The Monday Effect: A Disaggregation Analysis

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In this research we employ two statistical approaches not previously used to examine the Monday effect: exploratory data analysis and content analysis. While most previous Monday effect studies examine confirmatory analysis statistics (means and variances), exploratory data analysis employs counting and visual techniques to describe the empirical distributions of daily returns. The results indicate that Monday returns are highly affected by large, infrequent, negative outliers in both large and small cap stocks, regardless of the shift over time in the Monday effect for large cap stocks.

Content analysis is used to investigate whether there are any micro or macro events newsworthy enough to be cited more often by the financial press (as reported in the ***Wall Street Journal****) to explain these large, negative outlier Monday markets than are cited to explain the returns for other Mondays. Our results indicate that economic or psychological factors may be responsible for the Monday effect. This research points out new directions for researchers to consider when examining the causes of the Monday effect.*

Introduction

Many researchers have documented that average stock returns on Mondays are statistically negative, while returns on other days of the week are positive. Some authors have reported that average Mondays used to be negative for large stocks and then recently changed to neutral or even positive. Most authors agree, however, that average negative Mondays persist in small stocks. At the same time, researchers have not offered a consistent and convincing explanation for this effect. In fact, almost every study offers a different explanation, as the articles in this issue attest. To date, however, no one has characterized the underlying distribution as we do or used the analytical techniques we present here.

Our results are consistent with those of other researchers and demonstrate that the distribution of Monday returns shows evidence of negative outliers. That is, the

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negative average returns observed by other researchers appear to come from an underlying distribution with a negative mean and median occasionally interspersed with large negative returns. These outliers appear sporadically in both large and small stock indices with the available CRSP daily data from mid-1963 through the end of 2001. For large cap stocks the negative average Monday effect has lessened recently, but the negative outliers remain. For small cap stocks Monday's outliers are more numerous than for large cap stocks in all time periods and contribute to the negative average returns. The Monday effect, therefore, appears to be a mixture of at least two causes—an underlying tendency for negative returns and occasionally large negative outliers. We believe these negative outliers are an important part of the Monday effect. The purpose of this article, therefore, is to document these negative outliers and investigate their source.

Even with the insight gained from studying these occasional outliers, we have not found a definitive explanation. We suspect the cause or causes will continue to be difficult to detect because few daily relevant data are available to researchers. While it is reasonable to suppose (as previous authors have) that the Monday effect comes from information flows reflecting economic, behavioral, or technical factors, few data series are available to track likely suspects (e.g., changes in inflation, negative investor psychology, or price momentum) on a daily basis.

Content analysis is one way of ferreting out relationships that would be difficult to detect with standard economic or market data. Content analysis supposes text material contains repeated concepts that, when properly analyzed, reveal an underlying association with the treatment of interest. Content analysis parses text material using a structured dictionary containing entries one would expect to be associated with the treatment. The technique compares the frequencies of the words in the dictionary between the treatment and control groups. In our case we selected the Wall Street Journal columns that reported what market participants said on Tuesday caused the previous day's large negative market movements. Our null hypothesis is that there are no systematic differences in the factors cited by the WSJ between Mondays with negative outliers (defined below) and other Mondays.

The statistics from our content analysis tend to reject the null hypothesis and suggest that economic and behavioral factors (and technical factors to a much lesser extent) may be responsible. Statistically significant conclusions are difficult, however, because of the subjective nature of content analysis. If our suspicions are correct, though, it is satisfying that most previous researchers were pursuing relevant explanations but were hampered (and occasionally mislead) by previously undetected outliers and the difficulty of measuring the contemporaneous relationship between negative Mondays and their likely causes.

The Index Return Data

The index return data were drawn from the CRSP daily returns file. The Standard & Poor's 500 Index and Nasdaq value-weighted indexes were used to represent large and small cap stocks, respectively. Returns for the Standard & Poor's 500 Index were available from July 2, 1962 through December 31, 2001 distributed among the days of the week as shown below in Exhibit 1. Returns on the Nasdaq Index were available from December 15, 1972 through December 31, 2001, as shown below in Exhibit 2. In each of these exhibits Panel B contains the subset January 1982 through December 2001.

Exhibit 1—S&P 500 Returns by Day of the Week

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Panel A: 1962—2001					
Observations	1913	2030	2017	1998	1985
Mean	-0.00053	0.00048	0.0084	0.00028	0.00062
p-value	0.030	0.020	< 0.001	0.150	0.002
Panel B: 1982—2001					
Observations	962	1034	1032	1015	1007
Mean	0.00029	0.00076	0.0068	0.00032	0.00043
p-value	0.470	0.010	0.020	0.300	0.170

Exhibit 2—Nasdaq Returns by Day of the Week

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Panel A: 1972—2001					
Observations	1399	1499	1500	1470	1465
Mean	-0.00132	-0.00023	0.01181	0.00129	0.00139
p-value	< 0.001	0.47	0.012	0.011	0.011
Panel B: 1982—2001					
Observations	962	1034	1032	1015	1007
Mean	-0.00101	-0.00002	0.00145	0.00130	0.00116
p-value	0.03	0.95	< 0.001	0.001	0.003

Over the entire time period large cap stock returns (Exhibit 1—Panel A) on Mondays are, on average, negative and statistically different than zero. Over the twenty year period ending in 2001 (Exhibit 1—Panel B), however, the average Monday was positive and statistically insignificant. As has been observed by other authors[1] the negative Monday effect disappeared from large stocks. The Nasdaq tells a different story. For small cap stocks (Exhibit 2), Monday returns are negative on average and statistically different than zero for the entire time period and (although a bit less significant) for the last twenty years. Notice that the average Tuesday is also negative, but not statistically significant.

[1]Pettengill (2003) reviews the reported changes in the negative Monday effect in the section entitled "Shifts in the Monday Effect".

Exploratory Data Analysis

Confirmatory analysis uses parametric statistics to summarize the data while exploratory analysis uses counting and visual techniques to present a more descriptive picture of the underlying data. Exploratory data analysis focuses on the empirical distribution of returns and highlights outliers. Tukey (1977) is the source for the exploratory techniques in this article.

Monday Outliers

The unique properties of Mondays can best be seen by comparing exploratory and confirmatory data analysis. Confirmatory statistics (such as the means and t-tests in Exhibits 1 and 2) can be overly influenced by outliers (they are non-resistant, while exploratory measures are generally resistant). The characteristic of resistance suggests a comparison of confirmatory and exploratory measures to detect the presence or absence of outliers. Exhibits 3 and 4 contain a variety of exploratory measures, while Exhibits 5 and 6 contain Box and Whisker plots of the data.

Exhibit 3—Exploratory Data Analysis—Outliers
S&P 500 Returns by Day of the Week

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Panel A: 1962—2001					
Median	-0.00024	0.00011	0.00083	0.00029	0.00082
Skewness	-4.17460	0.49687	0.87286	0.17402	-0.66288
Lower Inner Fence	-0.01499	-0.01453	-0.01235	-0.01258	-0.01252
Observations below LIF	103	94	116	121	109
Lower Outer Fence	-0.01991	-0.1940	-0.01676	-0.01687	-0.01696
Observations below LOF	53	33	46	51	56
Panel B: 1982—2001					
Median	0.00073	0.00007	0.00063	0.00015	0.00074
Skewness	-5.39448	0.56254	1.12043	0.08293	-0.86326
Lower Inner Fence*	-0.01381	-0.01568	-0.01351	-0.01506	-0.01479
Observations below LIF	66	47	61	54	60
Lower Outer Fence**	-0.01864	-0.02091	-0.01822	-0.02005	-0.01995
Observations below LOF	33	17	20	23	28

*The Lower Inner Fence (LIF) is the median less 1.5 times the interquartile range
**The Lower Outer Fence (LOF) is the median less 2.0 times the interquartile range

In Panel A, Monday is the only day of the week with a negative median. Because the median is negative, over half the Monday returns must have been negative, which is consistent with the negative mean over this period. The positive median for the more recent observations in Panel B, however, shows that eliminating the early years changes the center point of the distribution. Other authors have also documented this positive shift, mainly by looking at Monday's negative average return. Our primary interest, however, is the difference in outliers between these two time periods.

Fences are commonly used to designate outliers. A fence is defined by the median and the interquartile range. The lower inner fence (LIF) is the median less 1.5 times the interquartile range, while the lower outer fence (LOF) is 2.0 times the interquartile range. Similar fences can be defined above the median, although they are not of interest here.[2] These logical boundaries allow us to consider the prevalence and strength of outliers in the daily return data. Panel A of Exhibit 3 shows that Monday's LIF and LOF are set at about the same level as the other days of the week and that Mondays have about as many outliers as the other days of the week. A few strong outliers are also consistent with Monday's strongly negative skew. In Panel B of Exhibit 3 using the last twenty years Monday's negative skew is larger than for 1962 through 2001. Monday's lower fences are smaller (a function of the median and interquartile range). Even though Monday's mean and median return over this period were positive, the returns themselves are characterized as having more negative skewness (-5.39—the most negative of any weekday) with more LOF outliers than the other weekdays (33 for Mondays versus Fridays with the second most at 28). As before with the confirmatory analysis, the exploratory perspective suggests the negative Monday effect has changed in recent years. The center of the distribution has shifted from negative to positive. At the same time, however, the Monday's skewness and the returns themselves continue to evidence the presence of more negative outliers than the other days of the week.

Exhibit 4—Exploratory Data Analysis—Outliers
Nasdaq Returns by Day of the Week

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Panel A: 1972—2001					
Median	-0.00049	0.00011	0.00189	0.00182	0.00201
Skewness	-1.57952	0.31919	0.80264	0.27965	-0.38858
Lower Inner Fence	-0.01665	-0.01489	-0.01256	-0.01254	-0.01125
Observations below LIF	100	115	124	117	111
Lower Outer Fence	-0.02197	-0.01987	-0.01737	-0.01731	-0.01566
Observations below LOF	62	71	69	70	68
Panel B: 1982—2001					
Median	-0.00041	0.00035	0.00188	0.00184	0.00176
Skewness	-1.61514	0.32148	0.90471	0.43373	-0.33612
Lower Inner Fence	-0.01757	-0.01603	-0.01381	-0.01417	-0.01239
Observations below LIF	68	87	80	81	75
Lower Outer Fence	-0.02323	-0.02146	-0.01901	-0.01948	-0.01705
Observations below LOF	42	55	51	52	43

[2]Monday has the smallest number of outliers beyond the upper outer fence (the median plus 1.5 times the interquartile range) in both time periods. Given the negative skewness, we investigated the negative outliers.

The Nasdaq returns in Exhibit 4 shows that the median is negative in both the full and more recent time periods. Monday's skewness is the most negative of the weekdays for both time periods. (Friday's skewness is also negative but by much less.) Monday also has the lowest lower fences (again a function of the median and interquartile range), but the fewest number of observations below these fences. Even so it is the only day with a statistically significant negative average return over both periods.

The Box and Whisker plots in Exhibits 5 and 6 further suggest that Mondays are characterized by occasional large outliers. Box and whisker plots highlight the outliers in a distribution. The left and right vertical edges of the boxes correspond to the third and first quartiles, respectively. Each box, therefore, contains 50 percent of the observations for that day, and the medians are marked within each box by a vertical line. The mean is indicated by the diamond within the box and lies to the right or left of the median, as appropriate. The whiskers are drawn from highest to the lowest observation. Each lower whisker is intersected by the two lower fences. Observations at and beyond the fences are plotted as squares (adjacent squares overlap). Only the lower fences are marked.

Exhibit 5 contains plots for the S&P 500. These box and whisker plots suggest that while every day has outliers, Mondays have more large negative outliers whether considering Panel A (1962-2001) or Panel B (1982-2001). Both plots of Monday's returns are anchored by a single extraordinarily negative return (-20.5 percent on October 19, 1987). Even without this extraordinary value the difference between Mondays and the other days of the week would still appear to be heavily influenced by a relatively few more strongly negative outliers.[3]

Exhibit 6 shows the same analysis for the Nasdaq. In both time periods (Panels A and B) Mondays display outliers that are a bit more negative than for other days of the week, and again the difference appears to be in the strength of a relatively few more outliers.

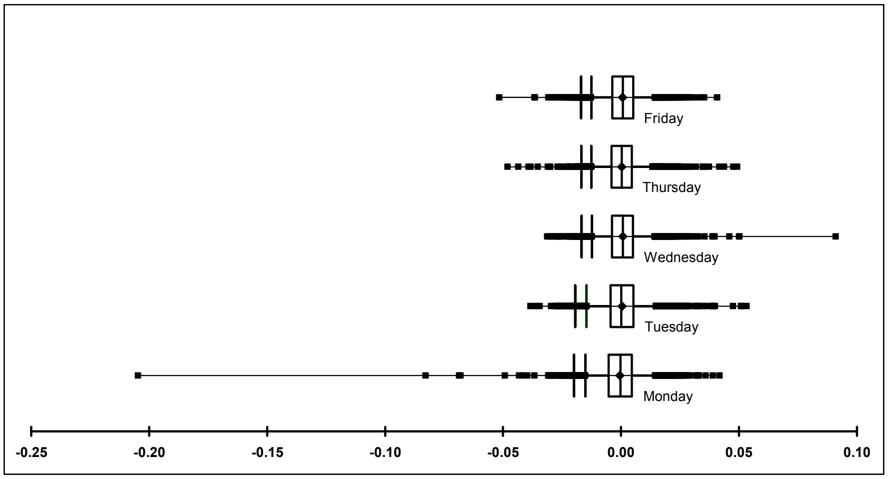
Monday Outliers in the Combined Observations

In the previous section we compared outliers by day of the week. In this section we consider the entire set of S&P 500 data (9,943 observations). Outliers here, therefore, are defined by all observations. We calculated one first quartile (Q1), one LIF, and one LOF for each time period and then counted the outliers. In this respect Exhibits 7 and 8 differ from Exhibits 3 and 4 where the definitions of outliers were specific to each day of the week. Here with a whole sample perspective, we can compare the number of outliers each day contributes to the total. Exhibit 7 displays

[3]We ran the confirmatory and exploratory analyses without this observation and the conclusions were the same—Monday's average return was still statistically significantly negative for the whole time period and the skewness, while reduced, was still negative.

Exhibit 5—Box and Whisker Plots
S&P 500 Returns by Day of the Week

Panel A: 1962—2001



Panel B: 1982—2001

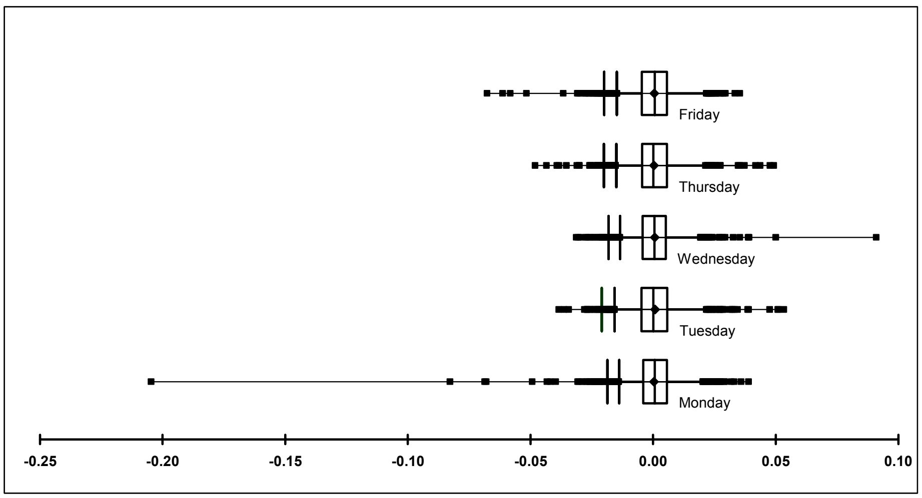
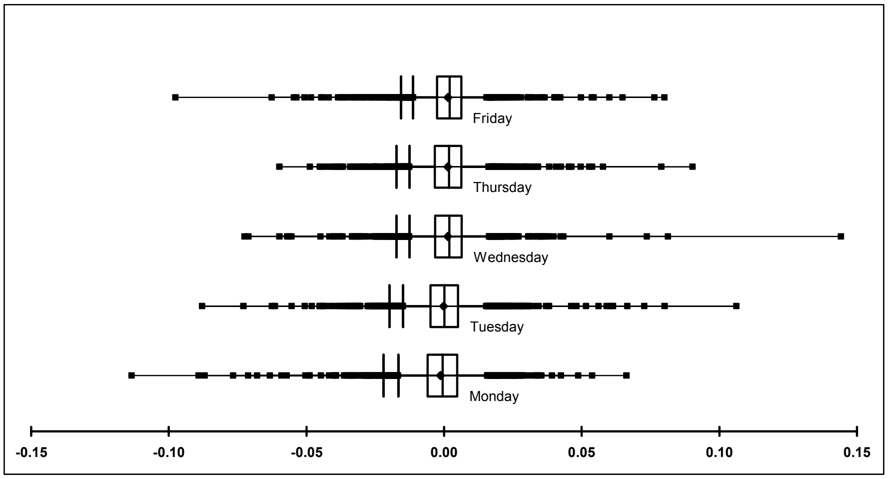
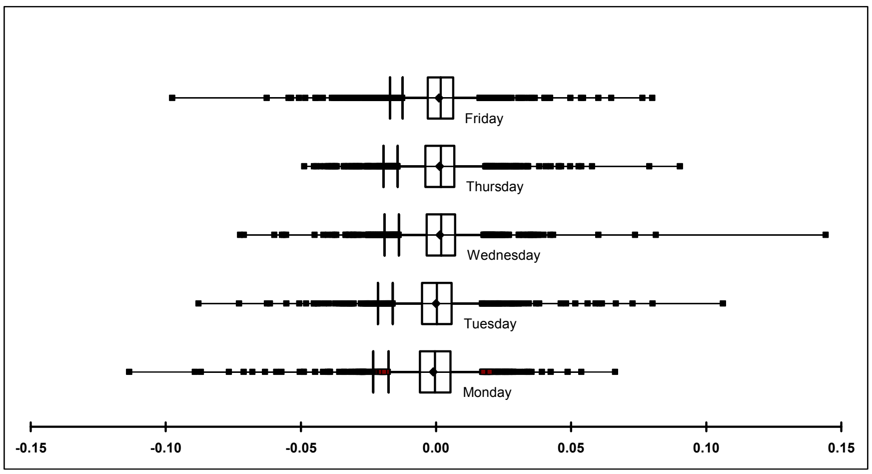


Exhibit 6—Box and Whisker Plots
Nasdaq Returns by Day of the Week

Panel A: 1972—2001



Panel B: 1982—2001



counts of the S&P 500 returns falling in the intervals defined by the fences calculated from the combined observations.

The final column of the Exhibit shows the percentage of the entire sample that qualified for that row's definition of outlier. Of course 25 percent of the days fall below Q1. Panels A and B both show that about 5.5 percent and just over 2 percent of the samples fell below the LIF and the LOF, respectively.

Exhibit 7—Outliers in the Whole Sample
S&P 500 Returns by Day of the Week

Outlier Designation	Monday	Tuesday	Wednesday	Thursday	Friday	All Days - % of sample
Panel A: 1962—2001						
Below Q1	545	518	472	486	454	2475 – 25.0%
% below Q1	22.0%	20.9%	19.1%	19.6%	18.3%	
Below LIF	136	113	99	96	97	541 – 5.5%
% below LIF	25.1%	20.9%	18.3%	17.7%	17.9%	
Below LOF	68	40	37	42	50	237 – 2.4%
% below LOF	28.7%	16.9%	15.6%	17.7%	21.1%	
Panel B: 1982—2001						
Below Q1	228	269	250	253	263	1263 – 25.0%
% below Q1	18.1%	21.3%	19.8%	20.0%	20.8%	
Below LIF	58	59	51	56	60	284 – 5.6%
% below LIF	20.4%	20.8%	18.0%	19.7%	21.1%	
Below LOF	32	18	15	23	28	116 – 2.3%
% below LOF	27.6%	15.5%	12.9%	19.8%	24.1%	

The percent rows display the percentage of observations falling below Q1, below the LIF, or below the LOF for each day of the week based on definitions derived from the whole sample. Panel B shows the results of the same analysis for the 5,050 observations from 1982 through 2001. These three designations: below Q1, the LIF and the LOF, are progressively more conservative definitions of outliers. In Panel A Monday has only a slightly larger share of observations below Q1 (22.0 percent). Recall that for this time period only the average Monday return was negative. Once we set the bar at the lower fences, however, we see that Monday contributed a disproportionate share of these outliers in the whole sample (25.1 percent of all observations below the LIF and 28.7 percent of all those below the LOF). The LIF and LOF rows both provide statistically significant chi-squares beyond the 0.01 level when these rows are tested individually against the null hypothesis of outlier frequency being the same as frequency of the days themselves in the sample.[4] The Q1 row does not produce a statistically significant chi-square statistic. These statistical tests suggest that Monday has a significantly larger share of the outliers in the sam-

[4]Using the sample frequency rather than allocating 20 percent to each weekday adjusts for trading holidays.

ple than the other days of the week. In Panel B with the more recent data we see the negative Monday effect only when the lower outer fence is used. In fact, Monday does not contribute the highest percentage of the outliers below Q1 or the LIF. In this sample the average Monday return was positive. Only the LOF row produces a statistically significant chi-square statistic for Monday's contribution of outliers to all the outliers below the LOF in the sample. For large cap stocks, Monday contributed more strong negative outliers (below the LOF) than the other days. In the more recent period, Monday continues to show the most outliers below the LOF despite the documented positive shift in the underlying distribution of Monday returns.

The Nasdaq results in Exhibit 8 display a different pattern than the S&P 500 results in Exhibit 7. First, the "All Days" column shows that small caps stocks produce proportionally more outliers below the LIF and LOF. Second, Monday has the highest percentage of outliers for each progressively more conservative definition. Comparing Panels A and B suggests that, unlike large cap stocks, Monday contributes the most small cap outliers of any weekday. At the same time the average small cap Monday returns are negative on average for both time periods. Chi-square tests of the rows in these two panels provide statistically significantly differences (beyond the 0.01 level) between the frequency of outliers and the frequency of the days of the week in the samples. In contrast, for large cap stocks (Exhibit 7), only the LOF produced a statistically significant difference in outliers by day of the week.

Exhibit 8—Outliers in the Whole Sample
Nasdaq Returns by Day of the Week

Outlier Designation	Monday	Tuesday	Wednesday	Thursday	Friday	All Days—% of Sample
Panel A—1972—2001						
Below Q1	449	433	333	336	282	1833 – 25%
% below Q1	24.5%	23.6%	18.2%	18.3%	15.4%	
Below LIF	149	129	110	107	84	579 – 8%
% below LIF	25.7%	22.3%	19.0%	18.5%	14.5%	
Below LOF	86	80	62	65	56	349 – 5%
% below LOF	24.6%	22.9%	17.8%	18.6%	16.0%	
Panel B—1982—2001						
Below Q1	292	289	235	242	205	1263 – 25%
% of below Q1	23.1%	22.9%	18.6%	19.2%	16.2%	
Below LIF	98	91	72	77	64	402 – 8%
% below LIF	24.4%	22.6%	17.9%	19.2%	15.9%	
Below LOF	61	54	44	51	46	256 – 5%
% below LOF	23.8%	21.1%	17.2%	19.9%	18.0%	

Our day-by-day analysis suggests that Mondays exhibit more outliers than other days of the week. As a proportion of the whole sample, the number of Mondays' outliers is statistically significantly larger than the other days of the week. While the other days of the week also exhibit outliers, they do not have the same intensity, and their average and median returns are positive. Strong negative outliers, therefore, are a relatively unique characteristic of Monday returns. We now turn to content analysis to uncover some clues as to what might be responsible for these occasional large negative outliers on Mondays. While this research may not fully explain the underlying negative distribution of Monday returns or the documented recent shift in large cap stocks (Exhibit 3), it should contribute to our understanding of this complex phenomenon.

Content Analysis

Most researchers who have investigated the negative Monday effect have offered economic, psychological, or technical explanations. Whatever the root causes, if Mondays are characterized by occasional outliers, then the associated events should be newsworthy. Content analysis is an exploratory tool that looks for an underlying commonality or structure in text.[5] In this case we have used the technique to parse the Wall Street Journal column that reports what Wall Street professionals are saying explained the previous day's market movement. We assume that whatever causes negative outlier Mondays should be newsworthy enough to be mentioned more frequently on the following Tuesday and less frequently on Tuesdays following other Mondays.

Content analysis cannot operate in a vacuum. The technique looks for words and phrases within a structure that is described by the researcher. This structure is expressed as a hierarchical list of terms (a dictionary in the content analysis literature) that the investigator expects to be associated with the effect. In our case we needed to decide which terms and phrases commonly used to describe market-related economic, psychological, and technical events should be included in our dictionary.

Obviously the way we built our dictionary would largely have determined any structure we might find and is a potential source of bias in our results. The content analysis literature suggests structured dictionaries should not be devised by the primary researchers, especially those who have studied the text to be analyzed. Our alternative was to convene a panel of experts to suggest concepts and factors they would expect to be associated with the general phenomenon, in this case daily stock market movements.[6] These concepts could then be converted into dictionary entries and the analysis directed to look for words and phrases that represented these entries.

To help us, we invited a panel of experts made up of the authors of the other papers in this edition. We asked our panelists to assume they had agreed to write a

[5]Content analysis has a wide variety of uses in other disciplines (e.g., discovering whether all of Shakespeare's plays had the same author).

[6]Avoiding the investigator bias was discussed in the content analysis literature as early as 1959; see Pool (1959) pp. 214-216. For the expert approach see Saris-Gallhofer et al. (1978) and a discussion of their work in Weber (1985) pp. 19-20.

daily market commentary for the business section of their local paper. Their charge was to describe and explain, in two or three paragraphs, the factors behind the market's behavior since the previous day's close. We asked them to be even-handed in attributing market movements to both economic and behavioral factors. Each panelist listed five economic and behavioral factors they would expect to regularly invoke in their columns. We entered these factors into a lexicographical program that provided grammatical variations on the panel's suggestions, expanding the dictionary entries without, we believe, changing the panel's intent. We then organized the words and phrases hierarchically into major categories. The resulting categories are shown in Exhibit 9, and the complete dictionary is contained in the appendix. Throughout the remainder of our analysis we have suppressed the grammatical variations without, we trust, a substantial loss of clarity.

Exhibit 9—Major Categories in the Content Analysis Dictionary

Economic Categories		
	Interest Rates	Bonds
	Price Levels	Fiscal Policy
	Fed Policy	Oil
	Trade	Exchange Rates
	Corporate Profits	Technology
	US Economy	US Politics
		Regulation
Psychological Categories		
	Positive Sentiment	Negative Sentiment
Technical Categories		
	Market Actors	Technical Factors

As shown in the appendix, each of these categories had a variety of words and phrases associated with it that directed the content analysis. For example the category "Price Levels" was further defined by the words and phrases: Consumer Price Index, Purchaser Price Index (and their abbreviations), Overheated Economy, Inflation, Wholesale Prices, and Deflation. Combinations or grammatical permutations of these words counted as a hit.

The panel's most significant contribution to the dictionary was the suggestion to add technical factors. While we had not originally considered technical factors, our subsequent analysis revealed that the Wall Street Journal occasionally invokes technical explanations such as momentum, resistance levels, and computer-generated trading. Economic and psychological factors were anticipated and, as shown below, useful.

The final dictionary combined the panel's suggestions and the words and phrases from the lexicographical program with our additions based on preliminary tests of the text against the dictionary. We added words and adjusted phrases to make the dictionary more consistent with the Wall Street Journal's choice of words while, in our opinion, maintaining the panel's intent. While we recognize that our additions may have been a source of bias toward finding significant categories in the text, we believe the need to conform our dictionary to the Wall Street Journal's style was worth more in results than it cost in potential bias. Unfortunately, without these adjustments, content analysis found too few occurrences of the words in the original dictionary to draw any conclusions.[7] As a final check on our dictionary, we let content analysis suggest words that it found differentiated between the two sets of Monday articles. These suggestions did not add significantly to the results, so only our dictionary results are reported here.

Validity is a concern to any researcher. Weber (1985, p. 18) gives the following example of validity in content analysis: a valid content analysis assumes "there is a correspondence between the category (economic) and the abstract concept that it represents (concern with economic matters)" (parentheses in the original). In our research, we assume there is a correspondence between the WSJ's explanation of market movements and the categories listed in Exhibit 9 and their constituent words listed in the appendix. As the WSJ's purpose in writing the column is to report market professionals' explanations of market movements, the assumption of association is reasonable. Content analysis, however, is not capable of discerning cause and effect; that is, the mention of the word does not necessarily mean professionals attributed the market's movement to the abstract concept that word or category was designed to represent. With this cause and effect caveat, we believe that our application of content analysis, guided by the expert panel, is valid.

Text Data

Once the dictionary was complete, we collected articles from the Wall Street Journal (WSJ) for all available Mondays below the LIF and an identically-sized sample of regular Mondays chosen at random. We used separate samples for the S&P 500 and Nasdaq. Our electronic WSJ files started in 1988. Using the LIF definition of outliers, our sample consisted of 46 negative Mondays for the S&P 500 (79 percent of the 58 since 1982; see Exhibit 7, Panel B row labeled "Below LIF") and 61 negative Mondays for the Nasdaq (62 percent of the 98 since 1982; see Exhibit 8, Panel B, row labeled "Below LIF"). The full samples were then 92 Mondays for the S&P 500 and 122 Mondays for the Nasdaq. We do not know if our conclusions would have been any different if we had more articles to analyze. Our analysis of the return data suggests, however, that a more recent sample is biased against finding any significant association with outlier Mondays in large cap stocks because the average over the last twenty years has been positive. Despite these drawbacks the analysis proved compelling.

[7]Our experience with content analysis reinforced one of the drawbacks cited in the literature—replicability. Different researchers with different dictionaries might have reached different conclusions. Despite this drawback we believe our dictionary is plausible and our results credible.

Results

The content analysis results are summarized in the two panels of Exhibit 10. This exhibit shows the frequencies with which the words within each category were mentioned in the WSJ, each row's statistical test and p-value, as well as the overall statistical significance of the combined categories. This exhibit is a fundamental part of our conclusions, so we cover it here in some detail.

Exhibit 10—Dictionary Categories
Frequencies and Statistical Significance

	Frequency Counts				
Category	Non-Outlier Mondays	Negative Outlier Mondays	Total	$\chi 2$	p-value
Panel A: S&P 500					
Bonds	198	399	597	67.67	0.00
US Economy	11	23	34	4.24	0.04
Exchange Rates	251	475	726	69.11	0.00
Fed Policy	90	130	220	7.27	0.01
Fiscal Policy	4	11	15	3.27	0.07
Interest Rates	43	112	155	30.72	0.00
Market Actors	8	31	39	13.56	0.00
Oil	27	39	66	2.18	0.14
Price Levels	37	57	94	4.26	0.04
Corporate Profits	26	135	161	73.80	0.00
Regulation	0	1	1	1.00	0.32
Sentiment	71	222	293	77.82	0.00
Technical Factors	6	18	24	6.00	0.01
Technology	110	260	370	60.81	0.00
Trade	1	3	4	1.00	0.32
US Politics	14	40	54	12.52	0.00
Totals	897	1956	2853	393.09	0.00
Panel B: Nasdaq					
Bonds	355	303	658	4.11	0.04
US Economy	30	17	47	3.60	0.06
Exchange Rates	466	316	782	28.77	0.00
Fed Policy	191	112	303	20.60	0.00
Fiscal Policy	11	7	18	0.89	0.35
Interest Rates	91	72	163	2.21	0.14
Market Actors	18	21	39	0.23	0.63
Oil	33	57	90	6.40	0.01
Price Levels	64	42	106	4.57	0.03
Corporate Profits	51	169	220	63.29	0.00
Regulation	0	0	0	NMF*	NMF*
Sentiment	123	220	343	27.43	0.00
Technical Factors	14	21	35	1.40	0.24
Technology	180	458	638	121.13	0.00
Trade	5	0	5	5.00	0.03
US Politics	23	41	64	5.06	0.02
Totals	1655	1856	3511	11.51	0.00

* Not meaningful

In a paired sample such as ours, the most reasonable test is whether each category is mentioned more often on outlier Mondays than non-outlier Mondays. We tested this hypothesis with a chi-square statistic.[8]

Both Panels in Exhibit 10 show that differences between the total negative outliers and non-outliers for large and small cap stocks are both significant in our χ^2 tests beyond the 0.001 level. Most of the individual categories also have significant differences in frequencies.

Before we analyze Exhibit 10, it is instructive to look behind these categories to their constituents. As an example, consider the Fed Policy category for large cap stocks. Exhibit 10 shows that overall the words and phrases in this category were mentioned 130 times on negative outlier Mondays versus 90 times on non-outlier Mondays. Exhibit 11 shows that in this category only two of the constituent words and phrases—"Fed" and "Federal Reserve" —had significantly different frequencies between outlier and non-outlier Mondays. "Tighten" was also significantly different, but only contributed three observations. The other words and phrases were not mentioned or mentioned with such similar frequencies as to be insignificantly different. These results were typical in the sense that for Exhibit 10's categories with significant p-values, less than half of their individual words and phrases showed significant differences. The categories themselves, however, showed significant differences because the predominant frequency favored either outlier or non-outlier Mondays. Exhibit 11, therefore, is a more detailed view of the "Fed Policy" row in Panel A of Exhibit 10 and typical of the detail behind the remainder of the rows. We believe that reporting statistical significance at the category level as in Exhibit 10 best reflects the intent of our content analysis.

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[8]Because we have an equal number of outlier and non-outlier Mondays our null hypothesis for each row is that the frequency counts are equal between outlier and non-outlier Mondays. Formally we used the statistic:

$$Q = \sum_{i=1}^{2} \frac{[N_i - E(N_i)]^2}{E(N_i)}$$

where N_i is the observed cell frequency and $E(N_i)$ is the expected cell frequency (i.e., row total/2). For example the statistic for the Bonds category in Exhibit 10 was computed using $E(N_i) = 597/2 = 298.5$, $N_1 = 198$, and $N_2 = 399$.

$$\text{The } \chi^2 = \frac{(198 - 298.5)^2}{298.5} + \frac{(399 - 298.5)^2}{298.5} = 67.67$$

which is approximately a χ^2 with 1 degree of freedom and significant beyond the 0.001 level.

Exhibit 11—Frequencies and Statistical Significance
Federal Reserve Policy Category Words and Phrases

S&P 500

Word or Phrase	Frequency Count: Non-Outlier Mondays	Frequency Count: Negative Outlier Mondays	Total	χ2	p-value
Ease	6	6	12	0.00	1.00
Fed	47	73	120	5.63	0.02
Fed Policy	2	2	4	0.00	1.00
Federal Reserve	21	37	58	4.41	0.04
Intervention	3	4	7	0.14	0.71
Looser Fed Policy	0	0	0	NMF*	NMF*
Loosen	0	0	0	NMF*	NMF*
Monetary	2	2	4	0.00	1.00
Monetary Policy	4	2	6	0.67	0.41
Refunding	2	4	6	0.67	0.41
Reserve	0	0	0	NMF*	NMF*
Tighter Fed Policy	0	0	0	NMF*	NMF*
Tighten	3	0	3	3.00	0.08
Total	90	130	220	7.27	0.01

* Not meaningful

Returning to Exhibit 10, we see that most of the categories in both panels are significantly different. From these results, we conclude that outlier and non-outlier Mondays are different. That is, our content analysis has identified categories of words and phrases that differentiate between outlier and non-outlier Mondays for both large and small cap stocks. These results suggest that the market may have different explanations for movements on outlier and non-outlier Mondays. This is the first dimension of our content analysis results.

We also observe some interesting differences between large and small cap stocks. In Panel A, all the categories are mentioned much more often on negative outlier Mondays. For half of the categories in Panel B, the opposite is true. Of the significant categories for Panel A's large cap stocks (all of which are predominant on negative outlier Mondays), only Sentiment, Technical Factors, Technology, Trade, and US Politics are also mentioned more frequently on negative outlier Mondays for small cap stocks. (Oil is significant for small caps, but insignificant for large caps). The other categories (Bonds, US Economy, Exchange Rates, Fed Policy, Fiscal Policy, Interest Rates, Market Actors, Price Levels, and Corporate Profits) are all more frequently mentioned on non-outlier Mondays for small cap stocks. Apparently the market associates these categories with large negative movements in large cap stocks, but not with similar movements in small cap stocks. This is the second dimension of our content analysis results. One could speculate that most of these categories are relevant on negative Mondays for large stocks because they are usually associated with macroeconomic factors, but that supposition, while attractive, is beyond the capabilities of the technique. Content analysis only reports that the words and phrases in these categories are mentioned significantly more often on negative outlier Mondays.

Like other statistical procedures, content analysis does not reveal causation. We cannot say that because, for example, the Fed Policy category was mentioned more often on large cap negative outlier Mondays that concerns over Fed policy caused the large cap market to drop sharply on those days. Without analyzing the full text of the articles, it is not possible to tell why the words and phrases in the Fed Policy category were mentioned more often on outlier Mondays.[9] We can only infer from the preponderance of statistically significant categories what sorts of terms were associated by the Wall Street Journal reporters—by attribution to market professionals—with the proximate events of the day. This example also illustrates how rumors about important economic variables might (and in an efficient market probably should) move markets but not show up in any economic time series.

The third dimension of our results concerns the only categories—Sentiment, Corporate Profits, Oil, Technology, and US Politics—that are associated with negative outlier Mondays in small cap stocks. A tenable hypothesis is that small and large cap stocks differ in their susceptibility to macro and microeconomic trends. Small caps might not be influenced much by the macroeconomic categories that affected large caps, but would respond on a microeconomic level to diminished prospects for corporate profits and specific industries such as technology. If true, this hypothesis could explain our results in both panels of Exhibit 10 and would be consistent with our speculation above about large cap stocks. Again, however, this speculation is not testable with the data we have collected or the content analysis technique.

Technical factors were suggested by our expert panel. They were mentioned by the WSJ more frequently on outlier Mondays for both large and small cap stocks. While the difference in frequency is significant for large cap stocks, the total number of observations is small for both large and small cap stocks. These results do not mean that technical factors or, for that matter, any of the other insignificant factors are not a potential explanation. The WSJ reporters may have had a personal bias or an editorial policy against technical analysis. The market participants consulted by these reporters may have had their own biases. Content analysis, like other techniques, cannot make inferences if the data do not contain the information, whether by accident or design.

While we cannot claim to have found an explanation for the negative outlier Mondays, we believe our content analysis results suggest market professionals

[9]We did review the context of each occurrence of all these terms. During the time period studied the WSJ repeatedly reported that the market was concerned that the Fed would raise rates and deflate the rally. Hints or rumors of pending Fed action (which, in fact, did not materialize) appeared to be enough to cause the market to fall. The point is that while we can infer this connection (given our biases), it is unfair to expect a statistical analysis to reveal causation.

believe economics and investor psychology are responsible. While large cap stocks did exhibit outlier Mondays during the period for which the WSJ articles were available, our earlier evidence suggests that not as many outliers occurred during this period as earlier. Small cap stocks, however, should provide a better test because they exhibited a more consistent pattern of outliers over the whole period studied.

If small cap stocks are a better laboratory for investigating outliers because outliers occur here more regularly than for large cap stocks, our content analysis results suggest previous researchers were on the right track. Factors that economists believe should matter, such as corporate profits and investor behavior, are associated with outlier Mondays. Whether these factors caused the market to decline on these days is beyond the ability of the statistics to tell us. One way to interpret these results is to take comfort in their familiarity—in the sense that we do not need to invoke explanations beyond efficient markets or investor psychology. At the same time, some things that we expected to be major contributors to the difference between Mondays (such as Technical Factors and Regulation) were not. We do not know whether those results stem from our inability to craft our dictionary skillfully enough or from the relatively short time span covered by our WSJ articles. From a broader perspective, however, these results are consistent with previous research and may help explain why some of the prior researchers reached the conclusions they did.

Relationship to Previous Research

If we believe the explanation for the Monday effect lies in rational pricing responses to information flows [in the lexicon of Pettengill (2003)], then our evidence is consistent with an announcement effect. Firms may wait until the market closes on Friday to release bad news. Government agencies often do the same. Unfortunately, as Pettengill (2003, p. 12) points out "… attempts to link such releases with the weekend effect have been only partially successful." Damodaran (1989), for example, fails to find a significant link between two likely suspects—earnings and dividend announcements—and the weekend effect. Other researchers have come to similar conclusions.

Our research suggests that while these investigators were on the right track, they were not—and probably could not—measure the variables that moved either individual stocks or the market. Efficient markets attempt to anticipate information flows and should respond to rumors—on the chance they turn out to be true. If so, measuring these effects will be difficult. We suspect, however, that macro effects and rumors about them will be a fertile area for future research.

Summary and Conclusion

Previous research has reported that only on Mondays have average returns been negative, but has not been able to identify a source of these negative returns. We have presented evidence that Monday's negative average return comes not only from consistently negative returns, but also from large infrequent outliers. These outliers have been present in both large and small cap stock returns for at least forty years. Large cap stock averages for the last twenty years have been positive, but the outliers, although somewhat weaker, remain. Small cap stocks average returns on Mondays continue to be negative and characterized by outliers.

Apparently, information that arrives in the capital markets either over the weekend or during the day on Monday is occasionally so strongly negative that it results in large negative returns. We have identified the dates of these negative outliers for both large and small cap stocks. They did not appear to follow any regular pattern and, given the rigorous efforts of previous researchers, we did not believe a search for an association with existing economic time series would be fruitful, largely because so few daily economic time series are available. As others before us, we hypothesized that economic, psychological, or technical factors might be at work. We then turned to the Wall Street Journal's daily explanation of what moved the market to look for an explanation. We used content analysis to parse the text of these articles with a dictionary suggested by a panel of experts in the field. The content analysis suggested that the causes offered by previous researchers based on economic or psychological factors might be responsible. While we may not have identified the cause, our results certainly suggest that previous researchers were on the right track. Further research might profitably focus on the variables suggested here as the search for the source of the Monday effect continues.

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Appendix—Dictionary Structure for Content Analysis

The dictionary allowed the content analysis routine to look for permutations and combinations of the basic words and phrases listed here. For example any mention of interest discount, or prime rates counted as a hit in the interest rate category. The program also counted plurals and different parts of speech of these words.

- Bonds
  - Convertible
  - Corporate
  - Coupon
  - Debenture
  - Government
  - Junk
  - High Yield
  - Municipal
  - Debenture
  - Treasury Obligation
- Corporate Profits
  - Earnings
- Exchange Rates
  - Central Bank Intervention
  - Dollar
  - Euro
  - Yen
- Fed Policy
  - Ease
  - Tighten
  - Intervention
  - Monetary Policy
- Fiscal Policy
  - Budget Deficit
  - Budget Surplus
- Interest Rates
  - Discount Rate
  - Prime Rate
  - Bond Yields
  - 30 year Yields & Price
  - Long Bond Yields & Price
- Market Actors
  - Bond Traders
  - Computer Driven
  - Arbitrageurs
- Oil
  - Oil Prices
  - Petroleum
  - Fossil Fuel
  - Crude Oil
- Price Levels
  - Consumer Price Index
  - Purchaser Price Index
  - Overheated Economy
  - Inflation
  - Wholesale Prices
  - Deflation
- Regulation
  - SEC
- Sentiment
- Positive
  - Comfortable
  - Confident
  - Fearless
  - Glad
  - Good News
  - Happy
  - Healthy
  - No Fear
  - Fearless
  - Positive
  - Reassure
  - Robust
  - Sunny
  - Upbeat
  - Welcome News

- Negative
  - Bad News
  - Bleak
  - Confused
  - Cringe
  - Depressing
  - Disappointing
  - Fragile
  - Jitters
  - Negative
  - Nervous
  - Fear
  - Gloom
  - Spook
  - Skittish
  - Worry
- Technical Factors
  - Buying Pressure
  - Inflection Point
  - Momentum
  - Point of Support
  - Selling Pressure
  - Point of Resistance
- Technology
  - Compaq
  - Dell
  - IBM
  - Hewlett Packard
  - Intel
  - Cisco
  - Lucent
- Trade
  - Balance of Payments
  - Trade Deficit
  - Purchasing Power Parity
- Trading
  - Program Trading
  - Profit Taking
  - Stock Index Arbitrage
- US Economy
  - Bankruptcy
  - GDP
  - GNP
  - Industrial Production
  - Leading Indicators
  - Payroll
  - Housing Starts
  - Employment
  - Unemployment
  - Jobs
- US Politics
  - Congress
  - President
  - Senate
  - House