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Glucksman Fellowship Program Student Research Reports:

Shourya Ghosh, "A Study of Differences in Standard & Poor's and Moody's Corporate Credit Ratings"

Kenneth McDermid, "An Analysis of Hedge Fund Equity Returns from Public Filings"

Joe Mellet, "The Impact of Special Dividend Announcements, Insider Ownership, and Tax Increases on US Equity Prices"

William L. Silber, editor

April, 2013

GLUCKSMAN FELLOWSHIP PROGRAM STUDENT RESEARCH REPORTS: 2012-2013

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The Impact of Special Dividend Announcements, Insider Ownership, and Tax Increases on US Equity Prices

WILLIAM L. SILBER, EDITOR

PREFACE

The Glucksman Institute for Research in Securities Markets awards fellowships each year to outstanding second year Stern MBA students to work on independent research projects under a faculty member's supervision. Three research projects completed by the Glucksman Fellows of 2012-2013 are included in this special issue of the Finance Department Working Paper Series. These papers focus on important topics in empirical financial economics.

Shourya Ghosh, under the supervision of Edward Altman, does a statistical comparison of credit ratings from Moody's and Standard & Poor's to see whether there are any consistent biases between the two rating agencies. Kenneth McDermid, under the direction of Jeffrey Wurgler, investigates the performance of hedge funds and confirms that institutions with fewer assets and more concentrated portfolios outperform the others and that the out-performance is the result of selection ability. Joe Mellet, under the supervision of David Yermack, examines the market's reaction to 320 special dividend announcements made in October, November, and December of 2012 in response to the looming tax increases and finds significant Cumulative Abnormal Returns (CARs) in the days surrounding the dividend announcement. These papers, reflecting the research effort of three outstanding Stern MBA students, are summarized in more detail in the Table of Contents on the next page.

William L. Silber, Director
Glucksman Institute

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size, which implies that investors reacted favorably to anticipated tax savings of receiving dividends prior to an expected tax increase. We also conclude that CARs were positively correlated with the percent of shares held by insiders, signaling the possible existence of agency problems associated with free cash flow and dividend payments.

A Study of Differences in Standard & Poor's and Moody's Corporate Credit Ratings

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March 4, 2013

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I. INTRODUCTION

Since the recent credit crisis and the downgrade of United States sovereign credit rating, there has been a lot of focus on understanding the implications and relevance of credit ratings. Credit ratings are letter designations assigned by credit rating agencies which evaluate the credit worthiness of a debtor (a company in the case of corporate credit ratings) based on its ability to pay back debt and the likelihood of default. Standard & Poor's (S&P) and Moody's are the two biggest and most important Nationally Recognized Statistical Rating Organizations (NRSRO) and their ratings are widely used for both regulatory and investment purposes. While both agencies have equivalent rating grades (ranging from AAA to D for Standard & Poor's and Aaa to C for Moody's) and most investors/regulators/analysts treat these ratings as the same, there are indeed subtle differences in what the credit ratings for the two agencies measure. Whereas S&P ratings are the agency's opinion on the likelihood or probability of default by a corporate or sovereign, Moody's ratings are based on *expected losses*, reflecting both on the likelihood of default and expected financial losses in the event of default (Loss Given Default).

"*Long-term ratings are assigned to issuers or obligations with an original maturity of one year or more and reflect both on the likelihood of a default on contractually promised payments and the expected financial loss suffered in the event of default.*"[1] (www.moodys.com)

"*Some agencies incorporate recovery as a rating factor in evaluating the credit Rating issuers and issues quality of an issue, particularly in the case of non-investment-grade debt. Other agencies, such as Standard & Poor's, issue recovery ratings in addition to rating specific debt issues.*"[2] (www.understandingratings.com)

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1. "Rating Symbols and Definitions"
http://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_79004
2. "Guide to Credit Rating Essentials"
http://img.en25.com/Web/StandardandPoors/SP_CreditRatingsGuide.pdf

The NRSROs rate bonds, loans and other shorter term debt issuances, as well as the issuing firm itself. This study will focus on analyzing whether the claimed differences in rating methodologies are actually reflected in the issuer corporate credit ratings for long term senior unsecured debt. A statistical comparison of credit ratings from the two agencies segmented by industry sectors has been analyzed to see whether there are any clear biases or differences between them. In case the different methodologies are being strictly followed, it would be expected that Moody's ratings should be different than S&P ratings for industry sectors with historically high recovery rates (low Loss Given Default) or low recovery rates (high Loss Given Default) in the event of default. On the other hand, no significant differences across industry sectors would indicate that the stated rating methodologies are not being followed. While the initial expectation would be that Moody's ratings should be higher for high recovery sectors and worse for low recovery sectors, other factors such as one agency being more or less conservative in its ratings, or having a higher or lower recovery expectation across all industries could significantly alter the results. In all cases though, clear differences in trends across sectors from the ratings comparison would indicate that the ratings from the two agencies are not equivalent and should actually not be treated equally.

II. DATA SELECTION

Current credit ratings from both Standard & Poor's and Moody's are readily available from various electronic data sources, like Bloomberg, Thomson Reuters and others, for both corporate and sovereign credits. Since features like covenants, security and embedded options in individual bond issuances can affect the credit ratings, only *issuer ratings* have been used to keep the rating comparison at the same seniority level across firms. For Moody's, this is the Senior

Unsecured Debt rating while for S&P, this is the Long Term Foreign Currency Issuer Credit rating. For this study, the dataset has been limited to only large cap US firms, as these are analyzed much more deeply and frequently by the rating agencies. Smaller firms may not have dedicated credit analysts covering the names and differences in ratings might be partially due to stale ratings than actual differences in rating methodologies.

To get a subset of firms to compare, the Russell 3000 index has been chosen. This index covers the largest 3000 US companies representing approximately 98% of the investable US equity market. The main concern here is that the universe of firms which are rated by both S&P and Moody's is much smaller than the universe of firms with publicly traded corporate debt issuances (which is not unexpected as the marginal benefit of getting rated by another agency is not high and the costs of getting rated, even though not substantial, is still significant). Only 728 of the three thousand firms in the index had credit ratings from both rating agencies as of December 15, 2012. The proportion is understandably higher for the S&P 500 index (355) given the higher trading volumes and importance of the names. This study has used historical ratings (as of December 15 for each year from 2006 to 2012) for the same set of firms to enlarge our set of data points considerably and refine our analysis. Clear trends and differences across an entire credit cycle would provide an even more compelling argument for any conclusion reached.

III. METHODOLOGY

Since letter ratings cannot be easily analyzed by statistical methods, numbered ranks from 0 to 20 have been assigned to each rating notch starting with AAA/Aaa assigned as 0. Accordingly, a higher number represents a lower rating and lower credit strength. The difference in ranks, or the rating gap, helps in measuring the number of notches that an issuer's ratings by

the two agencies differ from each other. For this paper, a positive rating gap represents a higher S&P rating (better credit quality) compared to Moody's rating. For example, if an issuer is rated B3 by Moody's (equivalent to B-) and B+ by S&P (equivalent to B1), the rating gap is +2. On the other hand, if an issuer is rated A1 by Moody's (equivalent to A+) and BBB+ by S&P (equivalent to Baa1), the rating gap is -3.

Table 1: Ranking chart for S&P and Moody's ratings

Investment Grade		
Moody's	**S&P**	**Rank**
Aaa	AAA	0
Aa1	AA+	1
Aa2	AA	2
Aa3	AA-	3
A1	A+	4
A2	A	5
A3	A-	6
Baa1	BBB+	7
Baa2	BBB	8
Baa3	BBB-	9

Non-investment Grade		
Moody's	**S&P**	**Rank**
Ba1	BB+	10
Ba2	BB	11
Ba3	BB-	12
B1	B+	13
B2	B	14
B3	B-	15
Caa1	CCC+	16
Caa2	CCC	17
Caa3	CCC-	18
Ca	CC	19
	C	19
C	D	20

Since the rating levels do not necessarily progress linearly, our ranking system is an imperfect measure but it is still useful to indicate the presence of trends. In addition, statistical tests designed for ordinal scale data are used to further confirm these trends. The first test used was an unpaired difference of means test (Welch's test) to test the null hypothesis that the average rating by the two agencies are equal. Rejection of the null hypothesis would indicate that the average ratings from S&P and Moody's do differ significantly from each other. This test does not assume any dependence among the distribution of S&P and Moody's ratings. But since we have ratings from the two agencies for the same set of firms, a paired test would be more relevant and powerful for our dependent dataset. Accordingly, a paired difference test (dependent

t-test) was also used to test the null hypothesis that the average ratings from both agencies do not differ significantly. Both tests assume a cardinal dataset and as such are not perfectly appropriate for use with our ranking system. The issue with ordinal datasets is that we know that AAA is better than AA+ but we don't know by how much it is better. Because of this, a non-parametric statistical test (Wilcoxon signed-rank test) was also used to test whether the median rating from the two agencies differ. Running the tests for the overall sample and for individual industry sectors helped us to find trends in differences in credit ratings. The same tests were then extended to a period running from December 15, 2006 to December 15, 2012 to check whether the observed trends persisted throughout the credit cycle or were a more remote temporary trend.

IV. RESULTS

Table 2: Summary Statistics for Moody's (M) and Standard & Poor's (S) ratings
This table shows the summary comparison of Moody's and S&P ratings by industry as of December 15, 2012

Industry	Average rating gap[1]	Average time gap[2]	Std Dev of rating gap	Average M rating	Average S rating	Std Dev of M rating	Std Dev of S rating	# of firms
Basic Materials	0.37	-0.20	0.66	9.27	8.90	2.75	2.56	51
Communications	0.26	-0.02	1.17	9.82	9.56	3.56	3.25	50
Consumer, Cyclical	0.74	0.53	1.19	10.86	10.12	3.58	3.06	109
Consumer, Non-cyclical	0.66	-0.27	1.18	9.48	8.82	3.71	3.31	138
Energy	0.69	-0.33	0.87	11.59	10.90	3.78	3.23	83
Financial	0.09	0.17	1.14	8.11	8.02	2.69	2.62	94
Industrial	0.63	-0.65	1.05	9.36	8.73	3.31	2.81	117
Technology	0.18	-0.23	1.00	8.46	8.28	3.64	3.06	39
Utilities	0.53	1.44	0.88	8.32	7.79	1.90	2.07	47
All Firms	**0.52**	**-0.03**	**1.09**	**9.61**	**9.10**	**3.50**	**3.09**	**728**

1. A positive number represents a higher/better S&P rating compared to Moody's rating
2. Difference between rating dates in years; e.g. +1.5 means Moody's assigned their current rating one and a half years before S&P assigned their current rating

Looking at the sample, it was clear that both overall and industry-wise S&P had a higher average rating than Moody's. For the overall sample, the average S&P rating was more than half a notch higher (better credit quality) than the average Moody's rating. One possible explanation would have been that one the rating agency has a lag in assigning ratings causing a trend towards higher ratings in case credit quality for all corporates was on average decreasing over the sample period. To make sure that this trend was not due to a mismatch of rating assignment dates, the rating dates were also compared between the two agencies. While for some sectors, Moody's had assigned ratings earlier on average than S&P, for other sectors the trend was the opposite. For most sectors, the timing gap was less than half a year. The only exceptions were Industrial (where S&P had assigned ratings 0.65 years earlier on average than Moody's) and Utilities (where Moody's had assigned rankings 1.44 years earlier on average than S&P). In both of these sectors the large timing gap is more due to outliers with almost a decade in timing gap. For the entire sample, the average timing gap was close to zero and would not have been a major factor in the observed trend.

The results of the three tests to see whether the differences were actually statistically significant are shown in Table 3. The p values indicate the probability of obtaining the observed test statistic assuming the null hypothesis is true. E.g. a Z score of 1.65 and p value of 5% is significant at the 0.05 level. Similarly, we can reject the null hypothesis with 99% confidence level for a p value of 1%.

Table 3: Tests scores and significance values for the statistical tests

This table shows the results of statistical tests for significant differences between Moody's and S&P ratings

	Unpaired difference of means test / Welch's test			Paired difference test / Dependent t-test			Wilcoxon signed-rank test for medians		
Industry	**t score**	**d.f.[1]**	**p value[2]**	**t score**	**d.f.**	**p value**	**W[3]**	**z score**	**p value**
Basic Materials	0.71	99	24.01%	4.02	50	0.01%	210	3.19	0.07%
Communications	0.38	97	35.18%	1.57	49	6.20%	125	1.50	6.74%
Consumer, Cyclical	1.65	211	5.04%	6.52	108	0.00%	1,825	5.45	0.00%
Consumer, Non-cyclical	1.56	270	6.03%	6.56	137	0.00%	2,925	5.51	0.00%
Energy	1.26	160	10.52%	7.20	82	0.00%	1,239	5.33	0.00%
Financial	0.22	186	41.32%	0.72	93	23.59%	178	0.69	24.60%
Industrial	1.58	226	5.81%	6.53	116	0.00%	1,938	5.67	0.00%
Technology	0.24	74	40.72%	1.12	38	13.39%	61	0.98	16.30%
Utilities	1.30	91	9.91%	4.14	46	0.01%	296	3.36	0.04%
All Firms	**3.00**	**1,432**	**0.14%**	**12.86**	**727**	**0.00%**	**73,436**	**13.53**	**0.00%**

For the overall sample, the average rating was lower for Moody's as compared to S&P at a significance level of 0.01 (for both the dependent t-test and the signed-rank test) showing that Moody' had more conservative ratings than S&P. Most of the industries also had statistically significant differences between Moody's and S&P. The only exceptions were the Communications, Financial and Technology sectors (where the difference was not statistically significant). These three sectors are traditionally lower recovery industries[4]. Due to the nature of these industries, they traditionally have a lower proportion of physical hard assets which can be sold to recover losses after default. Most of the value in these industries lie in soft and intangible assets which result in a lower recovery rate. Again the trend was observed in both the dependent t-test and the Wilcoxon signed-rank test.

1. Degrees of freedom
2. Probability of obtaining the observed test statistic assuming the null hypothesis is true
3. Test statistic equal to the absolute value of the sum of the signed ranks
4. References [3], [4], [5] & [6]

Table 4: Summary of historical data

This table shows the number of firms with ratings available from both agencies for the different years

	Average rating gap	Number of firms with data available						
Industry	**Dec-12**	**Dec-12**	**Dec-11**	**Dec-10**	**Dec-09**	**Dec-08**	**Dec-07**	**Dec-06**
Basic Materials	0.37	51	49	46	42	41	40	37
Communications	0.26	50	48	42	39	36	34	34
Consumer, Cyclical	0.74	109	101	96	89	83	83	79
Consumer, Non-cyclical	0.66	138	128	116	100	92	87	85
Energy	0.69	83	72	61	55	47	43	38
Financial	0.09	94	90	86	81	79	77	71
Industrial	0.63	117	111	104	94	91	89	83
Technology	0.18	39	32	26	20	19	17	15
Utilities	0.53	47	47	47	44	42	41	40
All Firms	**0.52**	**728**	**678**	**624**	**564**	**530**	**511**	**482**

Table 4 shows that there were 728 firms in our initial dataset. For this initial dataset, the historical ratings were taken for December 15 of 2006 to 2012 and the same tests were run for the different years. The number of firms, as time becomes more remote, was less due to some firms not having ratings earlier (by one or both the agencies). The results of the tests are shown in Table 5 and Table 6.

The trends observed as of December 2012 were also present in the historical ratings from 2006 to 2012. The overall sample had consistently significant differences and high test statistics showing in the last six years Moody's had consistently more conservative rankings. The higher recovery sectors continued to show statistically significant lower Moody's ratings. The only exception was the Energy sector for which December 2006 ratings were not significantly different. Communications, Financial and Technology sectors had non-significant differences in the ratings, except for 2006 and 2007 for Communications and 2007 for Financials sector when

they were significantly different. Apart from these instances, the trends were persistent throughout the years.

Table 5: Historical dependent t-test results

This table shows the t-test scores and p values for the different years

	Paired difference test / Dependent t-test scores						
Industry	**Dec-12**	**Dec-11**	**Dec-10**	**Dec-09**	**Dec-08**	**Dec-07**	**Dec-06**
Basic Materials	4.02	4.11	2.58	2.37	3.98	2.83	2.71
Communications	1.57	0.80	1.32	1.48	0.81	2.03	2.72
Consumer, Cyclical	6.52	6.59	7.26	6.34	4.96	5.82	4.18
Consumer, Non-cyclical	6.56	7.20	6.90	7.01	5.92	5.47	5.59
Energy	7.20	8.26	6.68	5.78	4.64	3.69	1.03
Financial	0.72	-0.42	-0.24	-0.47	-0.48	-2.03	-0.54
Industrial	6.53	6.42	5.46	5.81	5.43	5.63	5.80
Technology	1.12	-0.72	-1.27	0.00	0.25	-1.14	-0.62
Utilities	4.14	3.99	3.70	3.79	2.30	3.24	2.31
All Firms	**12.86**	**11.88**	**11.02**	**10.65**	**9.57**	**8.99**	**8.62**

	Paired difference test / Dependent t-test p-values						
Industry	**Dec-12**	**Dec-11**	**Dec-10**	**Dec-09**	**Dec-08**	**Dec-07**	**Dec-06**
Basic Materials	0.01%	0.01%	0.66%	1.12%	0.01%	0.37%	0.52%
Communications	6.20%	21.42%	9.63%	7.37%	21.10%	2.53%	0.52%
Consumer, Cyclical	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Consumer, Non-cyclical	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Energy	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	15.49%
Financial	23.59%	33.70%	40.37%	32.12%	31.53%	2.29%	29.49%
Industrial	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Technology	13.39%	23.73%	10.75%	50.00%	40.20%	13.47%	27.28%
Utilities	0.01%	0.01%	0.03%	0.02%	1.34%	0.12%	1.30%
All Firms	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**

Table 6: Historical Wilcoxon signed-rank test results

This table shows the z scores and p values for the different years

	Wilcoxon signed-rank test for medians z score						
Industry	**Dec-12**	**Dec-11**	**Dec-10**	**Dec-09**	**Dec-08**	**Dec-07**	**Dec-06**
Basic Materials	3.19	3.32	2.38	2.13	3.17	2.49	2.37
Communications	1.50	0.79	1.16	1.23	0.79	1.76	2.31
Consumer, Cyclical	5.45	5.36	5.73	5.15	4.21	4.73	3.67
Consumer, Non-cyclical	5.51	5.94	5.58	5.58	4.97	4.60	4.75
Energy	5.33	5.69	4.95	4.50	3.71	3.09	1.02
Financial	0.69	-0.53	-0.42	-0.73	-0.47	-1.90	-0.49
Industrial	5.67	5.34	4.65	4.89	4.59	4.72	4.81
Technology	0.98	-0.59	-1.12	-0.02	0.21	-1.06	-0.63
Utilities	3.36	3.30	3.07	3.09	2.23	2.73	1.98
All Firms	**11.26**	**10.39**	**9.83**	**9.55**	**8.52**	**7.95**	**7.62**

	Wilcoxon signed-rank test for medians p value						
Industry	**Dec-12**	**Dec-11**	**Dec-10**	**Dec-09**	**Dec-08**	**Dec-07**	**Dec-06**
Basic Materials	0.07%	0.04%	0.87%	1.66%	0.08%	0.63%	0.89%
Communications	6.74%	21.57%	12.36%	10.92%	21.37%	3.91%	1.04%
Consumer, Cyclical	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%
Consumer, Non-cyclical	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Energy	0.00%	0.00%	0.00%	0.00%	0.01%	0.10%	15.48%
Financial	24.60%	29.87%	33.80%	23.16%	31.78%	2.90%	31.18%
Industrial	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Technology	16.30%	27.66%	13.04%	49.11%	41.79%	14.54%	26.31%
Utilities	0.04%	0.05%	0.11%	0.10%	1.28%	0.32%	2.39%
All Firms	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**

The same trends were also observed in the historical signed rank tests. Apart from the four instances, both the overall sample and individual industries continued to show the same trends. Lower recovery sectors did not have a statistically significant difference in median ratings

while other sectors had a significant difference in median ratings with Moody's ratings being lower.

V. CONCLUSION

This paper analyzed the ratings from Moody's and S&P to study biases and trends between the two rating agencies. The results were both encouraging and surprising at the same time. The most important result was that Moody's ratings have been consistently lower than S&P ratings. The difference were not only statistically significant but were also present continuously throughout the last credit cycle. As suspected, there are clear biases in the ratings for different industry sectors which are apparent in the difference in average ratings. But what was contrary to expectation was that high recovery sectors, like industrials and utilities, show a lower Moody's ratings while low recovery sectors, like financials and technology, show almost converging ratings. Again factors like one agency being overall more lenient or conservative or having different rating policies for different industries may be the reason for this.

Overall, it appears that Moody's has a consistent bias towards a lower rating as compared to S&P. This trend is particularly distinct for a few industry sectors like Consumers and Industrials. While the gap appears to be small (within one notch), the observed differences could be very meaningful, particularly for the lower ranges of investment grade securities. A move into non-investment grade can have a very large impact on bond yields because of the ratings constraints for a large set of investors. Since the financial crisis of 2008-2009, a lot of firms have lower investment grade ratings, which makes the results even more important. It is therefore imperative for investors, regulators and analysts to note that the two ratings are not equivalent and should not be treated as the same.

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An Analysis of Hedge Fund Equity Returns from Public Filings[1]

Kenneth McDermid

The Leonard N. Stern School of Business

Glucksman Institute for Research in Securities Markets

Faculty Advisor: Jeffrey Wurgler

April 1, 2013

ABSTRACT

This study focuses on assessing the performance of portfolios constructed from publicly available filings of institutions managing hedge funds and several factors that affect that performance. Previous studies of mutual and hedge funds suggest that institutions with fewer assets and more concentrated portfolios will outperform and that the outperformance will be the result of selection ability with no contribution from timing ability. Previous work also suggests that portfolios consisting of the largest position and newly initiated positions will outperform. The paper confirms that institutions managing hedge funds with fewer assets and more concentrated portfolios (at the industry, sector and individual position level) outperform and that the outperformance is the result of selection ability alone. The paper finds no evidence that the largest position of a portfolio outperforms the aggregate portfolio, but does find evidence that newly initiated positions outperform terminated positions.

[1] The author would like to thank Novus Partners, Inc. for providing the data to allow this study to be done and Jeffrey Wurgler for helpful comments and guidance.

I. INTRODUCTION

Hedge funds have emerged as a vehicle for qualified investors to invest money in asset classes (futures, distressed, derivatives) and strategies (long/short, market neutral) that are not available through traditional retail investing. For this access, hedge funds charge a premium, historically 2% of assets under management and 20% of profits over a high water mark. Competition has increased and fees have come down, such that a recent average for fees was 1.6% and 18.7%[2]. Hedge fund management companies are required by law to file their holdings publicly with the SEC, if they manage over $100 million in certain securities (Brown and Schwarz 2011). Investors in some funds have limited information of the holdings of their current or potential investments, as the managers limit their disclosure of positions. The SEC filings are one limited way for investors to gain insight on a hedge fund.

The filings are done at a management company level, which means that a company with several funds (which could have different strategies) will file them together, further obscuring the information investors receive from the public filings.

The purpose of the paper is to determine, from the publicly available data, if there is any evidence that the funds provided selection ability in US listed equities and if that ability is affected by the composition of the portfolios (size, concentration, changes). The paper will attempt to quantify the affects of the portfolio's size, concentration and changes.

The paper finds any outperformance in the portfolios is due to selection ability and not due to timing ability, with no evidence that there is persistence in the outperformance. More concentrated portfolios (measured at the sector, industry and position level) and portfolios from

[2] New York Times Website, http://dealbook.nytimes.com/2012/12/28/imagining-a-future-of-lower-hedge-fund-fees/

institutions managing fewer funds have higher performance than less concentrated portfolios and portfolios from institutions managing more funds. Portfolios constructed from newly initiated positions and from increased positions outperform those constructed from terminated positions and decreased positions respectively. There is no evidence that the largest position in a portfolio performs differently from the aggregate portfolio, regardless of the portfolio's concentration.

Section II reviews the previous literature for hedge funds and position level data for mutual funds along with the hypotheses of this paper. Section III describes the data and methodology used for the analysis. Section IV elaborates on the results. Section V summarizes the report and reports the conclusions of this paper.

II. LITERATURE REVIEW & HYPOTHESES

More work has been done at the individual holding level with mutual funds than with hedge funds, as the data is richer for mutual funds. The literature suggests that mutual fund managers exhibit the ability to select stocks that outperform the general market by 100bps per year when controlled for size, value and momentum (DGTW 1997). This outperformance does not justify the fees charged by mutual funds. There is no indication that the managers are able to time the switch from large capitalization to small capitalization, value to growth or past winners to past losers.

The evidence is against mutual fund performance persistence; alpha persistence has been explained by the momentum effect (Carhart 1997). The selection ability of any mutual funds was shown not to be persistent when fund flows and momentum were accounted for (Wermers 2004).

It was found that investors would have been better off purchasing the stocks in the outperforming funds portfolios that by purchasing the funds themselves.

There is evidence that the top ideas of managers (as measured by the value of the position in the portfolio) do sizably outperform on a risk-adjusted basis, up to 188bps per month (Cohen, Polk, Silli 2008). The same paper also showed that positions, which the manager increased and positions that were largely distinct from the rest of the mutual fund holdings universe also outperformed. In another paper, evidence was provided that suggested that portfolios with above concentration at the industry level outperformed the average concentrated portfolios by 158bps per year (Kacperczyk, Sialm, and Zheng 2005) and in turn that less concentrated portfolios underperformed the mean.

For hedge funds the first paper to look at individual holding data did not find any significant increased selection ability in comparison to mutual funds, when equal weighted, but did find some outperformance in the value-weighted returns, despite the higher fee structures. Hedge funds did have higher turnover and their holdings deviated more from the market portfolio. In contrast to the Cohen study above for mutual funds, there was no evidence that the top position of hedge funds outperformed(Griffin, Xu 2009).

Hedge funds can file with the SEC for the ability to delay their disclosure of certain positions when "necessary or appropriate in the public interest for the protection of investors". These confidential holdings of hedge funds, which are filed publicly later in amendments to the original 13-F, outperform significantly. This could be cited as one reason hedge funds do not release holdings information, even to investors. These positions are not insignificant; they are on

average 1/3 of total portfolio value and outperform by 500bps per year value-weighted. (Agarwal, Weijiang, Tang, Yang 2010)

H1: Portfolios with less total assets will outperform portfolios with greater total assets. (Teo 2007)

Hedge funds have difficultly incorporating more capital without altering their investment process. The hedge funds should have a greater advantage in investments that are obscure and have a limited ability to absorb funds. Once a hedge fund accumulates a greater amount of funds, it must reduce the concentration of its investments or it must reduce the liquidity of its positions; both options appear to reduce the expected performance.

H2: The highest weighted position in a portfolio will outperform the portfolio as a whole.

From the mutual fund data (Cohen, Polk, Silli 2008), the best ideas of the managers outperformed by a large margin the rest of the holdings. It seems logical that managers would place the highest weighting on the positions for which they have the most conviction.

H3: Newly initiated positions and increased positions will outperform terminated positions and decreased positions.

The mutual fund data (Cohen, Polk, Silli 2008), showed that new positions outperformed the portfolio as a whole. If managers do possess skill, it seems likely that their newest positions, for which it would be expected they have the most up to date thesis, would outperform other positions.

H4: More concentrated funds will outperform less concentrated funds.

Kacperczyk, Sialm, and Zheng (2005) paper showed that mutual funds more concentrated at the industry level outperformed less concentrated funds. This appears intuitive and would be expected with hedge fund managers as well. Managers likely possess industry and sector specific expertise; the more they concentrate on their strengths the more it would be expected that they would excel. There is a second reason to expect concentration to correlate with alpha. The funds in the sample pursue many different strategies. Those pursuing quantitative strategies will likely hold portfolios that look much more like the market portfolio than a typical long-short fund. The quantitative funds are deriving their returns from much shorter time frames than would be captured in the quarterly filings.

III. DATA & METHODOLOGY

The hedge fund holdings used for this paper were obtained from the Novus Public Holdings Database, which is maintained by Novus Partners, Inc. The firm collected the data as a part of their business operations. The holdings include any amendments to the original 13-F filings and were filtered for US listed long equity positions. Novus' determination of which management companies represented hedge funds was used to filter which companies were included in the sample. The filings are done at the management company level; individual hedge funds file together if they share the same management company. The filings are available quarterly and returns were calculated as of the beginning of the quarter and not when the filings were available; the funds have up to 45 days to file.

Returns for individual institutions were value-weighted. Monthly returns were evaluated with a CAPM regression, a Carhart 4-factor regression (Excess Return on the Market (MKTRF),

Small Minus Big (SMB), High Minus Low (HML) and Momentum(UMD)) and DGTW characteristic benchmarks. The DGTW benchmarks[3] takes the universe of stocks and divides them into market capitalization quintiles, then book to market quintiles (adjusted for industry) and finally momentum quintiles. There are 125 buckets of stocks for which the average return is calculated. Individual stocks are compared against the returns of the bucket that matches the given stocks size, value and momentum quintile.

The returns were disaggregated in to a Characteristic Timing (CT), Characteristic Selectivity (CS) and Average Style (AS) according to the methodology in (DGTW 97). CS represents the weighted difference between the individual holdings and the corresponding characteristic benchmark. CT represents the difference between the characteristic benchmark returns from the last month and the characteristic benchmark returns from a year prior. AS represents the weighted characteristic benchmark return from a year prior.

The max weight (MaxWeight or MAXWT) of a portfolio was defined as the highest value position divided by the whole portfolio's value. The industry (IndustryHerfindahl or HIND), sector (SectorHerfindahl or HSEC) and normal Herfindahl (Herfindahl or HERF) indexes were calculated by summing the squares of industry, sector and individual position weights in the portfolio respectively. The MSCI/S&P Global Industry Classification Standard (GICS)[4] definitions were used for industry and sector. Management companies with less than 8 holdings or a total portfolio value of less than $25 million were eliminated. An institution had to meet the criteria for the previous four quarters to be included in the sample.

[3] The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

[4] http://www.msci.com/products/indices/sector/gics/gics_structure.html

The median number of holdings was steady in the vicinity of 50 holdings, while the average was a little over 100 holdings. If the number of holdings is weighted by portfolio value, the average jumps to close to 300 holdings. This supports the hypothesis above that the more capital invested in a fund, the less concentrated are the holdings of the fund.

The hedge fund holdings were weighted towards higher capitalization quintiles, higher momentum quintiles and very little value tilt. If weighted by portfolio value, the holdings quintiles, the momentum and value averages do not change, but the market capitalization increases. This makes sense intuitively, larger funds must increase the size of the companies in which they invest to accommodate all their investable capital.

The number of institutions increased steadily throughout the sample period, which began in 2000 and continued through 2011. There was a small decrease, as would be expected during the great recession, but the pre-recession high was surpassed.

The total value of the holdings, in the sample, followed a similar path, but the pre-recession high was not surpassed. Again, this follows from the markets drop and recovery. At the end of the sample, the major US market indices were still below their all-time highs.

There exists the possibility that there is a survivorship bias in the Novus data. The company began collecting the data in 2007. As can be seen in Figure 3, there are funds that exit the sample prior to 2007, which reduces the probability of a large survivorship bias. Note that the large number of funds at the far right of the graph corresponds to the last date of the sample, and not to institutions who were dropped from the sample because they ceased reporting.

As would be expected, for funds that ceased to report, there is an overweight percentage that were in the bottom quintile (quintile 1) in raw return and in CS for the previous twelve

months. Novus does not stop collecting a management company's filings unless the company stops reporting.

The variables used to measure the concentration fall in to two groups. MaxWeight and Herfindahl are highly correlated, while SectorHerfindahl and IndustryHerfindahl correlate highly. Value has a negative correlation with all the concentration variables. This is further evidence that hedge funds that have large amounts of capital to invest must lower their concentration to accommodate the extra capital.

The first evidence that portfolios with fewer funds to invest perform better than those with more funds to invest is in Table 5. The mean monthly return is well below the median monthly return for the portfolios.

The funds in the sample managed to provide positive CS returns in nine out of twelve years, while they had negative CT returns also in nine out of twelve years. This corresponds with the results further in the paper, that the hedge funds have positive selection abilities but there is no evidence that they can time the market.

IV. RESULTS

When a four factor Carhart regression was run on the equal weight returns, the hedge funds had significant alpha of 26bps per month. However, when the returns of the portfolios are value weighted, the alpha disappears and becomes insignificant. This is a clear indication that the smaller portfolios by value outperformed the larger portfolios. It should also be noted that the HML coefficient changes from positive to negative when we switch from equal weighting to

value weighting. This suggests that smaller weighted portfolios have a value tilt, while the higher weighted portfolios have the opposite.

The four-factor Carhart regression on the equal weight CS returns reduces the alpha estimate by 5bps a month. However, as we would expect there is no significant weighting on any of the size, value or momentum factors. The characteristic benchmarks account for these factors very well and we are left with a very small market beta.

When the four-factor Carhart regression is run on the CT returns, the estimated alpha is negative, but is insignificant. This provides evidence that the managers of the portfolios have the ability to select individual securities but no ability to systematically alter the size, value or momentum characteristics of their portfolios to positive effect.

When a fifth explanatory variable is added to the four factor Carhart regressions, there is further evidence that the size and concentration of the portfolio have significant effects on selection ability.

As predicted earlier, and shown in Table 8, the total value of a portfolio has a significant negative correlation with the ability of the manager to select securities that perform better than a matched benchmark.

Also, the overall concentration of the portfolio (HERF) is less significant than the concentration of the portfolio in sectors or industries (HSEC & HIND). This suggests that a manager’s commitment to utilize industry specific knowledge is more valuable than a manager's commitment to run a smaller concentrated portfolio that is spread out over more industries.

To further verify the difference in stock selection performance between managers with high value portfolios and those with low value portfolios, the portfolios were separated into value deciles and quintiles. At statistically significant levels, the portfolios from institutions with less total dollar value outperformed. When controlled for the characteristic benchmarks and the four factor regression, the lower valued quintile outperformed the highest quintile by 23 bps a month. The correlation was greater than 0.72 for the deciles and was significant at the 0.05 level.

As shown in Table 9, there is weak evidence that the concentration of the portfolio irrespective of industry or sector has a positive effect on CS. Only the Spearman coefficient on the deciles is consistently positive, with more concentrated portfolios having the higher CS. However, the top decile does not perform significantly better than the bottom decile in the CAPM or Carhart regressions. Essentially, the same results hold for MaxWeight in unshown results.

Surprisingly, given the significance of the HIND variable as an addition to the four-factor regression on CS, there is again weak evidence that more industry concentrated portfolios had higher CS. The same conclusions come from the unshown results for the HSEC regressions.

If the MaxWeight position is compared to the whole portfolio, no significant improved CS performance is shown. The same result holds for the top quintile MaxWeight positions.

Increased positions performed significantly better than positions that were decreased over the quarter, but remained in the portfolio. The quarterly returns were applied to the previous filings positions and compared to the reported position sizes in the newest filing. This gave an expected position if the manager had not changed the position. Positions that were greater than this simulated position value were deemed increased positions and positions less than the

simulated position value were deemed decreased positions. The results were even better for new positions when compared against terminated positions. This provides evidence, that at the margin, the managers do provide value in their changes to the portfolio from one quarter to another.

The performance of the increased positions portfolios correlated positively with the concentration of the portfolio. Using either the concentration by industry or the maximum weight in the portfolio as a measure of concentration increases the four -factor adjusted CS measure to between 49 and 57bps a month. The Spearman coefficient is statistically significant for all the different measures of performance for both concentration methods. The increased positions portfolios in the top MaxWeight quintile and decile outperform the bottom quintile and decile by a significant amount. The more concentrated portfolios seem to be loading on larger, low book to market, and low momentum stocks, as the 4-factor adjusted CS is consistently higher than the unadjusted CS measure.

There is not enough evidence to support that new positions outperformed the terminated positions as concentration increases. The Spearman coefficients are positive but insignificant.

There is no evidence that previous returns predict future excess returns. Portfolios sorted on the previous twelve months of raw performance or CS performance and rebalanced quarterly were constructed. The Spearman coefficient is negative for some measures of performance and insignificant for others. The top quintile shows no evidence of outperforming the bottom quintile. The same results hold if the past three years of performance are used to sort the portfolios.

Table 17 reinforces the lack of persistence. Although, the best performers did have a higher propensity to be the best performers in the next year, they also had a higher propensity to be among the worst performers as well. The same logic applies, to a lesser extent, to the worst performers; they have an increased probability of underperforming but also an increased probability of being among the best performers.

The dynamic is illustrated by Table 18. The best and worst performers have a higher probability of being the most concentrated portfolios. The concentration of the portfolio leads to a higher variance in CS performance. More concentrated portfolios increase the odds of being among the best performers and the odds of being among the worst performers.

V. CONCLUSIONS

Here is a summary of the results.

H1: There is a negative correlation between the value of a portfolio and the selection ability demonstrated by that portfolio. This result seems intuitive; an increase in the total amount of funds that need to be invested reduces a managers opportunity set for meaningful investments.

H2: There is no indication that the top position of the portfolio performs better than the rest of the portfolio. This result held even when only the most concentrated positions were considered. One explanation possible for the difference in this result between hedge fund managers and mutual fund managers is that hedge fund managers are already invested farther away from the market portfolio than their mutual fund peers, such that they have no significant restrictions on the weights of their positions.

H3: Increased positions exhibit a significant performance advantage over decreased positions. New positions show even higher returns over terminated positions. Increased positions for more concentrated portfolios show higher returns than in less concentrated portfolios. The changes in public hedge fund portfolios do have predictive ability for at least the next quarter. It was not studied if the public could mimic these, as returns were taken as of the beginning of the quarter, while the companies have up to 45 days to file. There are also amendments that are filed past the 45-day limit.

H4: More concentrated portfolios outperform less concentrated portfolios. The result is true if the individual positions are used as weights or if the GICS classifications of the securities are used. This implies that managers who concentrate by industry exhibit more selection skill, and managers who concentrate on fewer positions exhibit the same skill. It was also shown that concentrated managers had a higher chance of being among the worst performers for a year, despite the higher expected CS performance.

Characteristic	***Mutual Fund Previous Work***	***Hedge Fund Previous Work***	***Hypothesis***	***Result***
Top Position will Outperform	Significantly Positive (Cohen, Polk, Silli 2008)	No Outperformance (Griffin, Xu 2009)	Positive	No Outperformance
Positive Fund Flows Outperform	Significantly Positive (Cohen, Polk, Silli 2008)		Positive	Significantly Positive

More Concentrated Outperform	Significantly Positive (Kacperczyk, Sialm, Zheng 2005)		Positive	Significantly Positive
Selection Ability	Present, but does not cover fees (DGTW 1997)	Not significantly different from mutual Fund (Griffin, Xu 2009)		Positive, average does not cover fees
Timing Ability	No Ability (DGTW 1997)			No Ability
Persistence	No persistence (Carhart 1997)			No persistence
Small Value vs. Large Value			Small Value Better	Small Value Better

The managers did not exhibit the ability to time the characteristics of their portfolios between small to large capitalization, low to high book to market or low to high momentum.

Although, smaller portfolios and concentrated portfolios are expected to exhibit higher returns, there was little evidence of persistence in the raw returns or the CS performance. High returns in one year, implied a higher chance of again being among the best performers but also an increased chance of being among the worst performers.

The most concentrated portfolios had CS returns of 49 bps a month. Annualized, the excess returns are just over 600 bps a year. Transaction fees and the average asset under management fee of less than 200 bps likely do not reach 600 bps. It appears, that the most concentrated portfolios exhibited enough selection ability in the sample period to justify their

premium fees. However, there are many factors, including the short book, net exposure, gross exposure and any other asset classes, that have not been included in this study that affect the profitability of a hedge fund investment.

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Table 1. Holdings per Institution. Summary, by year, of the number of unique holdings for a given quarterly filing date per institution. The second column is weighted by portfolio value.

Year	Weighted Ave. # Holdings	25%	75%	Ave. # Holdings	Min	Median
2000	175.0	28.9	114.4	91.6	9	58.5
2001	237.6	29.8	105.1	92.3	9	54.8
2002	238.8	32.6	114.9	100.2	8	56.8
2003	230.2	29.0	120.3	102.5	8	55.8
2004	232.9	29.6	112.0	107.4	8	54.8
2005	255.0	28.2	111.5	110.0	8	48.0
2006	336.4	27.8	108.2	115.1	8	51.5
2007	342.6	27.3	110.2	112.1	8	50.0
2008	306.6	23.6	93.9	97.0	8	44.0
2009	291.0	27.1	112.1	108.1	8	48.0
2010	295.8	29.0	118.8	117.9	8	48.8
2011	285.3	27.7	121.9	116.1	8	51.0

Table 2. Holdings Quintiles. Summary, by year, of the average size, book to market and momentum quintiles (columns 2 through 4) and the same categories weighted by portfolio value (columns 5 through 7).

Year	Size	BM	Mom	Weighted Size	Weighted BM	Weighted Mom
2000	3.87	2.57	3.50	4.27	2.23	3.88
2001	3.76	2.68	3.03	4.11	2.69	3.05
2002	3.54	2.64	2.89	4.06	2.67	2.96
2003	3.40	2.77	3.25	4.01	2.75	3.24
2004	3.39	2.67	3.24	3.90	2.72	3.20
2005	3.29	2.62	3.05	3.86	2.72	3.10
2006	3.31	2.64	3.09	3.86	2.73	3.07
2007	3.37	2.64	3.10	3.89	2.71	3.18
2008	3.48	2.65	3.10	3.98	2.67	3.25
2009	3.56	2.82	3.10	4.13	2.85	3.21
2010	3.52	2.79	3.03	4.12	2.86	3.09
2011	3.52	2.93	3.05	4.09	2.98	3.08

Figure 1. Institutions in Sample by Date. Number of institutions in the sample, which qualify for inclusion, by filing date.

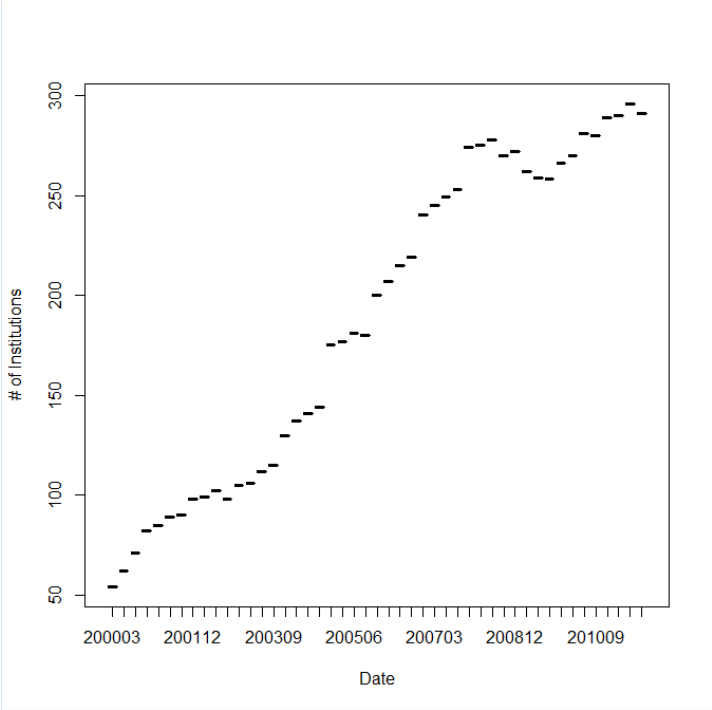

Figure 2. Total Value of Holdings (in millions) in Sample. Sum of portfolio values in the sample, which qualify for inclusion, by filing date.

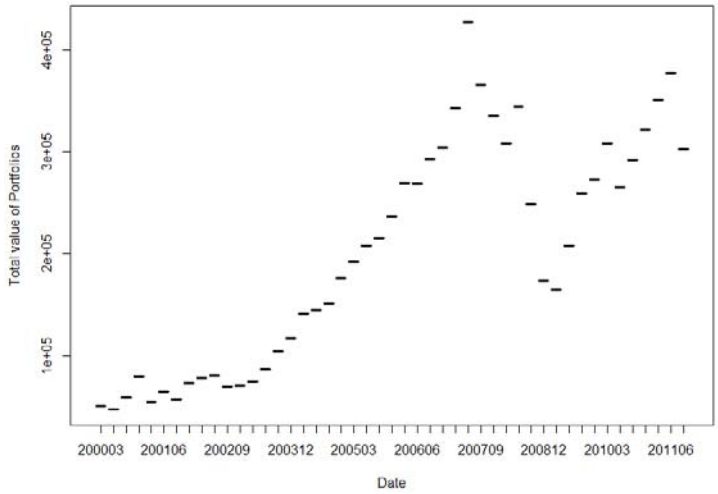

Figure 3. Last Day in Sample for Institutions. Count of last date in which institutions were included in the sample.

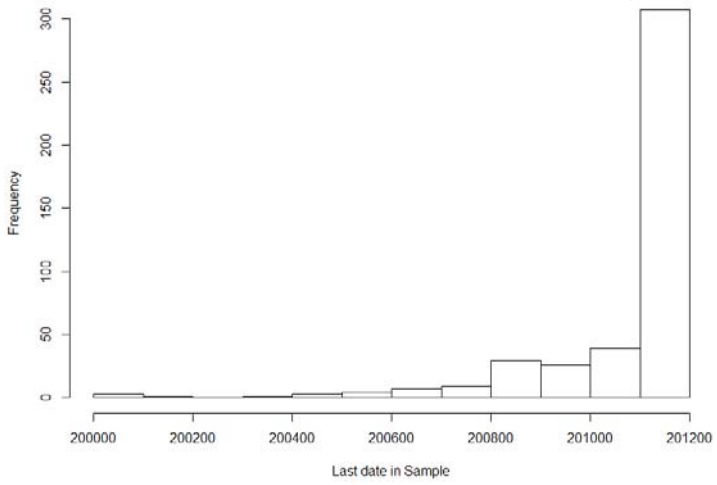

Table 3. Distribution of Return Quintiles Prior to Last Filing. First row is the percentage of institutions, who left the sample, in each respective previous twelve months of gross return quintile. Second row is the same sorted by the previous twelve months of CS.

Previous Twelve Month Return Quintile	1	2	3	4	5
% of Institutions	30.9%	14.4%	12.2%	19.4%	23.0%
Previous Twelve Month CS Return Quintile	1	2	3	4	5
% of Institutions	27.3%	15.8%	15.8%	20.9%	20.1%

Table 4. Correlation Between Explanatory Variables. Pair wise correlation between the concentration and portfolio value variables.

	Value	MaxWeight	Herfindahl	SectorHerfindahl	IndustryHerfindahl
Value	1.00	-0.15	-0.14	-0.12	-0.12
MaxWeight	-0.15	1.00	0.96	0.33	0.49
Herfindahl	-0.14	0.96	1.00	0.34	0.50
SectorHerfindahl	-0.12	0.33	0.34	1.00	0.88
IndustryHerfindahl	-0.12	0.49	0.50	0.88	1.00

Table 5. Summary Data for Explanatory Variables. The minimum, mean, median, maximum, 25th percentile and 75th percentile for gross monthly returns, portfolio value, size of largest position and Herfindahl measures.

	Min.	1st.Qu.	Median	Mean	3rd.Qu.	Max.
Monthly Return	-66.62%	-2.82%	1.16%	0.62%	4.48%	46.00%
Portfolio Value (mm)	$25.01	$175.80	$415.70	$1,064.00	$1,097.00	$43,950.00
Max Weight	0.6%	5.6%	9.4%	12.1%	15.2%	99.5%
Herfindahl	0.2%	2.4%	4.4%	6.2%	7.7%	99.1%
Sector Herfindahl	10.9%	16.5%	20.7%	28.7%	29.9%	100.0%
Industry Herfindhal	5.3%	9.2%	12.6%	18.2%	20.0%	100.0%

Table 6. Composition of Mean Month Returns by Year. Breakdown of returns between mean monthly selectivity (CS), timing (CT) and average style (AS) for each year.

Year	CS	CT	AS
2000	0.0085	-0.0390	0.0283
2001	-0.0002	-0.0011	-0.0003
2002	0.0014	-0.0135	-0.0021
2003	0.0047	0.0444	-0.0152
2004	0.0026	-0.0168	0.0293
2005	0.0023	-0.0051	0.0124
2006	0.0014	0.0043	0.0076
2007	0.0022	-0.0072	0.0118
2008	-0.0008	-0.0414	0.0048
2009	0.0067	0.0620	-0.0364
2010	0.0002	-0.0078	0.0265
2011	-0.0007	-0.0182	0.0185

Table 7. Four Factor Carhart Regression. First column: Regression of gross monthly returns, weighted by portfolio value, on market excess return (MKTRF), small minus big (SMB), high minus low (HML) and momentum (UMD) . Second Column: The same regression with equal weighted monthly CS. Third Column: The same regression on equal weighted monthly CT. Standard errors are reported in parenthesis.

	Gross Returns, Value Weighted	**CS, Equal Weight**	**CT, Equal Weight**
Alpha	0.00112	0.00211***	-0.00147
	(0.00124)	(0.00055)	(0.0045)
MKTRF	1.07571***	0.02618**	0.99663***
	(0.02917)	(0.013)	(0.10594)
SMB	0.19168***	0.01524	0.02408
	(0.04481)	(0.01997)	(0.16276)
HML	-0.10792***	0.00817	-0.21527
	(0.036112)	(0.0161)	(0.13119)
UMD	-0.01681	-0.00071	-0.0249
	(0.02156)	(0.00961)	(0.07832)

* = p < 0.1, ** = p < 0.05, *** = p < 0.01, number of observations = 141

Table 8. CS Regressions on Portfolio Value and Concentration. The below factors were each added as a fifth explanatory variable to the four factor CS regression from table 7. logVal represents the log of the portfolio value, HERF the individual position Herfindahl, HSEC the sector Herfindahl, HIND the industry Herfindahl and MAXWT the size of the largest position in the portfolio.

	Estimate	t-value	Significance	
logVAL	-0.00257	-5.667	***	
HERF	0.00468	0.532		
HSEC	0.00637	2.311	*	
HIND	0.00862	2.33	*	
MAXWT	0.00967	1.692	.	
Signif. Codes 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1**				

Table 9. Performance of Portfolios Ranked by Portfolio Value. The portfolios were ranked by portfolio value. The top and bottom quintile and deciles are reported along with the differences respectively. The Spearman coefficient are reported for the decile rankings. RET represents the gross monthly return, CS is monthly, 1-Factor α is the regression of RET on MKTRF, 4-Factor α is the regression of RET on MKTRF, SMB, HML and UMD, CS 4-Factor α is the regression of CS on the same four factors.

				PERFORMANCE BY VALUE RANKING					
	RET	**CS**	**Sign.**	**1-Factor α**	**Sign.**	**4-Factor α**	**Sign.**	**CS 4-Factor α**	**Sign.**
Top 10%	0.0037	0.0008		0.0014		0.0011		0.0010	
Top 20%	0.0042	0.0008		0.0020	*	0.0011		0.0008	
Bottom 20%	0.0081	0.0031	***	0.0058	***	0.0037	***	0.0031	***
Bottom 10%	0.0080	0.0033	***	0.0058	***	0.0035	***	0.0032	***
Top 20% - Bottom 20%	-0.0038	-0.0023	**	-0.0057	***	-0.0044	***	-0.0023	**
Top 10% - Bottom 10%	-0.0043	-0.0025	**	-0.0062	***	-0.0042	***	-0.0022	*
Spearman Coefficient	-0.7333	-0.7697	*	-0.7333	*	-0.6121	.	-0.7212	*

Table 10. Performance of Portfolios Ranked by Herfindahl of Individual Positions. The portfolios were ranked by the individual position Herfindahl. The top and bottom quintile and deciles are reported along with the differences respectively. The Spearman coefficients are reported for the decile rankings. RET represents the gross monthly return, CS is monthly, 1-Factor α is the regression of RET on MKTRF, 4-Factor α is the regression of RET on MKTRF, SMB, HML and UMD, CS 4-Factor α is the regression of CS on the same four factors.

				PERFORMANCE BY HERFINDAHL RANKING					
	RET	CS	Sign.	1-Factor α	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
Top 10%	0.0095	0.0043	*	0.0073	**	0.0060	**	0.0049	*
Top 20%	0.0068	0.0026	*	0.0045	**	0.0038	**	0.0033	**
Bottom 20%	0.0053	0.0014	***	0.0031	***	0.0016	*	0.0012	**
Bottom 10%	0.0050	0.0006		0.0028	*	0.0008		0.0003	
Top 20% - Bottom 20%	0.0015	0.0012		-0.0004		0.0004		0.0022	*
Top 10% - Bottom 10%	0.0045	0.0037	.	0.0027		0.0034		0.0046	*
Spearman Coefficient	0.9030	0.9273	***	0.9030	***	0.9879	***	0.9636	***

Table 11. Performance of Portfolios Ranked by Industry Herfindahl. The portfolios were ranked by the industry Herfindahl. The top and bottom quintile and deciles are reported along with the differences respectively. The Spearman coefficient are reported for the decile rankings. RET represents the gross monthly return, CS is monthly, 1-Factor α is the regression of RET on MKTRF, 4-Factor α is the regression of RET on MKTRF, SMB, HML and UMD, CS 4-Factor α is the regression of CS on the same four factors.

			PERFORMANCE BY INDUSTRY HERFINDAHL RANKING						
	RET	CS	Sign.	1-Factor α	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
Top 10%	0.0065	0.0024		0.0042	*	0.0046	*	0.0040	*
Top 20%	0.0068	0.0026	*	0.0045	**	0.0038	**	0.0033	**
Bottom 20%	0.0053	0.0014	***	0.0031	***	0.0016	*	0.0012	**
Bottom 10%	0.0054	0.0013	**	0.0032	***	0.0017	*	0.0010	**
Top 20% - Bottom 20%	0.0015	0.0012		-0.0004		0.0004		0.0022	*
Top 10% - Bottom 10%	0.0011	0.0011		-0.0008		0.0011		0.0029	.
Spearman Coefficient	0.8061	0.8424	**	0.8061	**	0.9152	***	0.9515	***

Table 12. Performance of Different Portfolio Constructions. First row: The performance of the largest position, by value, minus the whole portfolio. Second Row: The performance of increased positions (from the previous quarter) minus decreased positions, still in the portfolio. Third Row: The Performance of newly initiated positions minus positions present in the previous quarter's portfolio but absent from the current quarter.

		PERFORMANCE OF DIFFERENT PORTFOLIOS					
	RET	CS	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
Max Position - Whole	-0.0009	-0.0003		0.0000		-0.0001	
Increased Positions - Decreased Positions	0.0020	0.0018	**	0.0017	**	0.0016	**
New Positions - Terminated Positions	0.0134	0.0046	*	0.0239	*	0.0054	**

Table 13. Performance of Top Position Ranked by Weight of Top Position. The portfolios were placed in quintiles ranked by the size of the of the largest position as a percentage of the whole portfolio. Each quintiles performance metrics are reported.

	Top Position vs Whole Portfolio By Max Weight Quintile						
	RET	CS	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
1-Smallest Max Weight Quintile	-0.0025	-0.0016		-0.0009		-0.0009	
2	-0.0001	0.0013		0.0003		0.0008	
3	-0.0023	-0.0022		-0.0020		-0.0022	
4	-0.0001	0.0006		0.0008		0.0011	
5- Largest Max Weight Quintile	0.0006	0.0003		0.0016		0.0007	

Table 14. Performance of Increased Positions Ranked by Industry Herfindahl. The portfolios were ranked by the industry Herfindahl. The top and bottom quintile and deciles are reported along with the differences respectively. The Spearman coefficient are reported for the decile rankings. RET represents the gross monthly return of the increased positions, CS is monthly for the increased positions, 1-Factor α is the regression of RET on MKTRF, 4-Factor α is the regression of RET on MKTRF, SMB, HML and UMD, CS 4-Factor α is the regression of CS on the same four factors.

	PERFORMANCE of INCREASED POSITIONS BY INDUSTRY HERFINDAHL RANKING								
	RET	CS	Sign.	1-Factor α	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
Top 10%	0.0076	0.0033	.	0.0053	*	0.0056	**	0.0049	**
Top 20%	0.0087	0.0042	**	0.0064	***	0.0058	***	0.0050	***
Bottom 20%	0.0053	0.0015	***	0.0031	***	0.0016	*	0.0013	***
Bottom 10%	0.0051	0.0011	**	0.0029	**	0.0014	.	0.0008	*
Top 20% - Bottom 20%	0.0034	0.0027	.	0.0015		0.0023		0.0037	**
Top 10% - Bottom 10%	0.0024	0.0022		0.0005		0.0025		0.0041	*
Spearman Coefficient	0.8667	0.8667	**	0.8667	**	0.9758	***	0.9515	***

Table 15. Performance of Increased Positions Ranked by the Size of the Largest Position. The portfolios were ranked by the largest position size as a percentage of the whole portfolio. The top and bottom quintile and deciles are reported along with the differences respectively. The Spearman coefficient are reported for the decile rankings. RET represents the gross monthly return of the increased positions, CS is monthly for the increased positions, 1-Factor α is the regression of RET on MKTRF, 4-Factor α is the regression of RET on MKTRF, SMB, HML and UMD, CS 4-Factor α is the regression of CS on the same four factors.

	PERFORMANCE of INCREASED POSITIONS BY MAX WEIGHT RANKING								
	RET	CS	Sign.	1-Factor α	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
Top 10%	0.0096	0.0052	**	0.0074	***	0.0062	**	0.0057	**
Top 20%	0.0093	0.0045	***	0.0070	***	0.0059	***	0.0050	***
Bottom 20%	0.0053	0.0011	*	0.0031	**	0.0012		0.0008	
Bottom 10%	0.0057	0.0011	.	0.0035	*	0.0012		0.0007	
Top 20% - Bottom 20%	0.0039	0.0034	**	0.0021		0.0028	.	0.0042	***
Top 10% - Bottom 10%	0.0039	0.0041	*	0.0021		0.0032		0.0050	*
Spearman Coefficient	0.8667	0.9515	***	0.8667	**	0.9030	***	0.9515	***

Table 16. Performance of Top Position Ranked by CS. The portfolios were placed in quintiles ranked by the previous quarter's average CS. Each quintile's performance metrics are reported along with the difference between the top and bottom quintile and Spearman coefficients.

	PERFORMANCE by PREVIOUS PERIOD CS						
	RET	CS	Sign.	4-Factor α	Sign.	CS 4-Factor α	Sign.
1 - Worst Performers past 12 months	0.0073	0.0022	*	0.0051	***	0.0037	**
2	0.0052	0.0014	*	0.0030	**	0.0017	
3	0.0066	0.0023	***	0.0044	***	0.0025	**
4	0.0064	0.0022	**	0.0041	***	0.0026	**
5 - Best Performers past 12 months	0.0065	0.0030	**	0.0042	*	0.0025	.
Top Quintile - Bottom Quintile	-0.0008	0.0008		-0.0027		-0.0030	*
Spearman Coefficient	-0.3000	0.8000		-0.3000		-0.1000	

Table 17. Transition Matrix for CS Quintiles. The portfolios were ranked by the previous twelve month's average CS. The table shows what percentage of each quintile subsequently ended up in the same quintile and every other quintile when the portfolios were ranked by CS over the next twelve months.

		NEXT TWELVE MONTH CS QUINTILE				
		Worst Performers - 1	2	3	4	Best Performers - 5
	Worst Performers - 1	24.3%	17.7%	15.1%	20.7%	22.3%
TRAILING TWELVE	2	15.1%	27.1%	26.8%	18.1%	13.0%
MONTH CS QUINTILE	3	17.4%	26.7%	22.5%	18.3%	15.1%
	4	16.9%	21.5%	19.2%	23.1%	19.2%
	Best Performers - 5	27.2%	11.0%	16.3%	17.6%	27.9%

Table 18. Comparison of Herfindahl Quintile and CS. Portfolios were ranked by the individual position Herfindahl at the beginning of the twelve month period. Then ranked by the subsequent twelve month CS.

		HERFINDAHL				
		Least Concentrated - 1	2	3	4	Most Concentrated - 5
	Worst Performers - 1	12.7%	16.4%	19.3%	24.1%	27.5%
TRAILING TWELVE	2	28.1%	24.2%	19.2%	15.5%	13.1%
MONTH CS QUINTILE	3	30.7%	22.7%	19.4%	14.9%	12.2%
	4	21.2%	21.4%	21.2%	20.1%	16.1%
	Best Performers - 5	8.3%	15.0%	20.4%	24.9%	31.4%

The Impact of Special Dividend Announcements, Insider Ownership, and Tax Increases on US Equity Prices

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Abstract:

In the fourth quarter of 2012, large cash balances and looming tax increases led to unprecedented levels of special dividend payments by US corporations. This study examines the market's reaction to 320 special dividend announcements made in October, November, and December of 2012 and finds significant Cumulative Abnormal Returns (CARs) in the days surrounding the dividend announcement. We conclude that CARs were positively correlated with dividend size, which implies that investors reacted favorably to anticipated tax savings of receiving dividends prior to an expected tax increase. We also conclude that CARs were positively correlated with the percent of shares held by insiders, signaling the possible existence of agency problems associated with free cash flow and dividend payments.

I. Introduction

At the end of 2012, a variety of factors led to an unprecedented number of one-time discretionary payments by US corporations to shareholders, better known as special dividends. Non-financial US companies were holding a record $1.74 trillion in cash and liquid assets on their balance sheets at the end of September, 2012.[2] Low interest rates and high investor demand encouraged companies to borrow money. Investment-grade nonfinancial companies sold in excess of $100 billion of bonds in November of 2012, a record monthly total.[3] Tax rates for individual investors on dividend income had slowly and steadily declined for 40 years, culminating in 2003 when the Bush-era tax cuts reduced them to 15%. Those tax cuts were set to expire on December 31, 2012 and, barring legislative action, the federal tax rate on dividend income for individuals would rise to the level of ordinary income, which can be as high as 39.6%. Also set to begin on January 1, 2013 was an additional 3.8% tax on dividends for individuals earning above $200,000 per year or families earning above $250,000 per year. Thus, the dividend tax rate for some US taxpayers had the potential to rise from 15% to 43.4%.[4] The tightly-contested 2012 presidential elections added to the uncertainty. Political pundits believed a victory by Mitt Romney was likely to keep taxes on dividend income at existing levels while a Barack Obama victory virtually guaranteed some kind of tax increase. This paper focuses on the market's reaction to special dividend announcements that occurred in the fourth quarter of 2012 in anticipation of increases in tax rates on dividend income for individual investors.

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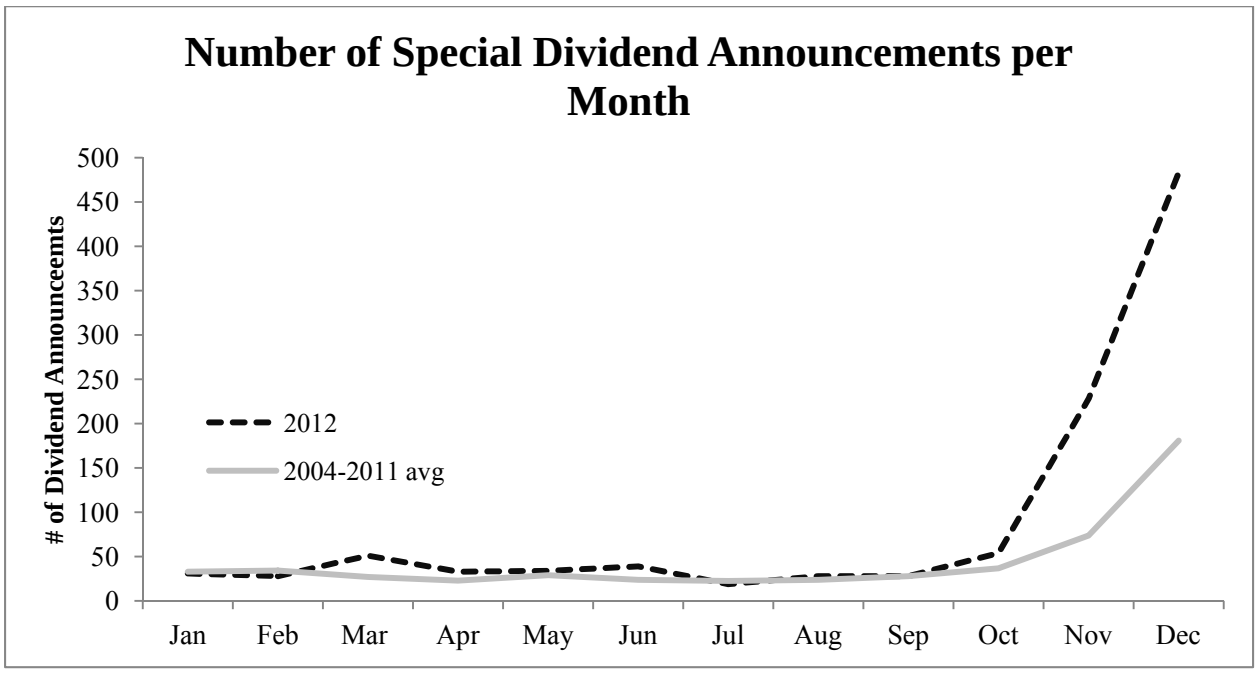
[2] Ben Casselman, "Cautious Companies Stockpile Cash," *The Wall Street Journal,* December 6, 2012, accessed February 28, 2012. Available at: http://online.wsj.com/article/SB10001424127887323316804578163394088244224.html

[3] Matt Wirz and Patrick McGee, "Firms Flood Bond Market to Finance Payouts," *The Wall Street Journal,* November 29, 2012, accessed February 28, 2012. Available at: http://online.wsj.com/article/SB10001424127887324020804578149641473505474.html?mod=ITP_moneyandinvesting_0

[4] Review & Outlook, "Costco's Dividend Tax Epiphany," *The Wall Street Journal,* November 30, 2012, accessed February 28, 2012. Available at: http://online.wsj.com/article/SB10001424127887324705104578149012514177372.html

As the likelihood of an Obama victory increased in the weeks leading up to the election in early November, companies began to announce one-time, special dividends at a frenzied pace. In the fourth quarter of 2012, common (non-fund) companies listed on the ASE, NYSE, NASDAQ, NGM, and NSC announced a total of 54, 228, and 483 special dividends in October, November, and December, respectively. These totals represented an increase of 46%, 209% and 167% above their respective 2004-2011 monthly averages. The accelerated rate of special dividend announcements and its relationship to recent historical averages can be seen in Figure 1. The end result of these factors (cheap debt, large cash balances, impending tax increases, etc.) was a record number of special dividend payments in October, November, and December of 2012.

Figure 1: Number of special dividend announcements per month in 2012 and recent historical average.[5]



[5] Howard Silverblatt, "Standard & Poor's Monthly Dividend Action Report," e-mail message to author, November 29, 2012.

The unprecedented number of special dividend announcements at the end of 2012 presents a unique opportunity to examine the market's reaction to special dividends and tax changes. In the first part of the analysis, we will determine if there were abnormal returns associated with the special dividend announcements. The latter part of the analysis will be spent identifying what factors, if any, were correlated the abnormal returns.

II. Previous Work

The academic discussion of how dividend policy affects security prices goes back over half a century, with Miller and Modigliani (1958) being among the pioneers in development of modern theory.[6] Frameworks like The Free Cash Flow Hypothesis first introduced by Berle and Means (1932)[7] and later updated by Jensen (1983)[8] are useful tools for developing hypotheses about the market's reaction to special dividend issuance by firms. The validity and merits of the various theoretical frameworks are beyond the scope of this paper, but during efforts to empirically prove these frameworks, several relevant studies that measured market reaction to special dividend announcements emerged.

One study that examined 2023 special dividend announcements from 1962-1982 found that the dividends were immediately followed by significant positive excess returns as measured by the mean adjusted returns model.[9] The study also found a significant negative relationship between the frequency with which a firm announced special dividends and the excess returns delivered on the day of the dividend announcement (Day 0). The study did not control for

[6] Merton H. Miller and Franco Modigliani, "Dividend Policy, Growth, and the Valuation of Shares," *Journal of Business*, October 1961, 34, 411 – 433.
[7] Adolph A. Berle and Gardiner C. Means, "The Modern and Private Property," New York: Macmillan, 1932.
[8] Michael C. Jensen, "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *American Economic Review*, May 1986, 76, 323–329.
[9] Narayana Jayaraman and Kuldeep Shastri, "The Valuation Impacts of Specially Designated Dividends," *Journal of Financial and Quantitative Analysis,* September 1988, 23, 310-312.

changes in tax rates or other factors (e.g., cash balances, corporate governance, company performance, etc.). Another study that examined 165 special dividend announcements from 1969 through 1979 also found significant abnormal returns on Day 0 and Day+1.[10] This study also did not control for changes in tax rates or other factors.

More recently, studies have examined the specific topic of corporate governance and special dividend issuances surrounding changes in personal income tax rates. One study showed that dividend payouts increased and decreased based on tax advantages or disadvantages relative to capital gains when large individual shareholders of a firm were affected by these changes.[11] Another study examined special dividends issued in 2010 in anticipation of a tax increase that never occurred and found that the likelihood of dividend issuance was positively correlated with the percentage of insider ownership.[12] These studies provide the foundation for the analysis conducted below where we examine the market's reaction to the flood of special dividend announcements made at the end of 2012 and try to determine what factors, if any, are correlated with whether a firm elected to pay a divided, the size of the firm's dividend, and the abnormal returns associated with the dividend announcement.

III.A Data Description – Data Sources, Inclusion Criteria, and General Observations

The dividend data was retrieved from Compustat's North American Daily Security service (Computstat) via the Wharton Research Database Services (WRDS). Inclusion criteria were as follows:

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[10] James A. Brickley, "Shareholder Wealth, Information Signaling and the Specially Designated Dividend," *Journal of Financial Economics*, August 1983, 12, 187–209.

[11] Perez-Gonzalez, Francisco, Large Shareholders and Dividends: Evidence from U.S. Tax Reforms (September 2002). Available at SSRN: http://ssrn.com/abstract=337640 or http://dx.doi.org/10.2139/ssrn.337640

[12] Hanlon, Michelle and Hoopes, Jeffrey L., What Do Firms Do When Dividend Tax Rates Change? An Examination of Alternative Payout Responses to Dividend Tax Rate Changes (May 23, 2012). Available at SSRN: http://ssrn.com/abstract=2065628 or http://dx.doi.org/10.2139/ssrn.2065628

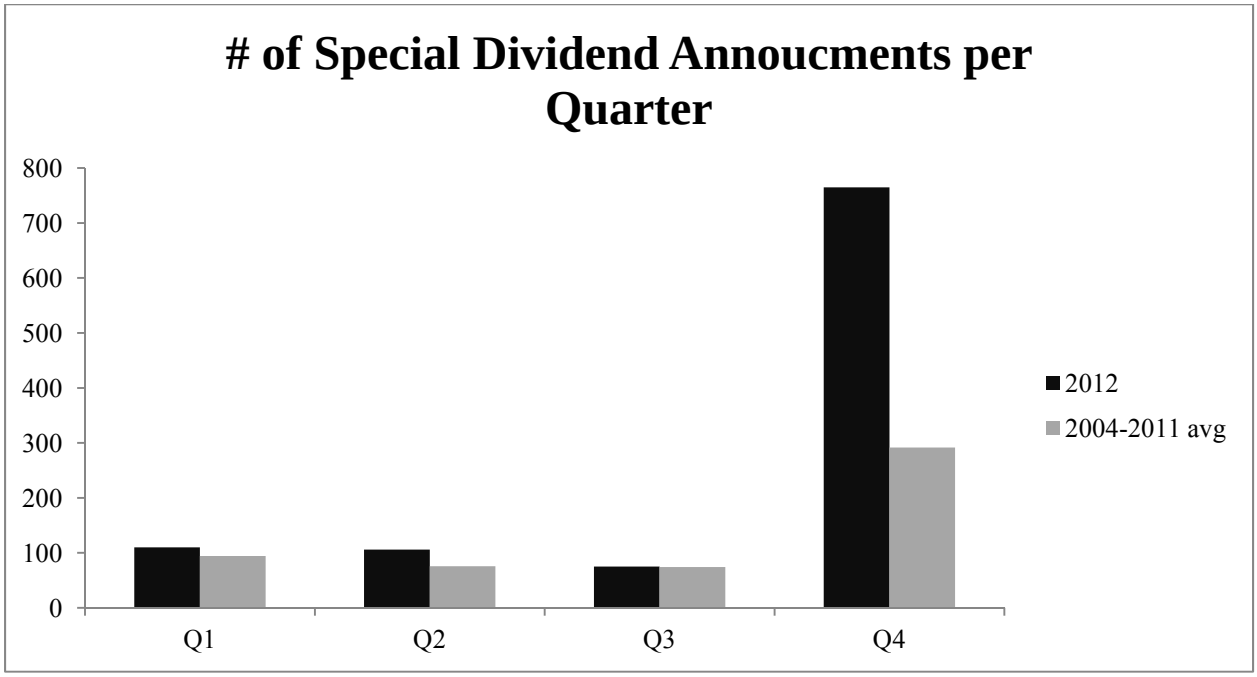
- Publicly traded North American non-fund equity security
- Traded on an either NYSE or NASDAQ
- Announced a special dividend in October, November, or December of 2012
- Special dividend was payable on or before December 31, 2012
- Dividend to be paid in USD

The dataset was limited to non-fund equities publicly traded on the NYSE and NASDAQ for several reasons. First, a large number of different types of funds are now publicly traded (e.g., Exchange Traded Funds, Mutual Funds, etc.), but the investment strategies and regulation of these funds varies greatly. The market's reaction to a fund's special dividend announcement may not be similar to that of a fund with a different investment strategy. Further, some types of funds (e.g., closed-end mutual funds) have a history of anomalous market behavior, and thus it is safest to exclude them from the sample. Second, the shares of firms traded on the NYSE and NASDAQ are highly liquid, improving the likelihood that any impact of the special dividend on the value of the security will be quickly incorporated into the stock price. Finally, stock price data and additional metrics (e.g., % institutional ownership) are more likely to be available for securities traded on these exchanges.

The time window of October, November, and December 2012 was selected due to the divergence of the number of special dividend announcements in those months from recent historical average. In the fourth quarter of 2012, common (non-fund) companies listed on the ASE, NYSE, NASDAQ, NGM, and NSC announced a total of 54, 228, and 483 special dividends in October, November, and December, respectively. Monthly averages of special dividend announcements for 2004-2011 were 36.9, 73.8, and 180.9 for October, November and

December, respectively. The 2004-2011 highs for those months were 53 (October 2010), 97 (November 2010), and 233 (December 2007).[13] Also of note is the seasonal pattern in special dividend announcements that is observed in the data, which can be observed in Figure 2 below.

Figure 2: Number of Special Dividend Announcements per Quarter.[14]



The number of special dividend announcements in the first three quarters (Q1-Q3) of 2012 is consistent with prior years. There were a total of 765 special dividend announcements in the fourth quarter (Q4) of 2012, which is dramatically higher than the number of special dividend announcements in the first, second, and third quarters of 2012 (110, 106, and 75, respectively). The 2012 increase of special dividend announcements in the fourth quarter relative to the first three quarters is consistent with historical patterns, but the level of increase is substantially greater than previous years.

[13] Howard Silverblatt, "Standard & Poor's Monthly Dividend Action Report," e-mail message to author, November 29, 2012.
[14] Ibid.

Given the discretionary nature of special dividends and the anticipated increase in taxes between 2012 and 2013, it was rational for firms to increase dividend payments in the fourth quarter of 2012. This seasonality in dividend payments is also observed in other years (i.e., 2004-2011) where changes in tax rates or other external factors were not anticipated or did not materialize (e.g., tax increase in 2010). In the absence of changing external factors that impact dividend decisions, there exists a seasonal pattern in special dividend announcements. One explanation for the increase in special dividend announcements during Q4 is that firms wait until the end of the year to examine their performance and financial needs before making dividend decisions. However, there appears to be no reason these decisions cannot be made in other quarters. We did not find any literature discussing the seasonality of special dividend payments and believe it may warrant further investigation.

III.B Data Description – Data Management and Refinement

All announcement dates provided in the Compustat dataset were verified via press releases, company investor relations, and other sources. Using these sources, we adjusted the dividend announcement dates when press releases indicated that the announcement date differed from the announcement date listed in Compustat. Dividend announcements are commonly made either in the morning before trading begins or after trading closes for the day. The announcement date reported by Compustat does not differentiate between announcements released pre- or post-trading, but our definition of Day 0 relies on this information because we define "Day 0" as the returns generated by the first daily closing price after the dividend announcement. Accurately identifying the time of the dividend announcement was critical to our calculations and warranted the investment in time and risk associated with manual data verification and adjustment. We

compensate for errors or imperfections (e.g., two sources that list conflicting announcement dates and times) in the process by examining Cumulative Abnormal Returns (CARs) over a five day window surrounding the dividend announcement date.

A total of 10 events that fit the inclusion criteria described in Section III.A were excluded for one of the following reasons: the company was acquired shortly after the announcement; the dividend was misclassified as a special dividend instead of regularly occurring (e.g., quarterly) dividend; a record of the dividend could not be verified (i.e., no mention of the dividend could be found outside of the Compustat dataset); or the dividend was announced in conjunction with a merger or buyout. A total of N=320 special dividend announcements were included in the final dataset.

Additional data for regression analyses were acquired from other sources. FactSet and Bloomberg were used to retrieve balance sheet information and performance data, Thomson Reuters and Bloomberg were used to retrieve holdings data, and RiskMetrics by ISS and the Corporate Library were used to retrieve corporate governance data.

IV. Daily Abnormal Returns Analysis

Daily abnormal returns on the days surrounding the dividend announcement were calculated. In the following discussion, "Day 0" is defined as the returns generated by the first daily closing price after the dividend announcement. For example, if the announcement came at 3:50 PM (before the markets closed) on December 3, 2012, then Day 0 is defined as December 3rd. If the announcement came at 5:00 PM (after the markets closed) on December 3, 2012, then Day 0 is defined as December 4th. Abnormal returns were calculated as follows:

Abnormal Return on Day N[15] = (Day N Stock Daily Return) - (Day N S&P 500 Daily Return)

Where:

$$\text{Stock Daily Return} = \frac{\text{(Day N closing price)-(Day N-1 Closing Price)}}{\text{(Day N-1 Closing Price)}}$$

Abnormal returns were calculated for Day 0 as well as the two days that preceded Day 0 (Day-2, Day-1) and the two days followed Day 0 (Day+1, Day+2). Cumulative abnormal returns (CAR) were then calculated by adding daily abnormal returns. For example, the CAR for Day+1 would be calculated as follows:

Day+1 CAR = (Day N-2 Abnormal Return on Day N-2) + (Day N-1 Abnormal Return) + (Day 0 Abnormal Return) + (Day+1 Abnormal Return)

In theory, cash on the balance sheet belongs to equity shareholders. A dollar inside of a healthy firm should have equal value to its shareholders as a dollar outside of the firm. In other words, if an individual owns shares in a firm, then cash on the firm's balance sheet is equal in value to cash in the individual's personal bank account. Thus, investors should be indifferent to special dividend announcements and our null hypothesis is that both average and median Cumulative Abnormal Returns are equal to zero.

Figure 3 below is a scatterplot of the Cumulative Abnormal Returns of each of the 320 equities in the sample shown versus dividend announcement date. CARs were calculated over a five day period from Day-2 to Day+2. Figure 3 clearly depicts two trends: first, we see that special dividend announcements became more frequent over time and peaked in late November

[15] Note: For all securities in the sample, abnormal return calculation assumes beta = 1

and early December and second, although there is a wide distribution to the CARs, they are generally above zero. In Figure 4, we show the average and median of these five day CARs.

Figure 3: Scatterplot of Cumulative Abnormal Returns versus Dividend Announcement Date.

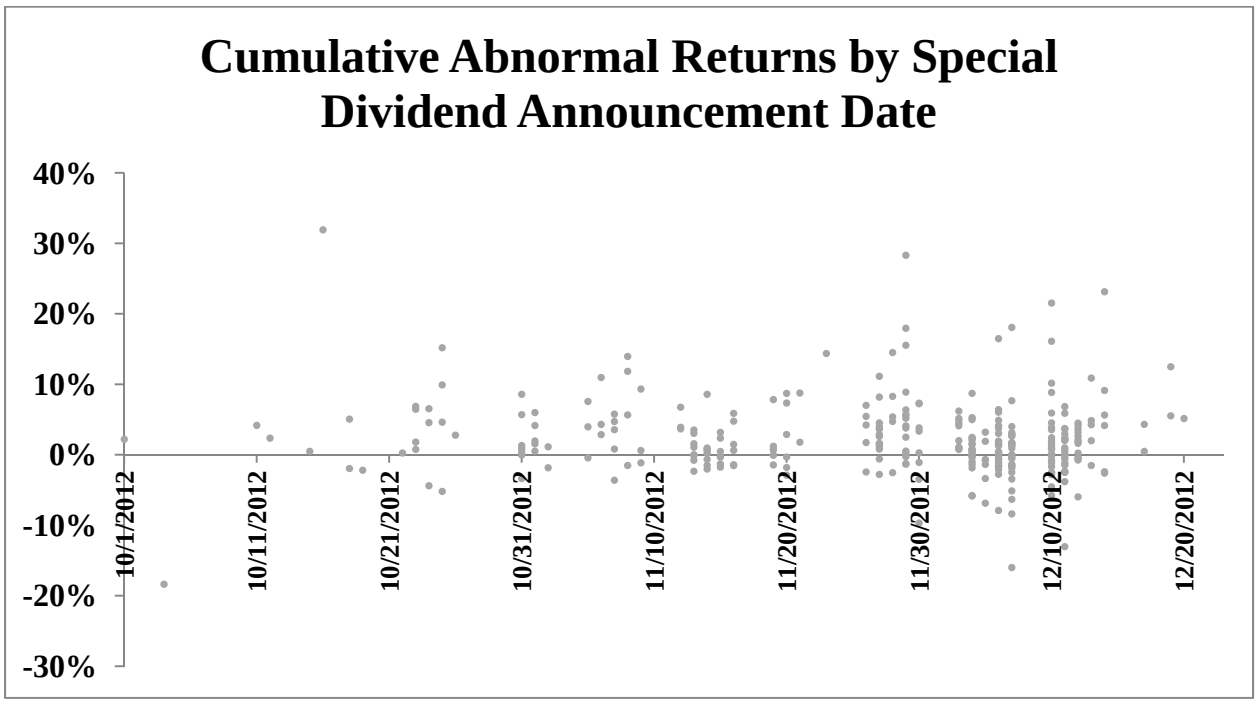
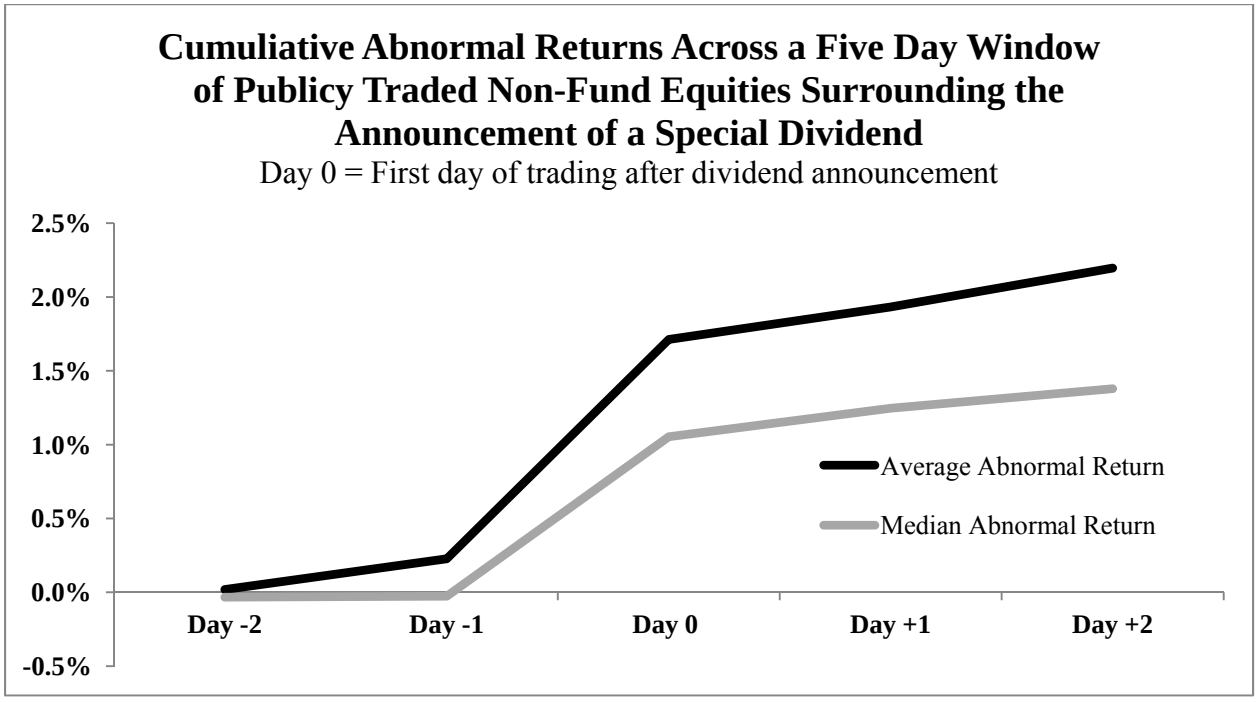


Figure 4: Cumulative Abnormal Returns in the Days Surrounding a Special Dividend Announcement.



Figures 3 and 4 suggest that our null hypothesis be rejected. Both median and average CARs rose to well above zero on Day 0, the first day of trading after the special dividend announcement, indicating a favorable market reaction to the announcements. Further, in Figure 4 we see no substantial median or mean CARs on Day-2. By Day-1, the median CAR remains close to zero while the mean CAR creeps up to 0.23%, but this result is not statistically significant ($p = 0.1743$).[16] By Day 0 and beyond, the average and median CAR jump above 1% and the results are all highly significant. We also examined CARs across two other windows: a one day window (Day 0 only) and a three day window (Day-1 to Day+1). The average and median CARs during these three windows as well as the statistical significance of these results are shown in Table 1.

Table 1: Cumulative Abnormal Returns across three windows: Day 0 only, Day-1 to Day+1, and Day-2 to Day+2

	Day 0	**Day-1 to Day+1**	**Day-2 to Day+2**
Average CAR	**1.49%**	**1.91%**	**2.20%**
p-Value[17]	$p \leq 0.0000$	$p \leq 0.0000$	$p \leq 0.0000$
z-Value	6.80	6.90	6.57
Median CAR	**0.75%**	**1.23%**	**1.38%**
p-Value[18]	$p \leq 0.0000$	$p \leq 0.0000$	$p \leq 0.0000$

These results imply two things. First, markets reacted favorably to the special dividend announcements, driving up equity prices and delivering returns that surpassed the broader market. The statistical significance of these results supports our rejection of the null hypothesis that median and average abnormal returns are equal to zero. Second, because the CARs in the

[16] Two-Tailed, Two Sample Unequal Variance T-Test
[17] Ibid.
[18] Mann-Whitney Two-Tailed Rank-Sum Test

two days leading up to the special dividend announcements did not differ from the null hypothesis at a statistically significant level, we can infer that the market was surprised by the special dividend announcements.

By extending the window beyond Day 0 and looking at three and five day windows, we see that the market continued to react favorably to the special dividend announcements as CARs continued to grow. However, the bulk of the returns were delivered on Day 0, thus we should not be surprised to see statistically significant results in the three and five day windows since those windows both include Day 0. Lastly, we note that the disparity between average and median returns can be attributed to a positively skewed distribution, with 19 equities delivering CARs in excess of 10%, as can be seen in the scatterplot shown in Figure 3.

The Cumulative Abnormal Returns found in this study are consistent with the findings of previous studies that examined special dividend announcements.[19] [20] Although these studies also found statistically significant abnormal returns on Day+1, this could be the result of the authors' definition of Day 0. Before we adjusted the announcement date provided in the Compustat dataset, we found similar results in our sample. For example, many of the announcement dates listed in Compustat were accurate, but the announcement occurred after markets had closed for the day. Thus, if we were to use the unadjusted Compustat announcement day, then the market's reaction to the dividend announcement would appear on Day+1 in our analysis. The prior studies that examined market reaction to special dividend announcements were written at a time when verifying the time of day of the dividend announcement would have been far more cumbersome than it is today.

[19]Narayana Jayaraman and Kuldeep Shastri, "The Valuation Impacts of Specially Designated Dividends," *Journal of Financial and Quantitative Analysis,* September 1988, 23, 310-312.
[20] James A. Brickley, "Shareholder Wealth, Information Signaling and the Specially Designated Dividend," *Journal of Financial Economics*, August 1983, 12, 187–209.

V. Regression Results

There are a number of theories that seek to explain dividend policy and firm behavior, many of which lack strong empirical evidence to support their arguments.[21] It may be that no single model or theory can fully explain dividend policy given the complexity of endogenous and exogenous factors that managers must consider when determining divided policy.[22] It is well beyond the scope of this paper to argue the merits of the various models, but by combining the sample described above with other metrics, we can investigate if common characteristics exist among the firms that paid special dividends. At the beginning of the paper, we introduced several hypotheses presented in news stories about the proliferation of special dividend payments (e.g., cheap debt, large cash balances, changing tax rates, etc.). In the following section we will use linear regression to test if there is evidence for these theories hypotheses.

We noted previously that individuals, institutional investors, and corporations are taxed at different rates on dividend income. Roughly speaking, institutional investors and corporations pay little to no taxes on dividend income while individuals have a more significant tax liability. Further, at the end of 2012 individual shareholders anticipated they would pay lower taxes on dividend income received before December 31, 2012 than they would on dividend income received after January 1, 2013. We expect individual shareholders to react favorably to a special dividend announcement to be paid prior to December 31, 2012 due to this tax increase. By extension, we expect that dividend size will be correlated with Cumulative Abnormal Return because the larger the size of the dividend, the greater the tax savings. The differential tax

[21]Frankfuter G. M., Wood B. G. Junior, 2002, Dividend policies and their empirical test, International Review of Financial Analysis, 11, pp. 111 – 138.

[22] Dhrymes, P. J., & Kurz, M. (1967). Investment, dividend, and external finance behavior of firms. In Ferber R. (Ed.), Determinants of investment behavior: a conference of the Universities–National Bureau Committee for Economic Research (pp. 427–485). New York: National Bureau of Economic Research.

treatment between individuals and institutional investors implies that institutions are indifferent to dividends while individuals' preference to dividends depends on tax rates. Thus it is expected that the CARs would be lower for companies with a higher proportion of institutional shareholders. In Table 3 below, we present the results of a series of univariate linear regressions as well as a multivariate linear regression. In each regression, the dependent variable is Cumulative Abnormal Returns across the five day window (Day-2 to Day+2).

Table 3: CAR versus Dividend Size as % of Day-1 Price, % Insider Ownership, and % Institutional Ownership.

	Univariate Regressions			**Multivariate Regression**
	Estimate *(t-Statistic)*	Estimate *(t-Statistic)*	Estimate *(t-Statistic)*	Estimate *(t-Statistic)*
Intercept	0.0087 *(2.46)*	0.1375 *(3.53)*	0.0356 *(4.56)*	0.0044 *(0.43)*
Dividend Size as % of Day-1 Closing Price	0.2575 *(6.12)*			0.2456 *(5.87)*
% Insider Ownership[23]		0.1357 *(3.40)*		0.0506 *(2.43)*
% Institutional Ownership [24]			-0.0191 *(-1.89)*	-0.0024 *(-0.22)*

In the univariate regression analysis, we compared Dividend Size as a % of Day-1 Closing Price (Dividend Size), % Insider Ownership, and % Institutional Ownership against Cumulative Abnormal Returns. Each of the three results yielded statistically significant results for both the intercept and the independent variable. When the three independent variables were used to perform a multivariate linear regression, the estimates for intercept and % Institutional Ownership moved towards zero and were no longer statistically significant.

[23] % Insider Ownership data obtained from Bloomberg on 3/3/2013.
[24] % Institutional Ownership data obtained from Bloomberg on 3/3/2013.

The univariate linear model comparing Dividend Size to CAR predicts that for every 1% increase in Dividend Size, there was a 0.26% increase in CAR. The highly significant result (t=6.12) means we can reject the null hypothesis that dividend tax rates are irrelevant to investor reaction to a dividend announcement. We noted earlier that marginal tax rates on dividends were projected to increase from 15% to up to 43.4% between 2012 and 2013, a difference of 28.4%. In other words, $100 in dividends paid out in 2012 versus $100 in dividends paid out in 2013 would save investors up to $28.4 in taxes. If we ignore differential tax rates between institutions and individuals and assume all investors were exposed to the same tax increase, then the model's estimate for the effect of dividend size on abnormal returns is almost exactly the magnitude predicted by the net tax savings to investors (25.8% versus 28.4%). In the multivariate linear model, the magnitude of the coefficient for Dividend Size barely changed from the univariate model and remained highly significant (t=5.87). This suggests that the effect of Dividend Size on CAR is largely independent of the other inputs we included in the multivariate analysis.

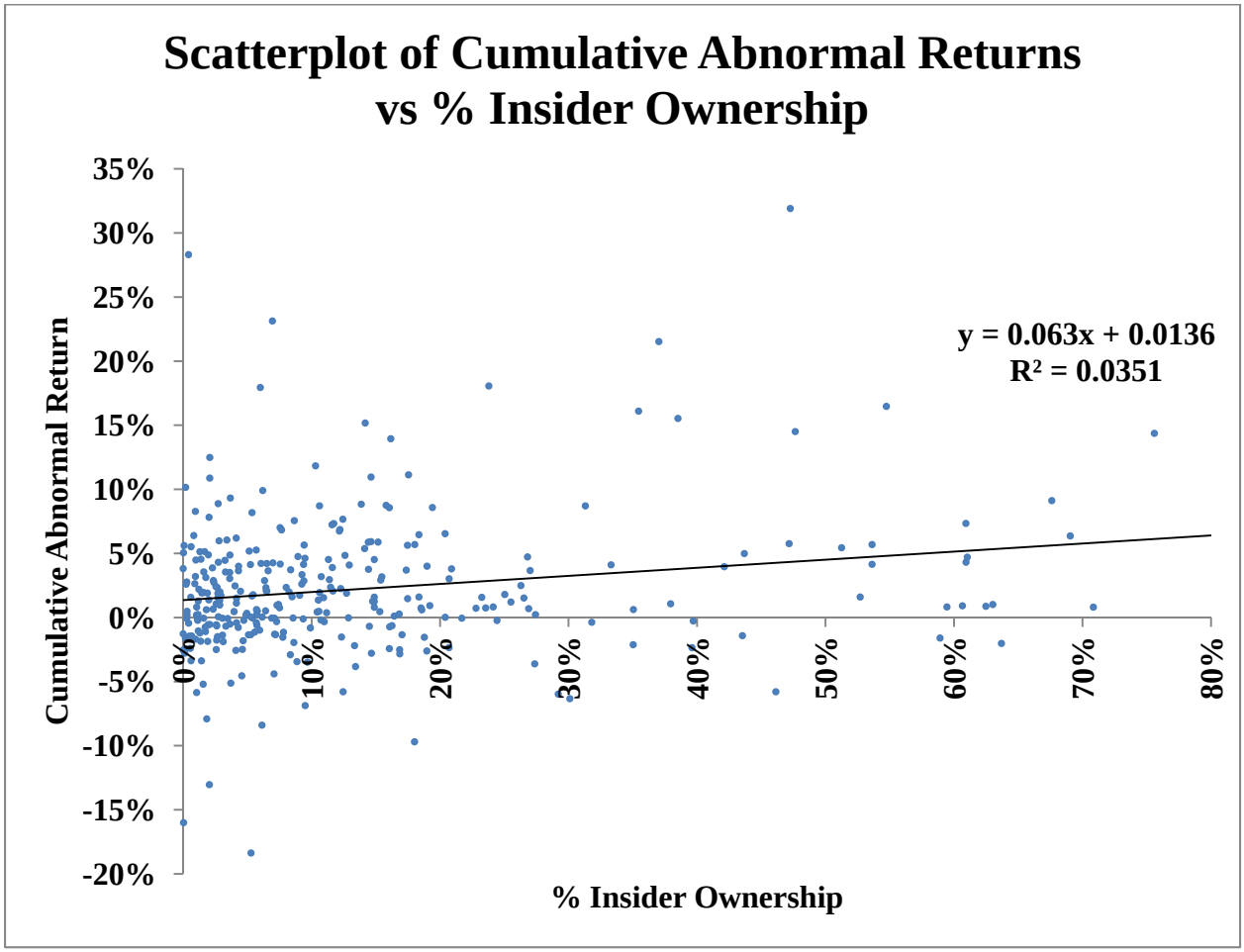
Of course, not all investors are taxed at the same rates on dividends. We also expected to see a significant relationship between % Institutional Ownership and Cumulative Abnormal Return due to the differential tax rates. In the univariate linear model comparing % Institutional Ownership to CAR, the estimate for the relationship between the two was -0.0191 with a t-statistic of -1.89. The negative value for the estimate matches the intuition – a larger percentage of institutional shareholders means that fewer shareholders are exposed to the anticipated tax increases and thus there should be a lower impact on CAR. Put differently, for every 1% increase in % Institutional Ownership, the model predicts a 0.019% decrease in CAR. In the multivariate linear model, the magnitude of the coefficient for % Institutional Ownership substantially decreased and was no longer statistically significant. This suggests that % Institutional

Ownership is likely correlated with one of the other independent variables in the multivariate analysis.

We also tested the effect of % Insider Ownership on Cumulative Abnormal Return. The univariate linear model predicts that for every 1% increase in % Insider Ownership, there was a 0.136% increase in CAR (t=3.40). One possible explanation for this relationship is potential agency problems between a firm's managers and its shareholders. For example, a high percentage of insider ownership increases the agency costs associated with free cash flow discussed in Jensen (1983).[25] Another related (but unproven) explanation is that firms with high insider ownership likely have CEOs or other executives with large holdings that are reluctant to pay dividends due to their own personal income tax exposure, which is another form of agency problem. In Figure 5 we created a scatterplot of five day CAR (y-axis) versus % Insider Ownership (x-axis). Upon first glance, the relationship between CAR and % Insider Ownership doesn't appear particularly strong; however, this is not too surprising given that we already know that Dividend Size also has an important effect on CAR. It is noteworthy that thirteen of the twenty largest CARs belonged to firms with % Insider Ownership above the population median of 7.52%.

[25] Michael C. Jensen, "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *American Economic Review*, May 1986, 76, 323–329.

Figure 5: Scatterplot of Cumulative Abnormal Returns versus % Insider Ownership.



The results of the multivariate regression reflect those of the univariate regression. The relationship between % Insider Ownership and CAR remains statistically significant (t=2.43), although the estimate is reduced to 0.0506. The t-statistic for the intercept declines to 0.43, which suggests that much of the variance in CAR can be explained by % Insider Ownership and Dividend Size. Finally, regardless of the root cause of the issue, the relationship between % Insider Ownership and Cumulative Abnormal Returns strongly implies the existence of agency problems and warrants further investigation into corporate governance, insider ownership, and dividend policy.

VI. Summary & Conclusion

In the discussion above, we established that tax rates on dividends greatly impact investor reaction to special dividend announcements. When investors anticipated an increase in tax rates on dividend income in the final months of 2012, they reacted favorably to special dividend announcements, which had the potential to save up to 28 cents on every dollar in dividend income. We also established that there is a significant relationship between % Insider Ownership and Cumulative Abnormal Returns. Large insider holdings predict a large abnormal return, which implies there may be agency problems related to insider ownership and dividend policy. The authors believe this warrants further investigation.

Despite the "fiscal cliff" warnings touted throughout the fall of 2012, tax rates on dividend income for individual investors increased modestly from 15% to 23.8% after a deal reached by congress on January 1, 2013. This increase only applied to individuals making over $400,000 per year or couples making over $450,000 per year,[26] leaving the vast majority of US taxpayers unaffected by the new laws. The credible threat of increased taxes, however, temporarily impacted firms' dividend decision making process as well as investor reactions to special dividend announcements.

[26] Binayamin Appelbaum and Catherine Rampell, "Bigger Tax Bite for Most Under Fiscal Pact," *The New York Times,* January 1, 2013, accessed March 2, 2013. Available at: http://www.nytimes.com/2013/01/02/business/economy/a-bigger-tax-bite-for-most-households-under-senate-plan.html?_r=0

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