.187e+01  4.805e+01  -1.080 0.283141
RDxHouseholdProducts                      1.895e+02  4.463e+02   0.425 0.672090
RdxHealthEquip                           -3.331e+02  3.801e+02  -0.876 0.383075
LogFirmAgeYears                           1.402e+00  1.475e+00   0.951 0.344231
SqrtRDtoAssets                            5.663e-01  1.934e+01   0.029 0.976703
SqrtDivYield                              1.238e+00  2.261e+00   0.547 0.585396
AvgDebtAssetsSq                           2.861e+01  9.076e+00   3.152 0.002187 **
AvgCapExAssetsSq                          1.401e+01  2.585e+01   0.542 0.589041

Diagnostic tests:
                 df1 df2 statistic p-value
Weak instruments   1  91         0   0.983
Wu-Hausman         0  92        NA      NA
Sargan             0  NA        NA      NA

Residual standard error: 5.946 on 92 degrees of freedom
Multiple R-Squared: 0.5954,   Adjusted R-squared: 0.4195 
Wald test: 3.385 on 40 and 92 DF,  p-value: 7.426e-07
```

Appendix C: List of Dual-Class Companies in Sample

*Company no longer has multi-class, but did for at least one year in the study period
**Company is no longer publicly-traded

Company	Ticker	2007 to 2015 Avg. PercSuperiorVote
1-800-FLOWERS.COM, Inc.	FLWS	0.92960816
A. O. Smith Corporation	AOS	0.686620533
Aflac Incorporated	AFL	0.499887544
Albany International Corp.	AIN	0.53763671
Alphabet, Inc.	GOOG	0.715633836
American Software, Inc.	AMSWA	0.532597614
Apollo Education Group, Inc.	APOL	1
Arlington Asset Investment Corp.*	AI	0.155162466
Artesian Resources Corporation	ARTNA	1
Astronics Corporation	ATRO	0.723685245
BBX Capital Corporation	BBX	0.47
Bel Fuse Inc.	BELFB	1
Berkshire Hathaway Inc.	BRK.B	0.929075232
BGC Partners, Inc.	BGCP	0.754973045
Bio-Rad Laboratories, Inc.	BIO	0.691827581
Brady Corporation	BRC	1
Brown-Forman Corporation	BF.B	1
Calamos Asset Management, Inc.	CLMS	0.973
Cal-Maine Foods, Inc.	CALM	0.395388471
Casella Waste Systems, Inc.	CWST	0.247043409
CBS Corporation	CBS	1
Central Garden & Pet Company	CENTA	0.526169424
Clear Channel Outdoor Holdings, Inc.	CCO	0.993329711
Coca-Cola Bottling Co. Consolidated	COKE	0.873298788
Comcast Corporation	CMCSA	0.333628831
Constellation Brands, Inc.	STZ	0.568130701
Covenant Transportation Group, Inc.	CVTI	0.274886034
Crawford & Company	CRD.A	1
Dick's Sporting Goods, Inc.	DKS	0.735197968
Discovery Communications, Inc.	DISCK	0.319740546
DISH Network Corporation	DISH	0.917916435
Dolby Laboratories, Inc.	DLB	0.916973518
Donegal Group Inc.	DGICA	0.734170842
DreamWorks Animation SKG, Inc.**	DWA	0.893282236
Eaton Vance Corp.	EV	1
EchoStar Corporation	SATS	0.921013715
Entercom Communications Corp.	ETM	0.704204545
Entravision Communications Corporation	EVC	0.788555655
Erie Indemnity Company	ERIE	1
Expedia, Inc.	EXPE	0.505448196
EZCORP, Inc.	EZPW	1

Company	Ticker	2007 to 2015 Avg. PercSuperiorVote
Federated Investors, Inc.	FII	1
First Citizens BancShares, Inc.	FCNCA	0.714687807
Ford Motor Company	F	0.4
Forest City Realty Trust, Inc.	FCE.A	0.626662418
GAMCO Investors, Inc.	GBL	0.964626327
General Communication, Inc.	GNCMA	0.420522653
Genesee & Wyoming, Inc.	GWR	0.325436784
Graham Holdings Company	GHC	0.7
Gray Television, Inc.	GTN	0.550319699
Greif	GEF	1
Haverty Furniture Companies, Inc.	HVT	0.630754383
HEICO Corporation	HEI.A	0.87056079
Hovnanian Enterprises, Inc.	HOV	0.627553337
Hub Group, Inc.	HUBG	0.264021644
Hubbell Incorporated*	HUBB	0.738155136
IAC/InterActiveCorp.	IAC	0.438243816
IDT Corporation	IDT	0.749150025
Ingles Markets, Incorporated	IMKTA	0.878252225
International Speedway Corporation	ISCA	0.788599599
Invacare Corporation	IVC	0.261803293
John B. Sanfilippo & Son, Inc.	JBSS	0.760300678
John Wiley & Sons, Inc.	JW.A	0.659506968
Johnson Outdoors Inc.	JOUT	0.589648967
Kelly Services, Inc.	KELYA	1
Kimball International, Inc.	KBAL	0.888888889
Lamar Advertising Company	LAMR	0.655175596
Lennar Corporation	LEN	0.667019497
Liberty Interactive Corporation	QVCA	0.360060841
Lithia Motors, Inc.	LAD	0.59882335
ManTech International Corporation	MANT	0.854048258
Marchex, Inc.	MCHX	0.872683164
MarketAxess Holdings Inc.*	MKTX	0.555555556
McCormick & Company, Incorporated	MKC	1
Meredith Corporation	MDP	0.699453937
MicroStrategy Incorporated	MSTR	0.728250623
Molson Coors Brewing Company	TAP	1
Monster Worldwide, Inc.*	MWW	0.063175574
Moog Inc.	MOG.A	0.497700249
Movado Group, Inc.	MOV	0.784744832
MSC Industrial Direct Co., Inc.	MSM	0.771699555
NACCO Industries, Inc.	NC	0.687387085
National Research Corporation	NRCIB	0.209685931
Nelnet, Inc.	NNI	0.760657584
Nexstar Broadcasting Group, Inc.*	NXST	0.669192089

Company	Ticker	2007 to 2015 Avg. PercSuperiorVote
NIKE, Inc.	NKE	0.75
Oil-Dri Corporation of America	ODC	0.800093858
Oppenheimer Holdings Inc.	OPY	1
Panera Bread Company	PNRA	0.13009702
PHI, Inc.	PHIIK	1
QAD Inc.	QADA	0.460081911
Quaker Chemical Corporation	KWR	0.482935717
Ralph Lauren Corporation	RL	0.844254167
Reading International, Inc.	RDI	1
Regal Entertainment Group	RGC	0.643885182
Regeneron Pharmaceuticals, Inc.	REGN	0.198547962
Republic Bancorp, Inc.	RBCAA	0.516919179
Revlon, Inc.*	REV	0.260900435
Rush Enterprises, Inc.	RUSHA	0.887982098
Saga Communications, Inc.	SGA	0.618535625
Scholastic Corporation	SCHL	0.8
Seneca Foods Corporation	SENEA	0.855982157
Sinclair Broadcast Group, Inc.	SBGI	0.83681724
Skechers U.S.A., Inc.	SKX	0.747634949
Sonic Automotive, Inc.	SAH	0.754279362
Spirit AeroSystems Holdings, Inc.*	SPR	0.582323091
Steelcase Inc.	SCS	0.830962868
Stewart Information Services Corporation*	STC	0.44
Telephone and Data Systems, Inc.	TDS	0.407057396
Texas Roadhouse, Inc.*	TXRH	0.145956339
The Boston Beer Company, Inc.	SAM	0.623677167
The Cato Corporation	CATO	0.388156059
The E. W. Scripps Company	SSP	1
The Estee Lauder Companies Inc.	EL	0.867040917
The Hershey Company	HSY	0.770990022
The Marcus Corporation	MCS	0.801516213
The New York Times Company	NYT	0.7
Tootsie Roll Industries, Inc.	TR	0.849880626
Twenty-First Century Fox, Inc.	FOXA	1
Tyson Foods, Inc.	TSN	0.702627241
Under Armour, Inc.	UA	0.730325955
UniFirst Corporation	UNF	0.77011301
United Parcel Service, Inc.	UPS	0.785458687
United States Cellular Corporation	USM	0.862815532
Universal Health Services, Inc.	UHS	0.808900184
Urstadt Biddle Properties Inc.	UBA	0.891010215
Viacom Inc.	VIAB	1
Vicor Corporation	VICR	0.802917713
Village Super Market, Inc.	VLGEA	0.868443144

Company	Ticker	2007 to 2015 Avg. PercSuperiorVote
Vishay Intertechnology, Inc.	VSH	0.470448911
Watsco, Inc.	WSO	0.611358567
Watts Water Technologies, Inc.	WTS	0.700153262
Weyco Group, Inc.*	WEYS	0.08210415