PENNY STOCKS, MARKET MICROSTRUCTURE, AND ANALYST FORECASTS

by

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ABSTRACT

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The first essay of this dissertation deals with the relationship between previous earnings, earnings forecasts, and future returns. I found that stocks with the worst previous earnings and the worst earnings forecasts outperform the ones with more optimistic outlooks. Value stocks also tend to outperform glamour stocks. I also found that previous earnings are the dominating factor in determining subsequent returns. The second essay deals with the Bid-Ask Spread (BAS) behavior of penny stocks throughout trading sessions. I ran the analysis by using different days of the week, months of the year, and analyst coverage. Finally, I regressed the minute-to-minute BAS against activity, risk, and information variables.

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CHAPTER 1

EARNINGS CHANGES, FORECASTS, AND CONTRARIAN PROFITS

1.1 Literature Review

Contrarian trading strategies, that is, trading against what is considered the appropriate way of investing, have been accurately demonstrated and well documented in the financial literature. However, significant research has not yet been conducted on profitability in terms of the difference between value and glamour stocks. Valuation ratios, such as the book-to-market equity ratio and price earnings (P/E) ratio, are used to determine whether stocks can be considered value or glamour. Firms that have high book-to-market ratios are considered value, whereas firms that have lower Book-to-Market Equity ratios are considered glamour.

Despite the fact that contrarian strategies have been shown to be profitable in the literature, some papers have postulated otherwise. Seigel (1995), Beneda (2002), and Cheh et al. (2008) have reported that high P/E ratio firms, or growth firms, outperform low P/E ratio firms, that is, have a higher value, for significantly longer holding periods. This difference is observed in the presence of bull markets and when portfolios are frequently rebalanced.

The financial literature has also demonstrated a negative relationship between stock returns and several other variables:

- Prior growth rates in earnings forecasts (LaPorta [1996] and Gleason and Lee [2003])
- Sales (Lakonishok, Vishny, and Shleifer [1994])
- Capital expenditures (Titman, Wei, and Xie [2004]; Xing [2008]; and Anderson and García-Feijóo [2006])
- Market share (Hou and Robinson [2006])
- Operating efficiencies (Nguyen and Swanson [2007])

- Total assets (Cooper, Gulen, and Schill [2008])

However, these studies do not account for heterogeneity within glamour and value groups; that is, they do not consider the differences in specific value and glamour groups. One of the approaches of this essay is to analyze those differences within value and glamour stocks and determine if they are significant.

Investors have different perceptions of earnings of value and glamour stocks, a fact that generates different issues for professional analysts and company management. Some of these issues are:

- Asymmetrically large response of glamour stocks to negative earnings surprises (Skinner and Sloan [2002] and Rees [2010])
- The implications of those surprises, specifically in terms of the management of analysts' expectations in order to avoid negative surprises in the first place (Matsumoto [2002])
- Monetary incentives for managers to report favorable estimates and establish good relationships with top executives (Francis and Philbrick [1993]; Carleton, Chen, and Steiner [1998]; Michaely and Womack [1999]; Lim [2001]; Hong and Kubik [2003]; and Sanchez and Zantout [2007])

There is also evidence in the literature that analysts will recommend glamour stocks to make them appealing to institutional investors, especially those who tend to invest in these types of firms. According to Jegadeesh et al (2004), these recommendations tend to cause stocks that have less favorable recommendations to underperform.

Rees (2005) found that predicting forecast errors is more important than predicting earnings changes. It is therefore important that models include two thresholds: meeting analysts' forecasts and having a positive earnings change. There is evidence that total return is greater when both of those thresholds are met rather than only one of them. Conversely, forecast errors have better prediction power than earnings changes.

In a 2010 paper, Rees demonstrated a positive relationship between the probability that earnings meet analysts' expectations and the number of analysts following stocks, market capitalization value of the firm, the use of conservative accounting practices, analyst forecast revisions, and recent profitability. On the other hand, she demonstrated a negative relationship in the dispersion of forecasts across analysts, accruals, net operating asset turnovers, and earnings yield.

Some findings, such as those reported by Au and Foley (2006), indicate that actual fund core portfolios tend to outperform style-based portfolios in domestic and international markets. Part of their conclusion, that for style investing, there is some blurring between value and core and growth and core, is particularly interesting because it defies the established relationship between value and glamour. However, the authors presume that the problem is related more to the construction of the portfolios by the funds than to the styles per se.

Other papers also demonstrate that analysts' forecasts tend to be extremely optimistic. Goedhart, Raj, and Saxena (2010) demonstrated that these optimistic predictions were met only in 2003–2006, which saw strong economic performance. However, forecasts in the other time periods were not met, and actual numbers were worse than the predictions.

Au and Shapiro (2010) demonstrated that value and momentum, in spite of being opposites, outperform the market. After periods of negative market returns, stocks with the lowest momentum have the highest betas, and if the market goes down, returns will also decline.

Callaghan, Murphy, Parkash, and Quian (2009) found that current stock prices accurately reflect long-term earnings growth forecasts. They showed that long-term earnings growth rates are related to P/E ratios, suggesting that stock prices reflect more than analysts' opinions. Nevertheless, Institutional Brokers Estimates System (IBES) forecasts, though inaccurate, still affect market prices.

Dunn and Nathan (2009) discovered that firm diversification affects the accuracy of analyst forecasts. The more diversified a company is, the more difficult to determine earnings accuracy. Diversification also increases disagreement amongst analysts. For long-term forecasts, Fortin, Gilkeson, and Michelson (2007) found that the more changes the analysts made to the forecasts, the lower their accuracy.

Sanchez and Zantout (2007) discovered that event-induced forecast revisions suggest irrelevance when announcing new products or abandonment of research and development. There is an asymmetric reaction between dividend change–induced revision and stock returns.

This essay contributes to the literature by determining if contrarian profits based on previous earnings and analyst forecasts are consistent between value and glamour stocks. There are three major findings:

1. Stock performance is related to recent changes in earnings, but this relationship is opposite for value and glamour stocks. There is a positive relationship in value stocks and a negative relationship in glamour stocks. Hence, value stocks should follow a previous earnings momentum strategy, and glamour stocks should follow a contrarian earnings growth strategy.
2. Contrarian strategies relative to analyst forecasts should be pursued by investors. In my sample period, firms with the most optimistic year-to-year forecast had the worst subsequent year performance, a significant difference of 0.48% per month for the sample period. There is no specific differentiation for value or glamour stocks. Then there are forecast changes, glamour stocks are more favored by analysts.
3. Fama-MacBeth (1973) cross-sectional regressions confirm that there are contrarian relationships for both recent earnings and earnings forecasts after controlling for beta. Time series regressions against the Fama-French (1993) three-factor model are not able to completely give a risk-based explanation to contrarian profits.

1.2 Hypotheses

This study addresses the following hypotheses.

1.2.1 Hypothesis 1: Analysts give better recommendations for firms that had better previous earnings changes.

It has been documented in the literature that analysts tend to favor glamour stocks. In this essay, I also intend to demonstrate that fact. In other words, most analysts will consider momentum when formulating their forecasts. I have designed earnings change and earnings forecast variables to test this hypothesis.

1.2.2 Hypothesis 2: Value firms outperform glamour firms when considering overall yearly returns.

This hypothesis has also been proven by the literature. However, my sample will further support that finding. It is important to note that the sample is based on available data from IBES. Therefore, it yields more information on glamour stocks than on value stocks; the data section of this essay goes into the sample in detail.

1.2.3 Hypothesis 3: Firms with worse previous earnings changes outperform firms with better previous earnings changes.

I formed quintiles based on BE/ME and changes in earnings to see if firms with better previous performance had worse subsequent returns. My expectation is that the difference between better previous earnings quintiles and worse previous earnings quintiles will be negative and significant.

1.2.4 Hypothesis 4: Firms with worse analyst recommendations outperform firms with better analyst recommendations.

As with the previous hypothesis, I formed quintiles based on BE/ME and earnings forecasts. If analysts were accurate, firms with better forecasts will have better subsequent returns. However, I expect to see negative subsequent return differences between better and worse earnings forecasts.

1.2.5 Hypothesis 5: Contrarian strategies have a significant influence on excess portfolio returns.

I will run a regression of excess returns against beta, change in earnings, and earnings forecasts. If contrarian strategies have an influence on excess returns, coefficients should be negative and significant. I expect to see that both coefficients, the one for change in earnings and the one for earnings forecasts, are negative and significant.

1.2.6 Hypothesis 6: Contrarian strategies' excess returns cannot be explained by risk factors.

Finally, I will run a time series regression of returns against the Fama-French three-factor model. I expect to see significant intercepts, hinting that these returns are not completely explained by risk variables. For the other factors, I expect to see a positive relation to the market and a negative relation to the Small-minus-Big factor (SMB) due to a dominant position of larger firms in the sample and a negative relation to the High-minus-Low Factor (HML) due to a dominant position of glamour firms in the sample.

1.3 Data

I retrieved consensus earnings forecasts from the IBES detailed database, accounting data from COMPUSTAT, and return data from The Center for Research in Security Prices (CRSP). The time period that covers this study is 1984–2010, and the three databases were merged.

Consensus earnings forecasts used in this analysis are the ones immediately generated after the release of the first quarter earnings of each year, as suggested by Elton, Gruber, and Bultekin (1981). BE/ME is calculated with the book value of equity plus balance sheet deferred taxes for the 4-quarter period ending in quarter 1, year y, divided by the marked value of equity available at the quarter 2, year y, earnings announcement. To avoid any mismatch in dates, I considered only firms with a fiscal year ending on December 31. Stocks priced less than $5 were eliminated as well as financial firms, REITs, and ADRs. Firms on this sample are traded in the NYSE, AMEX, and NASDAQ.

One of the variables that I use in this study is earnings growth forecast (F), which is calculated with the difference between the consensus one-year ahead earnings forecast and the most recent trailing 4-quarter earnings:

$$F_{y+1} = \frac{\left[E_y\left(EPS_{y+1}\right) - EPS_y\right]}{P_{2,y}}$$

$E_y(EPS_{y+1})$ is the forecast generated in year y for year y+1. EPS_y is the sum of the most recent four quarterly earnings, ending in quarter 1, year y. The difference is standardized by the quarter 2, year y, stock price.

The second variable that I have created for this analysis is the ΔE variable, which is the difference between the sum of quarterly realized earnings per share until quarter 1, year y, minus the sum of quarterly realized earnings per share until quarter 1, year y-1.

$$\Delta EPS_y = \frac{\left(EPS_y - EPS_{y-1}\right)}{P_{2,y}}$$

To illustrate the calculation of these variables, I chose to use an example based on General Electric (Ticker: GE, CUSIP: 36960410). GE's data is shown in Table 1.1.

Table 1.1 Variable Calculation Example

	2Q99	3Q99	4Q99	1Q00	2Q00	3Q00	4Q00	1Q01	2Q01
Release	7/8	10/07	1/20	4/13	7/13	10/11	1/17	4/12	7/12
EPS	0.283	0.2667	0.31	0.26	0.34	0.32	0.36	0.30	0.39
Forecast					1.44				1.72
Price									48.75

The F variable for 2002 is calculated as follows:

$$F_{2002} = \frac{[E_{2001}(EPS_{2002}) - EPS_{2001}]}{P_{2001}} = \frac{(1.72 - 1.32)}{48.75} = 0.008205$$

1.72 is the yearly earnings forecast for 2002, generated immediately after the release of the quarter 2, 2001, earnings, that is, on 7/12/2001. 1.32, on the other hand, is the sum of quarterly earnings per share (EPS), starting on quarter 2, 2000, until quarter 1, 2001, (0.34 + 0.32 + 0.36 + 0.30). GE's price at the end of quarter 2 was 48.75.

Finally, the ΔE calculation is as follows:

$$\Delta E_{2001} = \frac{[(0.34 + 0.32 + 0.36 + 0.30) - (0.2833\ +\ 0.2667\ +\ 0.31\ +\ 0.26)]}{48.75} = 0.0041025$$

The first term is equal to 1.32, the same figure as in the F calculation. The second term is equal to 1.12. Finally, the difference is scaled by the price at quarter 2, year y, earnings.

It is important to note that all of the data points are required to make the calculations. If for some reason one of the quarterly earnings data points was missing, that specific observation was discarded, and the ΔE and F variables were not calculated for that time period. This strict requirement caused the elimination of several observations. However, the final sample consists of accurate ΔE and F variables.

1.4 Analysis of the ΔE and F Variables

1.4.1 Portfolio Formation

In the first part of the study, I created three groups of tables of 25 value-weighted portfolios, one group based on independent sorts in ΔE and BE/ME, the second group based on independent sorts of F and BE/ME, and the third group based on the calculation of F from independent sorts of ΔE and BE/ME. Each group consists of five different tables based on the way returns are calculated: (1) equally weighted returns, (2) value-weighted returns, (3) and (4) equally and value-weighted returns with winsorization, and (5) medians. All portfolios are rebalanced each July of year y, and held for 12 months until June of year y+1. The reported numbers are yearly simple averages for those specific portfolios.

1.4.2 Group Based on Independent Sort in ΔE and BE/ME

The first five tables show the results of the portfolios calculated by the independent sort of ΔE and BE/ME. The sorting of ΔE was done within the sample. However, for BE/ME, I used Kenneth French's BE/ME breakpoints to avoid any sampling bias. A negative number implies that the most recent earnings were less than the least recent earnings. I expect to see negative numbers in the first rows of the table, that is, firms that have not performed well in the last year. For the BE/ME based sorting, I expect to see a more extreme behavior in value firms, that is, a higher best-worst difference.

1.4.2.1 Equally Weighted Mean

Table 1.2 shows the calculation of equally weighted portfolios sorted by ΔE and BE/ME. As expected, the first two lines in the ΔE sorting were negative. On the other hand, the best portfolio has some very large values. There is a chance that these values are driven by small firms. If that is in fact the case, the value-weighted mean calculation should give an insight. However, it is also possible that those values are being driven by outliers. If that is true, winsorizing the observations should mitigate the problem. Differences between best and worst changes in EPS for BE/ME quintiles are positive and mostly significant. This difference is expected since better-performing firms should have a greater change in EPS.

Table 1.2 Equally Weighted Mean

	BE/ME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.1397	-0.474	-0.09	-0.097	-0.119	-0.233	0.0205	0.81
2	-0.0055	-0.006	-0.007	-0.007	-0.008	-0.006	-0.002	-5.19
3	0.00371	0.0032	0.0035	0.0036	0.0035	0.0036	-0.0002	-1.08
4	0.01261	0.0125	0.0131	0.0134	0.014	0.0128	0.0009	4.13
Best	1.0221	0.8771	0.2139	0.1972	0.3705	0.572	-0.652	-0.85
All	0.2387	-0.001	0.0209	0.0124	0.0546	0.0697	-0.184	-0.93
B-W	1.1618	1.351	0.3041	0.2942	0.49	0.8051	0.5102	2.89
T-Stat	1.39	2.18	2.85	2.61	2.77	2.07	2.89	

1.4.2.2 Equally Weighted Winsorized Mean

I winsorized the value of ΔE for the top and bottom 1% of the sample. Results are shown in Table 1.3. The first two ΔE quintiles are still negative, as previously expected. However, the best quintile now has more stable numbers. The differences also became more significant due to winsorizing. This table clearly shows that value stocks have greater magnitudes for best and worst performance portfolios. However, there still might be questions concerning whether small firms drive the results. In order to avoid this problem, I have also calculated value-weighted portfolios.

Table 1.3 Equally Weighted Winsorized Mean

	BE/ME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.0887	-0.077	-0.077	-0.083	-0.097	-0.085	-0.008	-1.56
2	-0.0055	-0.0062	-0.0065	-0.0071	-0.0078	-0.0064	-0.002	-5.75
3	0.0037	0.0032	0.0035	0.0036	0.0035	0.0036	-0.0002	-1.09
4	0.01261	0.0125	0.0131	0.01346	0.0135	0.0128	0.0009	4.16
Best	0.076	0.0759	0.0697	0.0798	0.091	0.0775	0.015	2.26
All	0.0048	0.0036	0.0008	-0.003	-0.011	0.0005	-0.016	-6.35
B-W	0.16469	0.1532	0.1466	0.163	0.1878	0.1628	0.177	17.22
T-Stat	18.9	14.97	17.27	14.51	14.6	18.26	17.22	

1.4.2.3 Value-Weighted Mean

Table 1.4 shows value-weighted calculations for ΔE, with the weight based on market equity. Signs are consistent as in the other tables. There are still some problems, though, especially in the best quintile for change in EPS. The only reasonable assumption is that there are indeed outliers that are biasing the sample. In order to fully eliminate that influence, winsorization is necessary.

Table 1.4 Value-Weighted Mean

	BE/ME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.076	-0.125	-0.053	-0.068	-0.124	-0.089	-0.048	-1.43
2	-0.0044	-0.005	-0.008	-0.006	-0.007	-0.006	-0.002	-4.05
3	0.004	0.0031	0.0035	0.0036	0.0037	0.0035	-9E-05	-0.35
4	0.0118	0.0111	0.0119	0.0123	0.013	0.0118	0.001	2.96
Best	0.4645	0.7095	0.059	0.1608	0.1542	0.2767	-0.31	-1.01
All	0.11	0.0003	0.0024	0.0349	0.0027	0.031	-0.107	-1.12
B-W	0.5403	0.8349	0.113	0.2292	0.2781	0.3653	0.23	4.87
T-Stat	1.56	2.08	11.06	2.37	4.54	2.33	4.87	

1.4.2.4 Value-Weighted Winsorized Mean

Winsorized results, shown in Table 1.5, eliminate any problems related to size or outliers. These results are economically significant, and most of them are statistically significant. The first EPS quintiles are negative, and value stocks' results for extreme portfolios have a greater magnitude than those for glamour stocks. This table gives the best perspective of the ΔE variable. It is also important to note that the value/glamour difference for the worst quintile is significant as well as for the entire ΔE variable. On the other hand, all BE/ME quintiles are significant.

Table 1.5 Value-Weighted Winsorized Mean

	BE/ME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.062	-0.06	-0.05	-0.063	-0.08	-0.057	-0.021	-2.08
2	-0.004	-0.005	-0.008	-0.006	-0.007	-0.006	-0.0025	-4.05
3	0.004	0.0031	0.0035	0.0036	0.0037	0.0035	-9E-05	-0.35
4	0.0118	0.0111	0.0119	0.0123	0.013	0.0118	0.001	2.96
Best	0.0632	0.0587	0.0501	0.068	0.0736	0.0584	0.0105	1.16
All	0.0051	0.002	0.0018	0.0032	-0.005	0.0037	-0.01	-2.91
B-W	0.1255	0.1187	0.1	0.1307	0.1573	0.1156	0.136	12.4
T-Stat	14.11	9.49	11.32	11.93	10.48	13.33	12.4	

1.4.2.5 Median

A different way of mitigating problems derived from size and outliers is through the median of the sample. Table 1.6 shows the medians of the sample. Results are similar to those in the value-weighted winsorized table. However, the previous table is more specific since it includes all observations in the sample; magnitudes in the previous table are larger than in this table, suggesting some skewedness.

Table 1.6 Median

	BE/ME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.058	-0.05	-0.049	-0.056	-0.07	-0.053	-0.012	-1.54
2	-0.004	-0.005	-0.006	-0.006	-0.008	-0.005	-0.003	-5.72
3	0.0038	0.0033	0.0036	0.0037	0.0036	0.004	-0.0003	-0.93
4	0.0119	0.0121	0.013	0.013	0.0132	0.0122	0.0013	3.91
Best	0.0489	0.0527	0.0473	0.0559	0.064	0.0505	0.0152	2.09
All	0.0046	0.0036	0.003	0.0006	-0.0014	0.0697	-0.006	-2.93
B-W	0.1068	0.1031	0.096	0.1122	0.1337	0.1035	0.1219	9.88
T-Stat	13.34	10	9.92	8.62	7.86	10.87	9.88	

1.4.2.6 Sample Distribution

Finally, Table 1.7 presents the distribution of the 25 portfolios of the sample. The EPS quintiles are quite equally distributed, each of them accounting for about 20%. That is consistent with the study, since independent rankings were made based on the data. However, the BE/ME quintiles are not evenly distributed since I used Kenneth French’s BE/ME break points. There is a higher concentration on glamour stocks than on value stocks, which is also consistent with the fact that analysts follow more glamour stocks. Despite the fact that analyst recommendations are not considered in this table, the data’s coming from IBES might induce the difference.

Table 1.7 Sample Distribution

n = 20087	BE/ME						
ΔE	Low	2	3	4	High	All	H-L
Worst	4.46%	3.34%	3.34%	3.88%	4.93%	19.94%	0.47%
2	5.71%	4.46%	3.98%	3.46%	2.43%	20.03%	-3.28%
3	8.35%	5.09%	3.11%	2.20%	1.27%	20.02%	-7.07%
4	6.94%	5.05%	3.47%	2.60%	1.98%	20.03%	-4.96%
Best	5.63%	4.05%	3.72%	3.36%	3.21%	19.97%	-2.42%
All	31.08%	21.98%	17.62%	15.50%	13.81%	100%	-17.26%
B-W	1.17%	0.72%	0.38%	-0.53%	-1.72%	0.02%	-2.90%

1.4.3 Group Based on Independent Sort in F and BE/ME

The next tables show the results of the portfolios calculated by the independent sort of F and BE/ME. Consistent with the previous set of tables, sorting of F was done within the sample. However, for BE/ME, I again used Kenneth French's BE/ME breakpoints to avoid any sampling bias. A negative number implies that the next year's earnings forecast is less than recent earnings. I expect to see negative numbers in the first rows of the table and especially for value firms because it has been documented in the literature that analysts tend to be more pessimistic with value firms.

1.4.3.1 Equally Weighted Mean

Table 1.8 shows the calculation of equally weighted portfolios sorted by F and BE/ME. As opposed to its counterpart in change in EPS, results in this table seem more normal. There is a big difference between the best F quintile and the rest of the quintiles, hinting that analysts are very optimistic for those stocks. However, to avoid any size or outlier issues, I also calculated the tables with value-weighted returns and with winsorized returns.

Table 1.8 Equally Weighted Mean

	BE/ME							
F	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.005	-0.006	-0.007	-0.011	-0.015	-0.0081	-0.01	-3.78
2	0.006	0.0065	0.0065	0.0065	0.0065	0.0065	3.1E-05	0.26
3	0.0112	0.012	0.0124	0.0126	0.0126	0.0123	0.0006	3.02
4	0.022	0.0218	0.0226	0.0229	0.023	0.0223	0.0009	2.06
Best	0.0915	0.0765	0.0686	0.0784	0.0844	0.0823	-0.007	-0.85
All	0.0206	0.0207	0.023	0.0261	0.0306	0.023	0.01	2.79
B-W	0.0966	0.0822	0.076	0.0889	0.0996	0.0904	0.0895	19.84
T-Stat	14.69	16.03	19.22	10.32	17.48	23.01	19.84	

1.4.3.2 Equally Weighted Winsorized Mean

After winsorizing, portfolio magnitudes are reduced, and significance in differences is thus increased. This might hint that there were some outliers in the sample. However, and as opposed to the change in earnings tables, changes here were not drastic. An important difference between this table and the previous one is that the difference in the best F quintile is now positive, meaning that the value stocks had better future recommendations than the growth stocks for that quintile. If that is the case, the value-weighted tables should strengthen the conclusion.

Table 1.9 Equally Weighted Winsorized Mean

	BE/ME							
F	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.003	-0.0042	-0.005	-0.008	-0.011	-0.006	-0.008	-5.95
2	0.006	0.0065	0.0065	0.0065	0.0065	0.0065	3.1E-05	0.26
3	0.012	0.0124	0.0124	0.0126	0.0126	0.0123	0.0006	3.02
4	0.022	0.0218	0.0226	0.0229	0.023	0.0223	0.0009	2.06
Best	0.0749	0.0683	0.0623	0.0672	0.0772	0.071	0.0023	0.48
All	0.0186	0.0196	0.0218	0.0235	0.029	0.0213	0.0104	3.77
B-W	0.0778	0.0726	0.0675	0.0755	0.088	0.0769	0.0801	23.42
T-Stat	23.35	23.77	28.32	21.6	22.94	36.72	23.42	

1.4.3.3 Value-Weighted Mean

In the same vein as the previous results, Table 1.10 includes some interesting numbers. The difference in the best quintile still holds, and the overall magnitudes are even lower than in the equally weighted winsorized table. Significance in differences is reduced, but I expect to correct that problem with a winsorized version of the table.

Table 1.10 Value-Weighted Mean

	BE/ME							
F	Low	2	3	4	High	All	H-L	T-Stat
Worst	-0.0002	-0.0019	-0.003	-0.005	-0.0115	-0.002	-0.011	-3.59
2	0.0063	0.006	0.0065	0.0062	0.0062	0.0063	-0.0001	-0.47
3	0.012	0.0121	0.0123	0.0124	0.0124	0.0119	0.0007	2.29
4	0.0207	0.0208	0.0222	0.0229	0.0215	0.0214	0.0008	1.64
Best	0.0733	0.065	0.0626	0.0662	0.0736	0.0665	0.0002	0.02
All	0.0088	0.0125	0.0128	0.0137	0.014	0.0103	0.006	1.97
B-W	0.0735	0.0668	0.066	0.0716	0.085	0.0684	0.0736	12.94
T-Stat	13.61	12.33	13.81	14.64	14.05	23.34	12.94	

1.4.3.4 Value-Weighted Winsorized Mean

Table 1.11 provides the best insight for the F variable since it mitigates any potential size or outlier issues. I can conclude that analysts had extreme views for value stocks at both the pessimistic and optimistic ends. The difference for the complete sample of F, based on value and growth firms, is significant and positive. Differences within value and growth stocks were still large, positive, and significant.

Table 1.11 Value-Weighted Winsorized Mean

	BE/ME							
F	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0002	-0.0014	-0.0031	-0.0046	-0.009	-0.0014	-0.009	-4.66
2	0.0063	0.006	0.0065	0.0062	0.0062	0.0063	-0.0001	-0.47
3	0.012	0.0121	0.0123	0.0124	0.0124	0.0119	0.0007	2.29
4	0.0207	0.0208	0.0222	0.0229	0.0215	0.0214	0.0008	1.64
Best	0.0648	0.0594	0.056	0.0634	0.07	0.0609	0.0052	0.87
All	0.0083	0.0124	0.0121	0.0137	0.0146	0.0101	0.0064	2.82
B-W	0.0646	0.0608	0.0586	0.068	0.0789	0.0623	0.0699	14.04
T-Stat	16.78	17.02	21.77	16.43	15.45	27.63	14.04	

1.4.3.5 Median

Medians, reported in Table 1.12, allow conclusions similar to those drawn from the previous table. However, I still consider the value-weighted winsorized mean to be a better approach to the set since it includes all observations.

Table 1.12 Median

	BEME							
F2	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0015	0.0009	-0.0007	-0.0024	-0.005	0.0004	-0.006	-3.6
2	0.0063	0.0065	0.0066	0.0064	0.0064	0.0064	0.0001	0.64
3	0.0117	0.0123	0.0123	0.013	0.0127	0.012	0.001	3.68
4	0.021	0.0209	0.0223	0.0224	0.0227	0.0217	0.0015	2.66
Best	0.0576	0.052	0.0486	0.0536	0.0618	0.0533	0.0042	0.89
All	0.0094	0.0122	0.0147	0.0155	0.0166	0.023	0.0072	6.3
B-W	0.056	0.051	0.0493	0.056	0.0668	0.0528	0.0603	14.07
T-Stat	21.14	20.32	29.57	16.42	15.05	29.48	14.07	

1.4.3.6 Sample Distribution

Table 1.13 shows the sample distribution for F. As with the distribution of ΔE, the F quintiles are evenly distributed, while the BE/ME quintiles are not. This is due, as previously noted, to the fact that BE/ME is sorted based on French's break points. However, the number of observations decreases because, unlike the case with previously obtained earnings, analysts must come up with forecasts. If no analysts cover the stocks, there will be no forecasts at all. Regardless of this issue, the sample distribution is somehow similar to the change in EPS distribution.

Table 1.13 Sample Distribution

n = 15507	BE/ME						
F	Low	2	3	4	High	All	H-L
Worst	6.80%	3.73%	3.30%	3.22%	2.88%	19.94%	-3.91%
2	7.89%	5.07%	3.24%	2.26%	1.58%	20.03%	-6.31%
3	5.91%	5.49%	3.77%	2.72%	2.14%	20.04%	-3.77%
4	4.67%	4.91%	4.29%	3.50%	2.67%	20.04%	-2.00%
Best	5.09%	3.62%	3.80%	3.70%	3.75%	19.96%	-1.33%
All	30.35%	22.82%	18.40%	15.41%	13.03%	100.00%	-17.3%
B-W	-1.71%	-0.12%	0.50%	0.48%	0.87%	0.02%	2.58%

1.4.4 Group Based on the Value of F for Independent Sort in ΔE and BE/ME

In order to know whether previous performance has some influence in one-year-ahead forecasts, I calculated the value of F based on the sorting of EPS and BE/ME. That way, the ΔE quintiles will determine past performance, and the value of F will determine analysts' expectations. I expect to see a large difference between the best- and worst-performing quintiles as well as see negative values for the difference in the worst ΔE quintile.

1.4.4.1 Equally Weighted Mean

These calculations seem to support my previous expectations. Analysts are clearly more optimistic about firms that performed better in the previous year. On the other hand, the worst-performing value stocks receive an important downgrade. The results shown in Table 1.14 should be confirmed by winsorized and value-weighted analyses.

Table 1.14 Equally Weighted Mean of F

	BEME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0256	0.0186	0.0152	0.016	0.0216	0.0193	-0.004	-0.75
2	0.0104	0.0112	0.0131	0.0128	0.0151	0.0117	0.0044	2.48
3	0.009	0.0095	0.012	0.0112	0.0123	0.01	0.0033	1.9
4	0.0149	0.0144	0.0172	0.0176	0.0191	0.0156	0.0042	1.37
Best	0.0628	0.0502	0.0503	0.0623	0.0685	0.0588	0.0057	0.54
All	0.0206	0.0207	0.023	0.0261	0.0306	0.023	0.01	2.79
B-W	0.0372	0.0316	0.0351	0.0463	0.0469	0.0395	0.0429	4.86
T-Stat	4.57	6.99	8.25	5.52	7.66	11.4	4.86	

1.4.4.2 Equally Weighted Winsorized Mean

Relationships established in Table 1.14 still hold in Table 1.15, and significance levels increase. However, for the worst change in earnings quintile, significance is reduced. There might be some influence of outliers in the previous table. However, and as previously demonstrated, a value-weighted table gives a better perspective of the problem.

Table 1.15 Equally Weighted Winsorized Mean of F

	BEME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0247	0.0199	0.017	0.0172	0.023	0.0204	-0.002	-0.44
2	0.0104	0.0112	0.0131	0.0129	0.0148	0.0117	0.0041	2.42
3	0.009	0.0095	0.012	0.0113	0.0122	0.01	0.0032	1.87
4	0.015	0.0143	0.0173	0.0177	0.0192	0.0156	0.0042	1.4
Best	0.05	0.0445	0.0437	0.051	0.0595	0.049	0.0095	1.47
All	0.0186	0.0196	0.0218	0.0235	0.029	0.0213	0.0104	3.77
B-W	0.0252	0.0246	0.0267	0.0338	0.0365	0.0288	0.0348	6.56
T-Stat	4.96	8.34	10.99	9	8.73	16.85	6.56	

1.4.4.3 Value-Weighted Mean

In Table 1.16, previous conclusions hold, but magnitudes go down. However, I still prefer value-weighted tables since they account for firms with larger ME.

Table 1.16 Value-Weighted Mean of F

	BEME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.009	0.0099	0.0069	0.0085	0.0032	0.007	-0.006	-0.99
2	0.0066	0.0082	0.008	0.0083	0.0119	0.0073	0.005	2.8
3	0.0064	0.0081	0.009	0.0083	0.0091	0.007	0.0025	1.4
4	0.0114	0.0111	0.013	0.0137	0.012	0.0112	0.0006	0.3
Best	0.0321	0.0338	0.036	0.0437	0.044	0.0352	0.0121	1.67
All	0.0088	0.012	0.0127	0.0137	0.014	0.0103	0.0056	1.97
B-W	0.0227	0.024	0.029	0.0352	0.041	0.0283	0.035	5.4
T-Stat	5.36	6.01	6.3	6.23	5.4	11.63	5.4	

1.4.4.4 Value-Weighted Winsorized Mean

Table 1.17 is the most important table in this group. I can confirm the fact that outliers were dragging the difference in the worst ΔE quintile. However, the best quintile and the complete ΔE sample are significant, and the difference among BE/ME groups is highly significant.

Table 1.17 Value-Weighted Winsorized Mean of F

	BEME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0099	0.0111	0.0079	0.0097	0.0065	0.0079	-0.003	-0.73
2	0.0066	0.0082	0.008	0.0083	0.012	0.0073	0.005	2.7
3	0.0064	0.0081	0.009	0.0083	0.0091	0.007	0.0025	1.4
4	0.0114	0.0111	0.013	0.0138	0.012	0.0112	0.0006	0.34
Best	0.029	0.0316	0.0312	0.0409	0.0434	0.0324	0.0144	2.44
All	0.0083	0.0124	0.0121	0.0137	0.0146	0.0101	0.0064	2.82
B-W	0.019	0.0205	0.0234	0.0312	0.0369	0.0245	0.034	6.06
T-Stat	5	6.28	6.35	6.08	6.49	12.3	6.06	

1.4.4.5 Median

As in the previous example, medians confirm the trends. Still, value-weighted returns are a better benchmark since they include all observations.

Table 1.18 Median of F

	BEME							
ΔE	Low	2	3	4	High	All	H-L	T-Stat
Worst	0.0177	0.0159	0.014	0.0151	0.0169	0.0157	-0.001	-0.26
2	0.0062	0.0088	0.01	0.0082	0.0097	0.0077	0.0032	4.95
3	0.0063	0.0079	0.0086	0.0078	0.0098	0.0072	0.003	2.3
4	0.0115	0.0121	0.014	0.0143	0.0168	0.0123	0.0053	1.89
Best	0.0329	0.0295	0.0303	0.0394	0.0475	0.0319	0.0146	2.23
All	0.0094	0.0122	0.0147	0.0155	0.0166	0.023	0.0072	6.3
B-W	0.0151	0.0136	0.016	0.0243	0.0306	0.0162	0.03	5.28
T-Stat	3.35	5.74	8.51	7.36	5.62	10.25	5.28	

1.4.5 Conclusions

- Differences between glamour and value stocks for best- and worst-performing change in earnings are the largest, implying that value stocks have a more volatile behavior on previous performance.
- Earnings forecasts are more pessimistic for value stocks and more optimistic for growth stocks. However, good forecasts for value stocks tend to be more optimistic than those for growth stocks.
- When calculating earnings forecasts with a previous earnings sorting, analysts tend to be more optimistic with firms that had a good previous performance. However, forecasts become more conservative with worst-performing stocks. Analysts tend to favor glamour over value when previous performance was bad.

1.5 Future Returns Based on BE/ME Groups

1.5.1 Portfolio Formation

To determine whether value stocks outperform growth stocks in the sample, I have calculated equally weighted and value-weighted tables. It is important to determine this relationship, since two of the premises of this paper are that analysts tend to favor glamour stocks and that value stocks will outperform those glamour stocks. Hence, value outperforming growth is a necessary condition for analyzing the validity of the hypothesis.

Portfolios are rebalanced every July based on the most recent BE/ME calculation. I am sorting based on the sample's breakpoints, that is, not using any external breakpoints to determine the way in which stocks are classified. Firms could move into a different portfolio every year based on their current BE/ME. I am also including the CRSP portfolio returns, with and without dividends, as well as the S&P 500. All returns are expressed in monthly terms.

My calculations started with 1983 data; however, to save space, I commenced reporting with 1985 data. It is interesting to see how in 15 out of the 26 years value outperforms glamour. In some specific periods, such as the second half of the 90s, glamour stocks did perform particularly well. If this extraordinary period were ignored, value firms would have a clear lead throughout the sample.

Table 1.19 Value-Weighted BE/ME Future 12-Month Returns

12 mo start July	**CRSP VWD**	**S&P**	**All**	**Low**	**2**	**3**	**4**	**High**	**H-L**	**T-Stat**
1985	0.025439	0.023159	0.02106	0.028476	0.025542	0.019653	0.02444	0.00719	-0.021285	-2.15
1986	0.016444	0.017714	0.020451	0.014487	0.01911	0.019358	0.019724	0.029577	0.0150897	1.18
1987	-0.001984	-0.005528	0.000567	-0.003932	-0.001524	-0.003134	0.003638	0.007785	0.0117165	1.09
1988	0.014835	0.013147	0.014763	0.011992	0.010992	0.014302	0.018842	0.017684	0.0056921	0.77
1989	0.010833	0.01086	0.010944	0.022398	0.012023	0.008582	0.007956	0.003762	-0.018636	-1.98
1990	0.00679	0.004115	0.009523	0.007158	0.013317	0.002954	0.012866	0.011318	0.00416	0.84
1991	0.011581	0.008685	0.013428	0.012439	0.007276	0.012314	0.020194	0.014915	0.0024752	0.17
1992	0.012773	0.008437	0.016059	0.001767	0.014754	0.015414	0.016417	0.031945	0.0301782	2.22
1993	0.000973	-0.000872	0.00487	0.002259	0.007123	0.009222	-0.001803	0.007547	0.0052882	0.61
1994	0.018505	0.017423	0.01914	0.024777	0.020656	0.014271	0.017461	0.018535	-0.006242	-0.85
1995	0.019369	0.01759	0.018318	0.025834	0.017862	0.019941	0.015721	0.012233	-0.013602	-1.67
1996	0.022083	0.024192	0.018754	0.024775	0.023781	0.014203	0.015844	0.015166	-0.009609	-1.16
1997	0.021543	0.021659	0.016722	0.022325	0.012237	0.022289	0.008532	0.018228	-0.004097	-0.38
1998	0.016642	0.017976	0.017171	0.020771	0.018649	0.022705	0.010638	0.013094	-0.007678	-0.42

Table 1.19 - continued

1999	0.009833	0.005794	0.003857	0.021166	0.002751	0.001947	-0.001999	-0.004581	-0.025747	-1.51
2000	-0.012687	-0.012921	0.012765	-0.016567	0.004493	0.025184	0.025589	0.025124	0.0416907	1.94
2001	-0.013988	-0.016527	-0.015797	-0.016298	-0.00231	-0.008182	-0.016277	-0.03592	-0.019622	-1.62
2002	0.003655	0.000521	0.003311	0.005628	0.002836	0.001416	0.002593	0.004081	-0.001548	-0.11
2003	0.016725	0.013451	0.020188	0.01422	0.020433	0.019567	0.01946	0.027262	0.0130418	1.97
2004	0.007523	0.003885	0.010357	0.005902	0.003053	0.01495	0.006658	0.021219	0.0153167	2.39
2005	0.009163	0.005544	0.011828	0.008984	0.005212	0.013366	0.015523	0.016055	0.0070705	1.29
2006	0.016393	0.014311	0.016899	0.012806	0.018293	0.020237	0.01535	0.017809	0.0050028	0.93
2007	-0.008765	-0.012567	-0.00539	-0.001557	-0.011645	-0.002753	-0.000392	-0.010604	-0.009047	-1
2008	-0.022036	-0.023991	-0.016114	-0.010147	-0.021307	-0.024448	-0.012673	-0.011995	-0.001849	-0.19
2009	0.014068	0.01067	0.017544	0.015867	0.019065	0.015246	0.019028	0.018516	0.002649	0.31
All	0.0085781	0.0066254	0.010343	0.009741	0.009884	0.010467	0.010265	0.011358	0.0016165	0.55

Table 1.20 Equally Weighted BE/ME Future 12-Month Returns

12 mo start July	CRSP EWD	S&P	All	Low	2	3	4	High	H-L	T-Stat
1985	0.022721	0.023159	0.024795	0.029211	0.026538	0.025874	0.023353	0.019001	-0.01021	-1.46
1986	0.008903	0.017714	0.014488	0.013113	0.013298	0.010905	0.011076	0.024048	0.0109346	1.14
1987	-0.003824	-0.005528	0.008452	0.006512	0.008279	0.010866	0.007939	0.008665	0.0021532	0.15
1988	0.007726	0.013147	0.015045	0.012187	0.007899	0.012383	0.018474	0.02428	0.0120921	2.37
1989	0.000027	0.01086	0.008394	0.017479	0.014422	0.004949	0.002112	0.003007	-0.014472	-2.24
1990	0.007218	0.004115	0.012685	0.015247	0.012184	0.013922	0.010623	0.011447	-0.0038	-0.72
1991	0.018935	0.008685	0.013129	0.012489	0.013448	0.008998	0.013366	0.017344	0.0048552	0.32
1992	0.02219	0.008437	0.020187	0.016486	0.017428	0.022836	0.017109	0.027075	0.0105892	0.95
1993	0.005306	-0.000872	0.008649	0.004246	0.009716	0.0056	0.013429	0.010254	0.0060077	1.02
1994	0.014403	0.017423	0.021157	0.029538	0.020813	0.019112	0.017851	0.01847	-0.011068	-2.05
1995	0.023068	0.01759	0.021749	0.028607	0.024564	0.020859	0.018324	0.016389	-0.012217	-1.34
1996	0.008924	0.024192	0.0158	0.007915	0.016479	0.018325	0.016688	0.019594	0.0116793	1.09
1997	0.013359	0.021659	0.018772	0.021173	0.017695	0.021018	0.015008	0.018969	-0.002204	-0.32

Table 1.20 - continued

1998	0.008137	0.017976	0.018469	0.028342	0.016156	0.014387	0.01832	0.015143	-0.013199	-1.03
1999	0.02011	0.005794	0.023243	0.046667	0.02708	0.022106	0.013189	0.007172	-0.039495	-1.9
2000	0.00263	-0.012921	0.024223	0.001838	0.018831	0.031415	0.035738	0.033292	0.0314543	1.45
2001	-0.000064	-0.016527	0.008716	-0.007333	0.004292	0.009848	0.021683	0.015092	0.0224248	1.91
2002	0.017494	0.000521	0.008689	0.015056	0.008456	0.008467	0.004786	0.006678	-0.008378	-0.92
2003	0.030007	0.013451	0.033065	0.033714	0.031072	0.027822	0.033231	0.039488	0.0057738	0.82
2004	0.010371	0.003885	0.014428	0.013106	0.012807	0.015341	0.013131	0.017756	0.0046502	1.02
2005	0.012595	0.005544	0.019559	0.019921	0.019961	0.022898	0.018477	0.016536	-0.003386	-0.57
2006	0.014745	0.014311	0.019472	0.019806	0.020835	0.018647	0.016575	0.021494	0.0016881	0.56
2007	-0.018075	-0.012567	-0.010271	-0.007143	-0.005876	-0.009736	-0.014091	-0.014511	-0.007368	-0.94
2008	-0.007236	-0.023991	-0.003324	-0.003548	-0.006471	-0.012347	-0.000474	0.00622	0.0097682	1.33
2009	0.023546	0.01067	0.028326	0.026335	0.026328	0.025443	0.028263	0.035259	0.0089242	1.25
All	0.0096519	0.0066254	0.014953	0.0148994	0.0142884	0.0142708	0.0146225	0.0166823	0.0017829	0.63

1.5.2 Value-Weighted Table

Table 1.19 presents value-weighted returns for different BE/ME combinations. It is interesting to note that for that second half of the 90s, return difference was negative, mainly due to a strong bull market. However, results for all of the periods show a difference of 0.16% per month, or 1.92% per year, in favor of value stocks. In other words, and in spite of those strong bull markets, value stocks outperformed growth stocks.

It is also interesting to note that the returns for the complete sample were higher than any of the other benchmarks, primarily because analysts tend to concentrate on better-performing stocks. Therefore, the sample will leaned toward stocks with better performance. On the other hand, most of the t-stats are not significant. There needs to be a very strong difference between the two groups to show a significant difference, and that occurred when there were strong bear or bull markets.

1.5.3 Equally Weighted Table

On the other hand, Table 1.20 presents equally weighted results. The conclusions don not change; value outperforms growth. I can therefore proceed with the analysis of returns based on change in earnings and earnings forecasts.

1.6 Future Returns Based on ΔE and BE/ME and F and BE/ME

1.6.1 Portfolio Formation

The purpose of these tables is to measure the post–12 month returns of the portfolios formed based on ΔE and BE/ME and F and BE/ME sorting. Through this analysis, I expect to demonstrate that contrarian strategies, that is, going against good changes in earnings and good analyst forecasts, prove to be more profitable than momentum strategies. Each portfolio is rebalanced every year based on an independent sort. As with the previous portfolios, ΔE and F are sorted within the sample, whereas BE/ME is sorted based on Kenneth French's breakpoints.

1.6.2 Returns Based on ΔE and BE/ME Sorting

The first part of the analysis consists of measuring the returns of changes in earnings and BE/ME. I have calculated equally weighted and value-weighted tables, and I also measured the difference between high and low BE/ME groups and high and low change in earnings quintiles. I expect to see a higher return for value stocks and a better return for worst-performing stocks.

1.6.2.1 Equally Weighted Mean

Table 1.21 shows equally weighted results for portfolios sorted by earnings and BE/ME. It is interesting to note that for the worst-performing quintile, glamour stocks had a better and significant performance than value stocks. However, the story changes as we move to the best-performing quintiles. Quintile 4 has a significant difference of 0.78%, and quintile 5 has a difference of 0.32%, implying that as changes in earnings became better, value firms outperformed growth firms.

For BE/ME quintiles, we can also make an interesting observation. Within glamour firms, worst-performing stocks outperformed better-performing stocks. This situation is repeated in the second BE/ME quintile. Therefore, it is convenient to invest with a contrarian earnings strategy in glamour stocks. However, the conclusion was exactly the opposite for value stocks. Best-performing firms significantly outperformed worst-performing firms. It is also interesting to note that for the complete sample, a contrarian strategy will also produce significant results, of about 0.4% per month.

Table 1.21 Equally Weighted Returns Based on ΔE

	BE/ME							
ΔE	**Low**	**2**	**3**	**4**	**High**	**All**	**H-L**	**T-Stat**
Worst	0.02030	0.017098	0.015054	0.0125	0.011063	0.015853	-0.00924	-2.71
2	0.014416	0.016431	0.015482	0.013497	0.012307	0.015256	-0.00211	-0.87
3	0.010075	0.010823	0.012413	0.013175	0.016204	0.013705	0.006129	2.27
4	0.007602	0.010711	0.012982	0.011927	0.015441	0.011232	0.007839	1.9
Best	0.014968	0.010165	0.013456	0.013627	0.018175	0.01184	0.003207	0.72
All	0.014056	0.012783	0.013686	0.012931	0.014895	0.013492	0.000839	0.3
B-W	-0.00533	-0.00693	-0.0016	0.001126	0.007112	-0.00401		
T-Stat	-1.71	-2.64	-0.77	0.55	2.28	-2.01		

1.6.2.2 Value-Weighted Mean

In order to strengthen the results of the previous table, I also calculated value-weighted returns, shown in Table 1.22. Prior conclusions still hold, but significance levels drop. This suggests that smaller firms in the sample play an important role in performing the contrarian strategy. In other words, small firms are dragging differential returns upward and making them significant. Therefore, it is imperative to pursue this strategy with equally weighted portfolios.

Table 1.22 Value-Weighted Returns Based on ΔE

	BE/ME							
ΔE	**Low**	**2**	**3**	**4**	**High**	**All**	**H-L**	**T-Stat**
Worst	0.015796	0.015214	0.012572	0.006533	0.007211	0.010899	-0.00859	-1.69
2	0.008662	0.010447	0.011362	0.007562	0.012005	0.01077	0.003343	1.11
3	0.005498	0.007337	0.01103	0.01139	0.012677	0.010417	0.007179	1.71
4	0.005503	0.007797	0.010501	0.009348	0.011546	0.007413	0.006043	1.54
Best	0.009555	0.004149	0.009672	0.0134	0.014941	0.008606	0.005385	0.79
All	0.010047	0.009276	0.010831	0.009634	0.010479	0.006691	0.000432	0.13
B-W	-0.00624	-0.01107	-0.0029	0.006866	0.00773	-0.00229		
T-Stat	-1.42	-4.1	-0.94	1.41	1.71	-0.95		

1.6.3 Returns Based on F and BE/ME Sorting

The second pair of tables show portfolio returns but now based on earnings forecasts and BE/ME. I expect to see firms with worst earnings forecasts outperform the ones with best earnings forecasts, and I also expect to see value stocks outperform glamour stocks for every earnings forecast interval. I have again calculated the tables with equally weighed and value-weighted approaches to analyze any size effects.

1.6.3.1 Equally Weighted Mean

Table 1.23 shows equally weighted means for the portfolios. Most of the differences are negative, which suggests that the best analysts' recommendations do not provide the best post–12 month returns. For glamour stocks, this significant difference is 0.73% per month. For the whole sample, the difference is 0.25%. For all of the forecast quintile groups, the difference between glamour and value is negative, closer to zero, and insignificant.

Table 1.23 Equally Weighted Returns Based on F

	BE/ME							
F	**Low**	**2**	**3**	**4**	**High**	**All**	**H-L**	**T-Stat**
Worst	0.018233	0.013333	0.015819	0.015129	0.017971	0.016453	-0.00026	-0.07
2	0.016577	0.015217	0.014674	0.014749	0.015584	0.014713	-0.00099	0.02
3	0.015238	0.014211	0.012559	0.011142	0.014068	0.011623	-0.00117	-0.26
4	0.010558	0.011727	0.011569	0.01127	0.008944	0.010928	-0.00161	-0.37
Best	0.010944	0.009952	0.014728	0.012366	0.010929	0.01395	-1.5E-05	0
All	0.014056	0.012783	0.013686	0.012931	0.014895	0.013492	0.000839	0.3
B-W	-0.00729	-0.00338	-0.00109	-0.00276	-0.00704	-0.0025		
T-Stat	-2.2	-1.13	-0.35	-0.96	-1.5	-1.38		

1.6.3.2 Value-Weighted Mean

Results change when we use a value-weighted approach. The first important conclusion is that the difference between worst- and best-performing forecast quintile becomes significant, with a 0.48% monthly return. However, the rest of the BE/ME quintiles are not significant. This result is interesting since it can be concluded that a contrarian strategy should be used in a diversified portfolio and not for particular BE/ME quintiles. Another interesting result is that for the worst-performing quintile, value stocks significantly outperform glamour stocks by 0.75% per month. These two results show that large-firm influences are important when using analyst recommendations. Value-weighted Table 1.24 is more robust than the equally weighted table.

Table 1.24 Value-Weighted Returns Based on F

	BE/ME							
F	**Low**	**2**	**3**	**4**	**High**	**All**	**H-L**	**T-Stat**
Worst	0.009024	0.011857	0.007857	0.013429	0.016543	0.01379	0.007519	2.29
2	0.011294	0.011449	0.011764	0.007453	0.012339	0.008424	0.002398	0.46
3	0.010632	0.011999	0.012349	0.009919	0.010855	0.007065	0.000286	0.07
4	0.006621	0.007278	0.011127	0.011064	0.006512	0.008134	-0.00011	-0.02
Best	0.006258	0.007657	0.010922	0.00978	0.01113	0.008979	0.004872	0.68
All	0.010047	0.009276	0.010831	0.009634	0.010479	0.006691	0.000432	0.13
B-W	-0.00277	-0.0042	0.003065	-0.00365	-0.00541	-0.00481		
T-Stat	-0.73	-1.01	0.85	-0.95	-0.69	-1.92		

1.6.4. Conclusions

- When considering previous earnings performance, contrarian strategies are significant for glamour stocks, whereas momentum strategies are significant for value stocks. However, contrarian strategies are significantly more important when considering the complete sample.
- For worst-performing stocks, glamour stocks yield greater and significant returns than value stocks. However, when considering the best-performing stocks, value outperforms growth.
- Value-weighted results yield the same conclusions, but significance levels go down, which suggests that smaller firms are dragging down the returns and, therefore, the significance levels in previous performance sorting.
- On the other hand, when considering future earnings forecasts, contrarian strategies work for every BE/ME. However, it is only when using value-weighted returns and the

complete sample that a significant difference of 0.48% per month can be noted between value and glamour stocks.

- When comparing forecast quintiles on equally weighted returns, glamour stocks outperform value stocks throughout the sample. However, when switching to value-weighted returns, glamour significantly outperforms growth in the worst forecast quintile by 0.75% per month.

1.7 Cross-Sectional Analysis

1.7.1 Portfolio Formation

I ran several cross-sectional regressions to determine which factors dominate the portfolio returns. First, I calculated betas for the different ME groups following the Fama-MacBeth procedure. For the complete sample, I sorted the stocks into ME deciles per year and then calculated equally weighted and value-weighted excess returns for every ME group. Finally, I ran a time series regression against the Fama-French excess market return. I used equally weighted betas in my analysis, but I include both beta calculations here.

Results of the analyses are very similar. For the smallest ME decile, betas are rather low and alphas are highly significant. This result, despite appearing to be somewhat odd, does make sense for the sample since the smallest firms usually do not receive much attention from analysts. Beta is the lowest, and highly significant, for the largest firms. Finally, I allocated equally weighted betas to every firm per year based on its current ME value. Table 1.25 shows value-weighted betas, and Table 1.26 shows equally weighted betas.

Table 1.25 Value-Weighted Betas

ME	Alpha	T-stat	Beta	T-stat
1	1.185178	5.21	0.939864	19.21
2	0.639784	3.11	1.044535	23.59
3	0.598046	2.86	1.091396	24.23
4	0.476634	2.6	1.137018	28.84
5	0.384734	2.21	1.027296	27.49
6	0.457135	2.92	1.067593	31.65
7	0.32939	2.26	1.084423	34.62
8	0.29254	2.32	1.044181	38.54
9	0.158917	1.19	1.027381	35.69
10	0.10707	1.16	0.906791	45.78

Table 1.26 Equally Weighted Betas

ME	Alpha	T-stat	Beta	T-stat
1	1.249686	5.56	0.918986	19.01
2	0.688577	3.31	1.041335	23.29
3	0.585858	2.77	1.096264	24.14
4	0.469765	2.57	1.138892	28.93
5	0.397679	2.29	1.030877	27.57
6	0.452934	2.89	1.070731	31.77
7	0.343069	2.35	1.087332	34.62
8	0.319889	2.53	1.03911	38.16
9	0.152821	1.16	1.031925	36.54
10	0.153983	1.86	0.934831	52.47

1.7.2 Cross-Sectional Regressions

After calculating betas, I resorted the whole sample. For every month, I created three change in earnings portfolios, based on the top 30%, middle 40%, and bottom 30% of the sample, and I did the same for earnings forecasts and betas. Portfolios were rebalanced every year. I then ran cross-sectional monthly regressions. In this paper, I report the average monthly coefficients with their respective t-stats.

1.7.2.1 First Model

For this model, I am including all of the variables at contemporaneous times to show how much beta, change in earnings, and earnings forecasts influence today's excess returns. The model is the following:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left[\ln(1+\Delta E_{p,y})\right] + \gamma_{3t}\left[\ln(1+F_{p,y})\right] + \nu_{pt}.$$

Results are summarized in Table 1.27. As expected, beta is positive and significant, meaning that market returns have a direct and positive influence on portfolio returns. Change in earnings and earnings forecasts, on the other hand, are negative and in this specific model insignificant. Negative signs in both variables imply contrarian strategies because excess portfolio returns will increase if these two variables decrease.

Table 1.27 Cross-Sectional Regression, First Model

Independent Variable	**Beta**	**ΔE**	**F**
Coefficient	**γ_1**	**γ_2**	**γ_3**
Estimate	3.641973	-2.944669	-2.868728
t-stat	2.73	-1.45	-1.07

1.7.2.2 Second Model

For this model, I lagged both change in earnings and earnings forecast. This model, in my opinion, is the most realistic since it includes the one-year effects of the two calculated variables. The model is:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left[\ln(1 + \Delta E_{p,y-1})\right] + \gamma_{3t}\left[\ln(1 + F_{p,y-1})\right] + \nu_{pt}.$$

Results are summarized in Table 1.28. Both beta and change in earnings are significant and keep their original signs. However, the forecast variable becomes positive and insignificant. In other words, previous earnings subsumed the effects of earnings forecasts, suggesting that analysts base their recommendation on previous analysis.

Table 1.28 Cross-Sectional Regression, Second Model

Independent Variable	**Beta**	**ΔE**	**F**
Coefficient	γ_1	γ_2	γ_3
Estimate	3.382671	-6.544153	0.8299254
t-stat	2.45	-2.88	0.29

1.7.2.3 Third Model

Finally, I lagged the forecast variable and left change in earnings contemporaneous. The model is:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left[\ln(1 + \Delta E_{p,y})\right] + \gamma_{3t}\left[\ln(1 + F_{p,y-1})\right] + \nu_{pt}.$$

Results are quite similar to those yielded by previous model. It seems that F and the lag of F have no relevant effect on excess returns of the portfolios, as shown in Table 1.29.

Table 1.29 Cross-Sectional Regression, Third Model

Independent Variable	**Beta**	**ΔE**	**F**
Coefficient	γ_1	γ_2	γ_3
Estimate	3.537935	-4.174765	0.0852364
t-stat	2.56	-2.07	0.03

1.7.3 Pooled OLS Regressions

In order to double-check these findings, I ran pooled ordinary least squares (OLS) regressions, that is, I regressed all of the portfolios for all months at once. I used the same three models as described for cross-sectional regressions and report the results below.

1.7.3.1 First Model

Table 1.30 summarizes the results of using all contemporaneous variables and the following model:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left[\ln(1 + \Delta E_{p,y})\right] + \gamma_{3t}\left[\ln(1 + F_{p,y})\right] + \nu_{pt}.$$

Once again, beta and change in earnings are significant and moving in the direction that I expected. However, the forecast variable is not significant, even though it is also moving in the expected direction. This suggests that for a contemporaneous pooled OLS model, change in earnings subsumes earnings forecasts.

Table 1.30 Pooled OLS Regression, First Model

Independent Variable	**Intercept**	**Beta**	**ΔE**	**F**
Coefficient	γ_0	γ_1	γ_2	γ_3
Estimate	-2.308407	3.126968	-5.392211	-0.1046705
t-stat	-1.66	2.31	-2.34	-0.03

1.7.3.2 Second Model

This model lags both the change in earnings and earnings forecast variables:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left\lfloor \ln(1 + \Delta E_{p,y-1}) \right\rfloor + \gamma_{3t}\left\lfloor \ln(1 + F_{p,y-1}) \right\rfloor + \nu_{pt}.$$

It is noteworthy that for this case, the change in earnings variable becomes insignificant, and the forecast variable gets closer to significance. The negative sign implies a contrarian strategy. It seems that when considering a panel data approach, the forecast variable becomes more important in the analysis.

Table 1.31 Pooled OLS Regression, Second Model

Independent Variable	**Intercept**	**Beta**	**ΔE**	**F**
Coefficient	γ_0	γ_1	γ_2	γ_3
Estimate	-2.477089	3.358757	1.017119	-4.347617
t-stat	-1.75	2.44	0.4	-1.36

1.7.3.3 Third Model

Finally, I ran the following model with a lag in forecasts:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{pt} + \gamma_{2t}\left\lfloor \ln(1 + \Delta E_{p,y}) \right\rfloor + \gamma_{3t}\left\lfloor \ln(1 + F_{p,y-1}) \right\rfloor + \nu_{pt}.$$

Beta and change in earnings are significant, and they both move in the predicted direction, as shown in Table 1.32. F also moves in the predicted direction, and it is relatively close to significance. This definitely suggests that both change in earnings and future earnings forecast move in a direction opposite that of actual portfolio return, indicating that employing contrarian strategies would be profitable.

Table 1.32 Pooled OLS Regression, Third Model

Independent Variable	**Intercept**	**Beta**	**ΔE**	**F**
Coefficient	γ_0	γ_1	γ_2	γ_3
Estimate	-2.317327	3.170685	-6.109618	-3.775287
t-stat	-1.64	2.3	-2.58	-1.21

1.7.4 Conclusions

- When running cross-sectional regressions, change in earnings has a negative coefficient and subsumes the effect of future earnings forecasts. In other words, following a contrarian earnings strategy will produce positive excess returns. However, a contrarian future earnings forecast strategy is not significant.
- On the other hand, pooled OLS regressions move future earnings forecasts close to significance. These regressions also confirm that previous earnings change is a determinant variable. I can therefore conclude that contrarian strategies for both change in earnings and earnings forecasts will lead to positive excess returns.

1.8 Time Series Regressions

1.8.1 Portfolio Formation

I ran time series regressions against the Fama-French (1993) three-factor model to see if returns can be completely explained by risk. If so, the intercepts should be close to zero or insignificant. In order to run these regressions, I have calculated a new factor called EXP, a zero-cost hedge portfolio that longs stocks with the most pessimistic forecasts and shorts stocks with the most optimistic forecasts using value-weighted returns; the differences are between the top and bottom 30% of each variable. The formula shows the EXP factor calculation:

$$EXP = \frac{R_{F1,\Delta E1} - R_{F3,\Delta E1}}{3} + \frac{R_{F1,\Delta E2} - R_{F3,\Delta E2}}{3} + \frac{R_{F1,\Delta E3} - R_{F3,\Delta E3}}{3}$$

$$= \frac{R_{F1,\Delta E1} + R_{F1,\Delta E2} + R_{F1,\Delta E3}}{3} - \frac{R_{F3,\Delta E1} + R_{F3,\Delta E2} + R_{F3,\Delta E3}}{3}.$$

The complete model for the time series regression is the following:

$$EXP_t = \alpha + \beta\left(R_{mt} - R_{ft}\right) + sSMB_t + hHML_t + \varepsilon_t.$$

1.8.2 Monthly Returns

I first decided to run the model with monthly returns. Interestingly, the intercept is close to significance and has a positive value. The rest of the factors are negative and significant. It is interesting to note that the three-factor model explains most of the returns. However, since the intercept is also really close to significance and its magnitude is rather large, part of the return cannot be explained by risk.

Table 1.33 Time Series Regression on Monthly Returns

Independent Variable	**Intercept**	**Rm-Rf**	**SMB**	**HML**
Coefficient	**α**	**β**	**s**	**h**
Estimate	0.2815332	-0.1697845	-0.4912484	-0.1168609
t-stat	1.44	-3.9	-7.98	-1.76

1.8.3 Yearly Returns

When switching to yearly returns, the time series regression becomes completely insignificant. Therefore, risk factors cannot explain the EXP variable (Table 1.34).

Table 1.34 Time Series Regression on Yearly Returns

Independent Variable	**Intercept**	**Rm-Rf**	**SMB**	**HML**
Coefficient	**α**	**β**	**s**	**h**
Estimate	1.682714	0.0833968	-0.2752398	-0.0963537
t-stat	0.54	0.63	-1.25	-0.5

1.9 Conclusions

- Analysts tend to give better earnings forecasts to firms that had good previous earnings performance. This effect is observed for both glamour and value stocks and when using different calculation methods. Surprisingly, forecasts for the best-performing value stocks are higher than those for the best-performing glamour stocks, suggesting that analysts are interested in any potential value effect.
- For the period between 1985 and 2009, value stocks outperformed growth stocks in 15 out of the 24 analyzed years as well as for the overall sample. This difference is of 0.16% per month or 1.92% per year. Returns in the sample are greater than benchmark returns due to the fact that analysts prefer to observe and give forecasts for better-performing stocks.
- After calculating realized earnings based on previous performance, profit from value stocks comes from a momentum trading strategy. On the other hand, glamour stocks follow a contrarian strategy. For the overall sample, contrarian strategies will work better.
- Contrarian strategies should be followed when considering earnings forecasts. When considering equally weighted returns, glamour firms provide a significant difference. However, the overall sample will provide a significant difference when calculating

equally weighted returns. Value firms also significantly outperform glamour firms for the worst-forecast quintile.

- Cross-sectional regressions show that previous earnings forecasts have a significant influence on excess portfolio returns. Earnings forecasts seem not to have an influence. However, when calculating the regression through panel data, both previous earnings and earnings forecasts have significant and negative relationships with excess returns, confirming contrarian strategies.
- Finally, I calculated time series regressions of earnings forecast portfolios against the three-factor model. The factors are significant when using monthly data, and the intercept is large and close to significance. On the other hand, regressions with yearly data make all coefficients insignificant, leading to the conclusion that returns on contrarian forecast-based portfolios are not explained by risk.

CHAPTER 2

BID-ASK SPREAD ANALYSIS FOR PENNY STOCKS

2.1 Literature Review

Market microstructure, which deals with the behavior of market makers during specific circumstances of the trading session, is one of the most important subfields in finance. It is very important for researchers to analyze these movements, since transaction costs can be determinant in calculating actual returns. On the other hand, there has not been much research in the field of penny stocks. In fact, it is conventional in the financial literature to cut off any stocks priced under $5. However, some stocks that fall into that group are liquid enough to have an interesting behavior.

Analyst coverage, on the other hand, also provides an interesting insight to the market. Analysts are supposed to fill the information gap that exists between firms and investors. Despite the fact that some papers argue fact that analysts do not add value, many people do pay attention to their opinions. However, some stocks, known as “neglected stocks,” do not garner any attention from the analysts, and very few publications have been devoted to that a study of neglected stocks.

The purpose of this essay is to tie market microstructure, penny stocks, and analyst recommendations. This is a new approach that deserves a close examination.

2.1.1 Market Microstructure

McInish and Wood (1992) examined the behavior of Bid-Ask Spreads (BASs)throughout a trading session. They identified a reverse J-shaped pattern when plotting the BAS in minute-to-minute intervals. Spreads prove to be higher at the beginning and at the end of the trading session as opposed to the mid-session period. The authors identified four different sets of variables that determine the BAS:

- **Trade activity**. Researchers have discovered that a larger holding period for a security by market makers will increase the security's BAS. Papers utilize total risk (Tinic [1972], Tinic and West [1972], Branch and Freed [1977], Hamilton [1978], Stoll [1978]) and systematic and unsystematic risk (Benston and Hagerman [1974], Stoll [1978]).
- **Level of risk**. As stated by Hasbrouck (1988), large trades carry more information than small trades. As market makers know, informed traders usually have larger trading volumes, therefore affecting bid-ask quoting. Schwartz (1988) also argues that the spread goes up when there is an important information change in the market.
- **Information from the market**. There is an inverse relationship between information and spread according to Demsetz (1968), Tinic and West (1972), Benston and Hagerman (1974), Hamilton (1976, 1978), and Branch and Freed (1977).
- **Level of competition**. Previous studies have demonstrated that volatility of returns presents a U-shaped pattern over the trading session (Wood, McInish, and Ord [1985], Harris [1986], and McInish and Wood [1990]). Volatility is a direct measure of risk and an indirect measure of level of information (French and Roll [1986]).

Chelley-Steeley and Park (2011) examined intraday patterns of exchange-traded funds (ETFs) in the London Stock Exchange through the McInish and Wood (1992) methodology. They found an increase in the BAS at the beginning of the trading session but not at the end. A way to explain this finding is that there is an accumulation of information after the market closes, and as a consequence, that information will impact spreads when the market reopens.

Stoll (1989) modeled the relation between the square of a quoted BAS and two serial covariances, of transaction returns and quoted returns, as a function of the probability of a price reversal and the magnitude of the price change. These factors are influenced by the components of the spread, adverse information costs, order processing costs, and inventory holding costs.

Heston, Korajczyk, and Sadka (2010) examined intraday predictability in a cross section of stock returns and demonstrated a return continuation in half-hour intervals the effect of which lasts 40 trading days. Volume, order imbalance, volatility, and BASs also have similar patterns but do not explain returns. Short-term reversal is driven by temporary liquidity imbalances.

2.1.2 Neglected Firms

Arbel and Strebel (1982) were pioneers in revealing the effects of neglected firms. Defining a neglected stock as a stock that has no analyst coverage, they suggest that there is a “neglected-firm effect: in terms of superior performance of these less-researched companies and that this effect persists over and above the small-firm effect. This is an anomaly, since the Capital Asset Pricing Model (CAPM) cannot explain the differences.

Arbel, Carvell, and Strebel (1983) address the fact that small firms are unsuited to the investment requirements of financial institutions and therefore attract minimum coverage. Therefore, these securities may offer a premium, since there is a lack of information about them. They found out that 510 firms neglected by institutions outperform significantly and that the performance is above and beyond the small-firm effect.

Beard and Sias (1997) addressed this neglected-firm effect. With a large and up-to-date sample, they could not find any evidence of neglected premium. They also state that there probably was no neglected-firm effect in the past 14 years.

Elfakhani and Zaher (1998) analyzed neglected stocks from financial analysts a January effect, if there was a relationship between the size effect and neglect of smaller firms, and if individual investors could benefit from neglecting. They found out that there was a neglected-firm effect from 1986 to 1990.

Finally, Demiroglu and Ryngaert (2010) analyzed new coverage for neglected stocks. In a sample of 549 stocks that were neglected for at least a year, they noted a 4.86% abnormal return after the initiation announcement, which was positive only if the coverage was positive. The returns were also consistent with liquidity increases.

2.2 Hypotheses

This study addresses the following hypotheses.

2.2.1 Hypothesis 1: Scaled Big-Ask Spreads in penny stocks are significantly different at various points of the trading session.

I expect to see as did McInish and Wood (1992) a big spike at the beginning of the session, some more normalized behavior during the middle of the session, and then an increase toward the end of the session. Therefore, there will be a significant difference at different points in time.

2.2.2 Hypothesis 2: Scaled Big-Ask Spreads in penny stocks are significantly different based on the day of the week.

There is evidence in the literature that some days of the week are better for trading than others. If that is the case, I would expect a significant difference between scaled bid-ask spreads among the days of the week and from the overall average.

2.2.3 Hypothesis 3: Scaled Big-Ask Spreads in penny stocks are significantly different based on the month of the year.

Again, there is evidence in the literature that some months of the year offer greater results than others. If that is the case, I would expect a significant difference between scaled BASs among the months of the year and from the overall average.

2.2.4 Hypothesis 4: Scaled Big-Ask Spreads in penny stocks are significantly different if analysts are following their performance.

Finally, and in order to link my previous essay to this essay, I will differentiate those penny stocks that are followed by analysts and those that are not. If analysts add information to trading, scaled BASs of stocks that are followed by analysts should be lower than those of neglected stocks.

2.2.5 Hypothesis 5: Activity, risk, information, and competition factors have different influences on scaled Big-Ask Spreads based on whether analysts are following their performance.

I will determine this difference through panel data regressions, to the complete sample and to two subsamples based on analyst coverage. Since the two samples have different fundamental characteristics, I expect to see a variation in the results.

2.2.6 Hypothesis 6: Market equity, total assets, and stock price have a significant influence in determining analyst coverage.

Finally, I will try to determine which variable—total assets, market equity, or the price of the stock—plays the most important role in determining whether a stock is followed by analysts. Through this hypothesis, I will try to see if coverage is exclusively a function of size.

2.3 Data

2.3.1 Sample Selection

Since I was dealing with intraday quote data, I decided to analyze one year of data. Because there were no major financial fluctuations during 2006, I decided to use that year's data for the analysis. The S&P 500 index performance for 2006 is shown in Figure 2.1. Trading days during the period were from January 3, 2006, to December 29, 2006. This gives a grand total of 251 trading days for the year. Trading times, on the other hand, were from 9:30 am to 4:00 pm, Eastern (New York) time.

Figure 2.1 S&P 500 Index Performance for 2006 (From Yahoo! Finance)

I had to define "penny stock" for my essay. In this case, I decided to use stocks whose price was less than \$5. I also decided to include an extra constraint: these stocks had to be traded at least once per day during the period. Therefore, I used the CRSP database in order to determine which stocks traded every day and had closing prices of less than \$5. A total of 502 stocks met those requirements for the 2006. Among those stocks, 199 stocks had analyst information on IBES.

Once the sample was restricted, I utilized the Tradings and Quotes (TAQ) database in order to get the quotes information, with more than 192 million data points for the sample. Finally, some invalid observations had to be eliminated. For example, some quotes have bid prices of one cent and ask prices of more than 99 dollars. These observations are obviously invalid. In order for an observation to be valid, its midpoint had to be greater than 0.01 and less than 5 and bid and ask quotes had to be positive and less than 5.

2.3.2. Bid-Ask Spread Calculation

I used the following formula to calculate the scaled BAS:

$$BAS = \frac{(ask - bid)}{\frac{(ask + bid)}{2}}$$

In other words, the scaled BAS is the actual BAS divided by the midpoint of that specific quote. Every quote should have a scaled BAS greater than 0. Any numbers greater than or equal to five were manually revised and discarded if they were invalid quotes.

Finally, Figure 2.2 is a graph from McInish and Wood (1992).

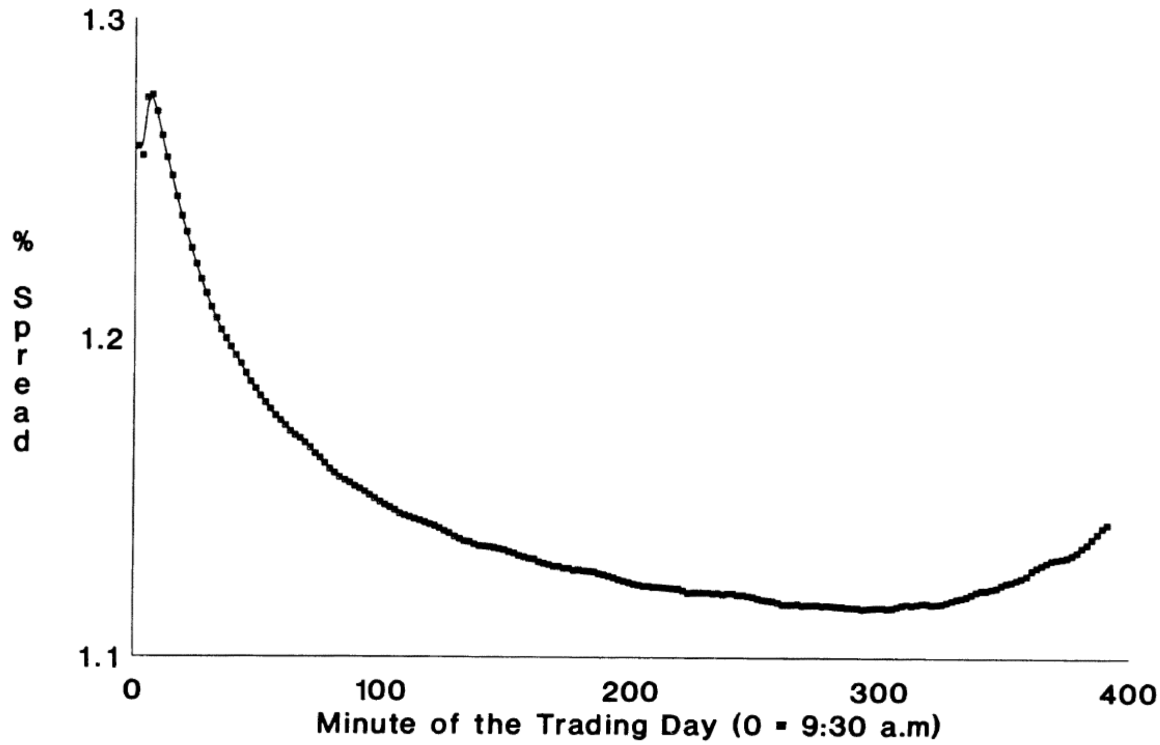

Figure 2.2 Minute-by-Minute Scaled Bid-Ask Spread (McInish and Wood [1992])

I expect to see the same behavior of BAS during the trading session, that is, I expect to see a large number in the opening minutes, then a downward sloping trend, and finally an increase when the market approaches its closing time. However, since this analysis involves penny stocks, I expect the magnitude to be larger and the line to be less smooth.

<u>2.4 Bid-Ask Spread during the Trading Session</u>

2.4.1. Second-by-Second Analysis

Figure 2.3 shows the average scaled BAS for every second of the trading session.

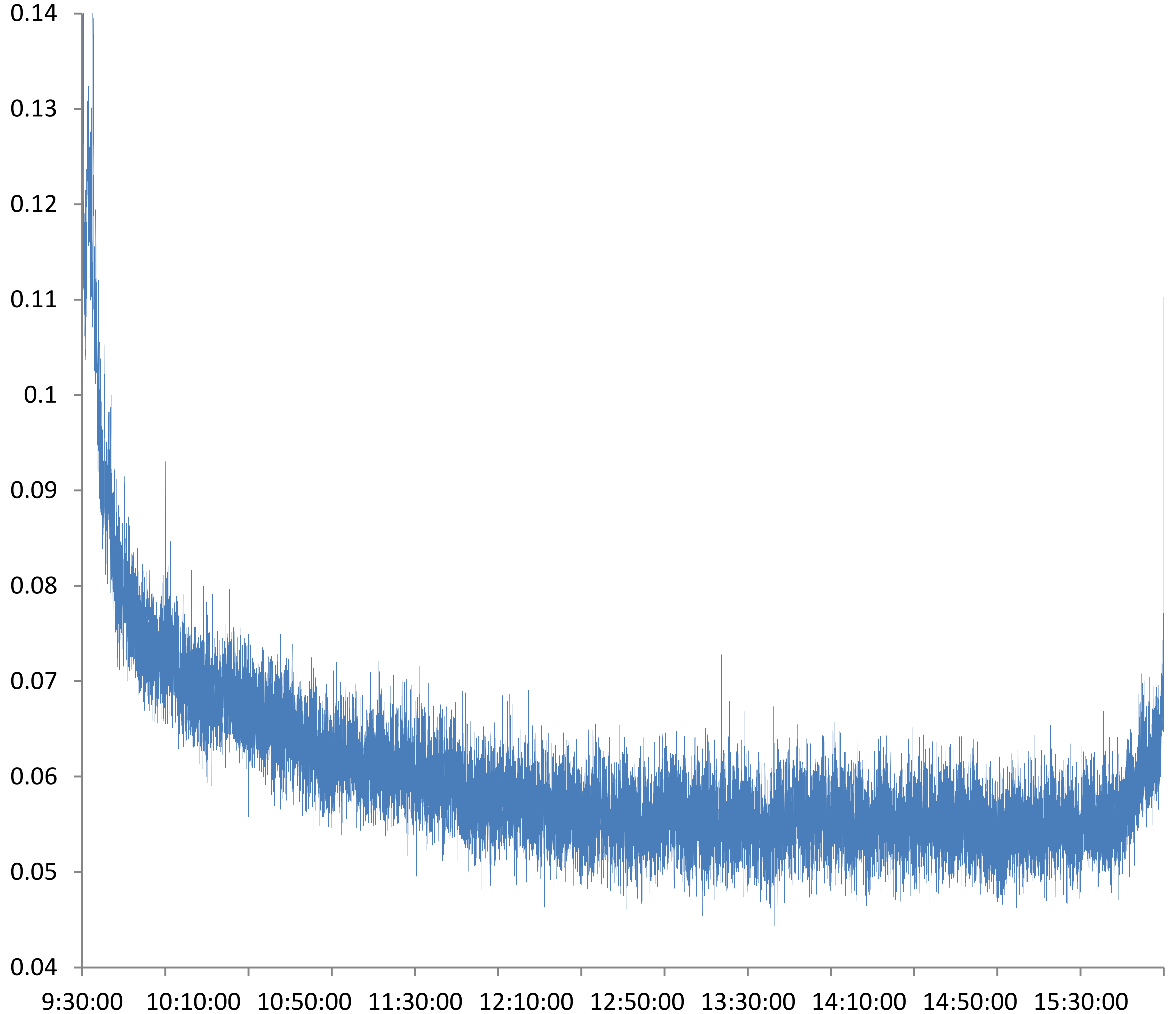

Figure 2.3 Second-by-Second Scaled Bid-Ask Spread

It is really interesting to see in Figure 2.3 that most of the series looks like white noise, except at the beginning and at the end. BAS opens the trading session with an upward movement and then settles down. It goes up once again toward the end of the session. This behavior will be analyzed in the following section.

2.4.2. Minute-by-Minute Analysis

Figure 2.4 shows the minute-by-minute scaled BAS.

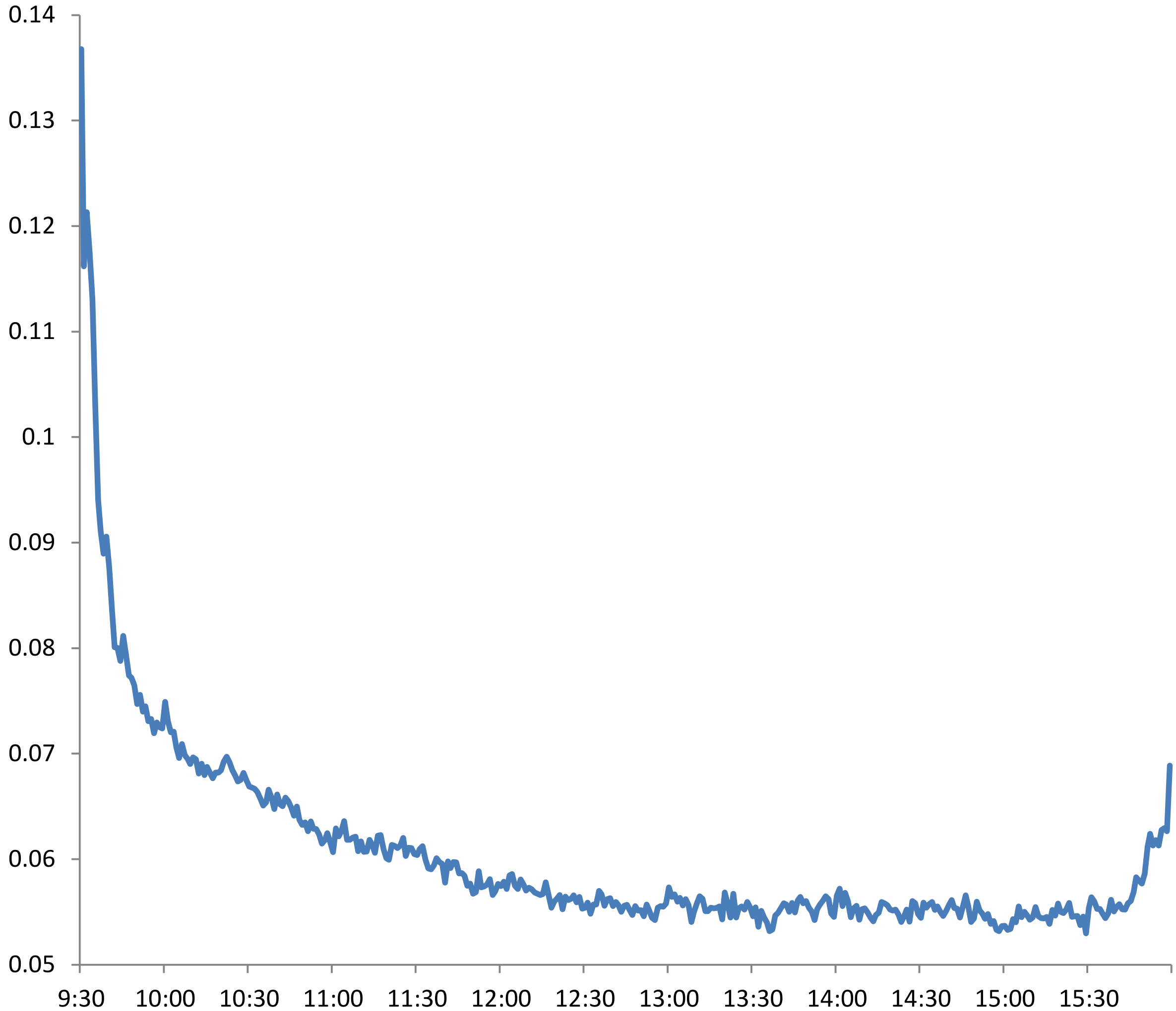

Figure 2.4 Minute-by-Minute Scaled Bid-Ask Spread

Figure 2.4 can be directly compared with the graph from McInish and Wood (1992). Both graphs follow the same patterns, but magnitudes are greater in the penny stocks graph. This graph is also consistent with Figure 2.3: it follows the same pattern. However, the lines are smoother as a consequence of averaging every second into minutes.

2.4.3. Thirty-Minute Interval Analysis

Figure 2.5 shows the average 30-minute BAS.

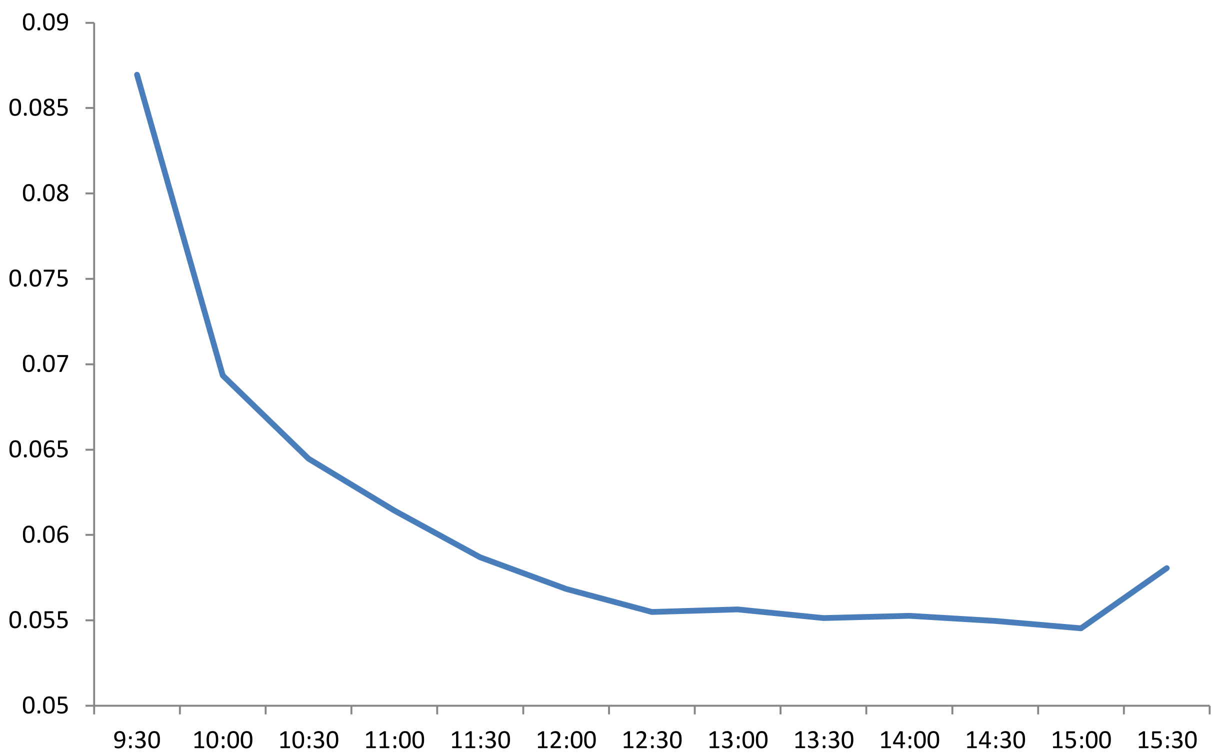

Figure 2.5 Thirty-Minute Interval Scaled Bid-Ask Spread

This line is smoother than the previous ones. Thirty-minute intervals are useful for performing econometric analysis. It is interesting to see how BAS starts high, then drops, and then goes back up by the end of the session.

2.5 Bid-Ask Spread in Different Months of the Year

I analyzed this BAS behavior for different scenarios. The first of these scenarios is months of the year. In some months of the year, BAS should be lower, and in some, BAS should be higher. In order to check that assumption, I calculated the second-by-second mean for every month and then tested the differences. Figure 2.6 shows the months that have the more extreme behaviors. July and August had, on average, higher BASs. On the other hand, November and December had lower BASs.

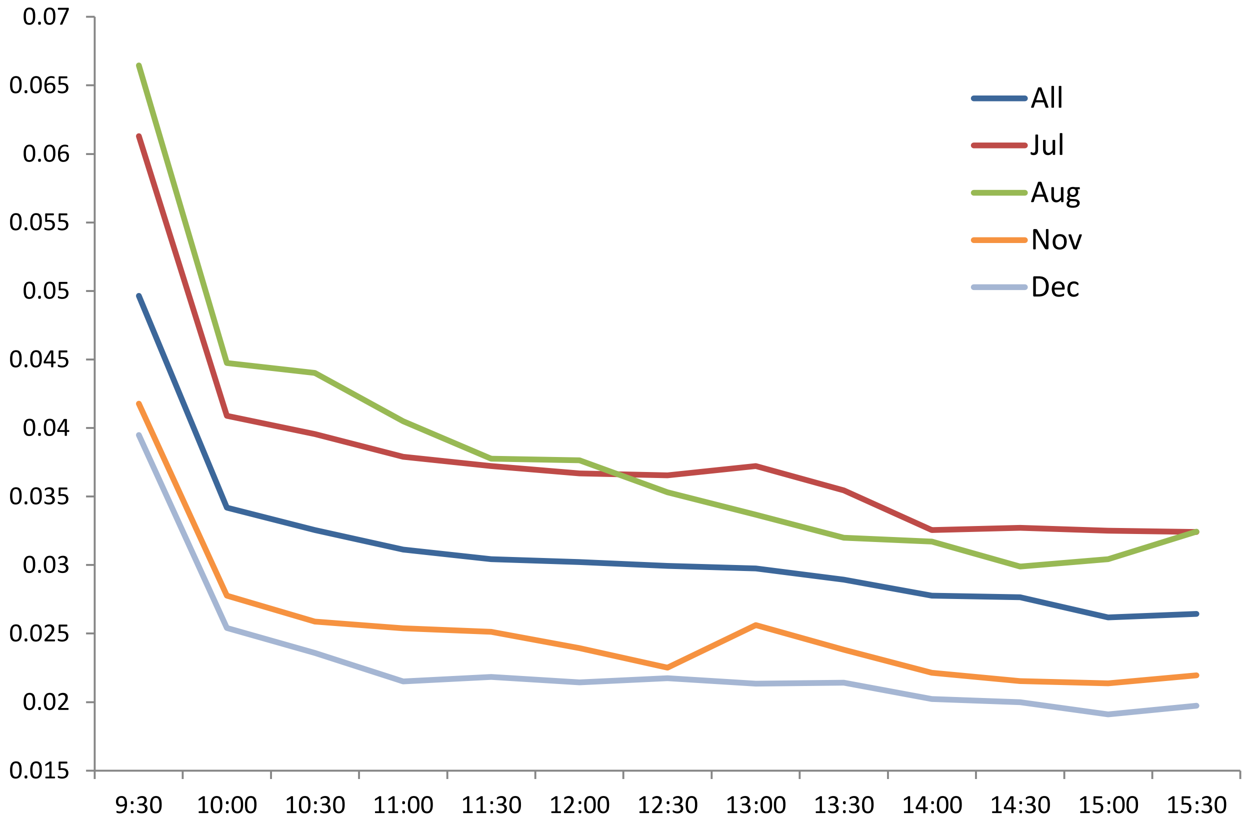

Figure 2.6 Bid-Ask Spread for Different Months of the Year

Table 2.1 shows the calculations of the difference from the mean for every month for the complete sample. First of all, it is really interesting to see that only January and May actually behave like the mean. It is interesting to see January behaving like the mean, since it has been documented in the literature that market returns are higher in January. The rest of the months are actually above or below the mean. July and August, as demonstrated in the graph, are quite above the mean. On the other hand, November and December are clearly below the mean. In broad terms, five months are above the mean, five are below the mean, and two are at the mean.

I also calculated differences for thirteen 30-minute intervals for every month. Table 2.2 summarizes the results. In spite of the fact that some months have larger or smaller differences to the mean, when analyzing these intervals we can see that there are different dynamics within each month. Some of those months, especially the ones in Figure 2.6, are consistent throughout the sample. January and May are the months whose intervals often switch signs. It would be interesting to further analyze these months using a larger sample.

Table 2.1 Bid-Ask Spread Differences among Months for the Complete Sample

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Coef	-2.7E-06	0.00129	-0.0022	-0.0025	2.6E-06	0.0027	0.0069	0.0071	0.0033	-0.0002	-0.0058	-0.0082
T-Stat	-0.1	41.87	-85.74	-94.11	0.1	95.12	217.29	182.91	107.35	-8.19	-253.85	-348.24

Table 2.2 Bid-Ask Spread Differences among Months for 30-Minute Intervals

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Int 1	-0.0041	-0.0024	-0.0063	-0.005	0.00005	0.0063	0.0113	0.01673	0.0055	0.0017	-0.0079	-0.01
T-Stat	-32.01	-19.81	-53.12	-48.25	0.46	38.1	72.71	103.39	36.82	12.32	-65.19	-70.52
Int 2	-0.0015	0.0003	-0.0025	-0.004	0.001	0.00373	0.00679	0.01068	0.00484	-0.001	-0.0064	-0.0088
T-Stat	-16.71	3.19	-29.85	-49.45	11.96	39.12	67.55	92.21	45.71	-11.73	-82.9	-119.46
Int 3	-0.0004	0.00007	-0.0033	-0.004	-0.001	0.0038	0.00707	0.01153	0.00505	-0.0002	-0.0067	-0.0089
T-Stat	-3.96	0.63	-39.76	-51.46	-5.83	40.58	63.08	84.52	42.27	-2.25	-91.78	-115.56
Int 4	0.00017	0.00002	-0.0019	-0.0028	-0.0012	0.0029	0.00685	0.009	0.00516	-0.0001	-0.0057	-0.0096
T-Stat	1.91	0.18	-23.33	-32.59	-13.99	30.43	66.48	78.32	44.41	-1.2	-76.17	-127.79
Int 5	-0.0009	0.0019	-0.002	-0.0007	-0.0008	0.00191	0.00687	0.00741	0.00301	0.00016	-0.005	-0.0085
T-Stat	-10.01	17.72	-28.46	-7.08	-8.85	21.82	64.53	63.87	29.26	1.65	-67.6	-105.87
Int 6	-0.0006	0.00162	-0.0026	-0.0007	0.00048	0.0011	0.00656	0.00749	0.00347	-0.00034	-0.0062	-0.0088
T-Stat	-6.42	15.44	-30.32	-7.19	5.04	11.95	63.03	83.21	34.56	-3.41	-77.25	-119.2
Int 7	0.00119	0.00263	-0.0008	-0.0023	-0.0005	0.0023	0.00669	0.00538	0.00263	-0.0003	-0.0074	-0.0081
T-Stat	11.75	23.48	-9.16	-24.2	-5.61	24.07	61.76	65.73	27	-3.49	-100.78	-99.51
Int 8	0.00064	0.00164	-0.0005	-0.0027	-0.0006	0.0025	0.00752	0.0039	0.00178	-0.0007	-0.0041	-0.0084
T-Stat	6.41	14.93	-5.82	-29.86	-6.25	25.82	60.72	46.93	18.62	-7.69	-47.27	-101.36
Int 9	0.00196	0.0021	-0.0016	-0.0021	0.0001	0.0023	0.0066	0.0031	0.00234	-0.001	-0.0051	-0.0075

Table 2.2 - continued

T-Stat	20.07	19.58	-19.49	-22.33	1.59	26.2	63.81	35.75	24.57	-10.83	-64.66	-89.24
Int 10	0.00235	0.00256	-0.0006	-0.0017	-0.0005	0.00204	0.00495	0.004	0.00203	-0.001	-0.0056	-0.0075
T-Stat	25.2	24.59	-6.78	-20.37	-6.04	23.84	50.11	44.84	21.72	-10.43	-83.74	-97.62
Int 11	0.00127	0.00334	-0.0009	-0.0012	0.00129	0.0017	0.00522	0.0023	0.00156	-2E-06	-0.006	-0.0077
T-Stat	14.47	31.37	-11.95	-14.5	13.25	20.62	52.81	29.2	16.97	-0.03	-92.54	-102.53
Int 12	0.00045	0.00132	-0.0028	-0.0015	0.00061	0.00212	0.0065	0.0043	0.0025	0.00024	-0.0048	-0.0071
T-Stat	5.94	15.4	-41.46	-19.28	7.84	27.21	69.1	53.14	27.77	3.26	-70.23	-111.44
Int 13	-0.0007	0.00174	-0.0022	-0.0028	0.00055	0.0021	0.00624	0.0061	0.00245	-0.0004	-0.0044	-0.0066
T-Stat	-9.59	16.74	-31.72	-39.33	7.52	27.81	72.56	74.19	28.41	-4.75	-69.29	-105.71

2.6 Bid-Ask Spread in Different Days of the Week

This analysis is similar to the one in the previous section, but now I am sorting by days of the week instead of months of the year. This calculation was also made second-by-second for the complete period, and for 30-minute intervals.

Figure 2.7 shows the behavior of the complete sample plus Thursday and Friday. Friday was the day with the highest BAS, while Thursday was the day with the lowest BAS. As opposed to months of the year, days of the week seem to have a closer difference from the mean. However, there are some specific points during the trading session at which differences are wider or narrower.

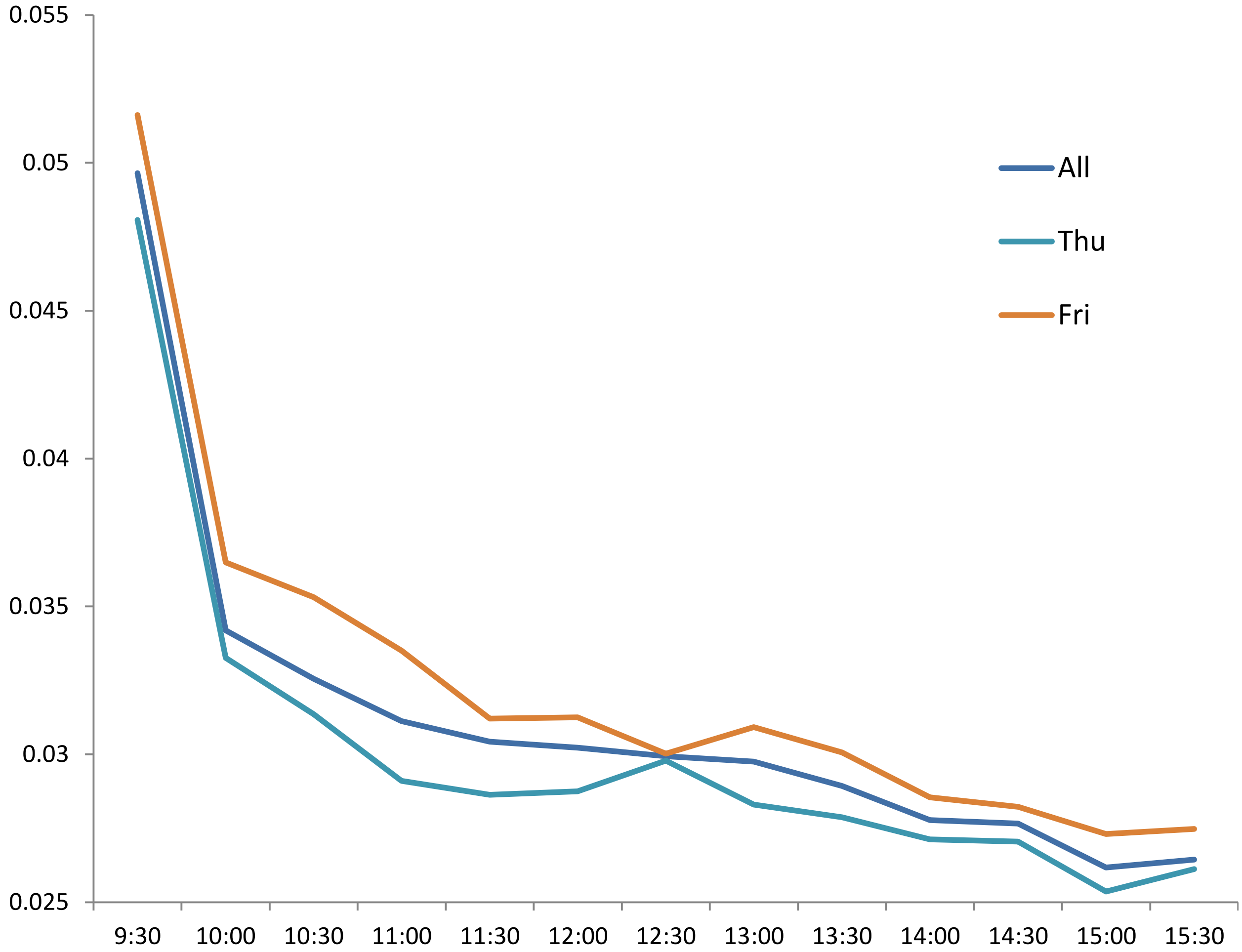

Figure 2.7 Bid-Ask Spread for Different Days of the Week

Table 2.3 provides the difference with the mean for the complete sample. On one day, Tuesday, the difference was insignificant. Two of the days, Monday and Friday, had positive differences, and Wednesday and Thursday had negative differences. Friday's case is interesting, since it has been documented in the literature that Fridays provide higher returns than the rest of the days of the week. Table 2.4 gives a 30-minute interval analysis for every day of the week. As with months of the year, Tuesday, the day that was insignificant, fluctuates between positive and negative differences.

Table 2.3 Bid-Ask Spread Differences among Days of the Week for the Complete Sample

	Mon	Tue	Wed	Thu	Fri
Coefficient	0.0006708	-7.80E-06	-0.0007003	-0.0010477	0.0013745
T-Stat	38.71	-0.53	-47.29	-69.17	80.69

Table 2.4 Bid-Ask Spread Differences among Days of the Week for-30 Minute Intervals

	Mon	Tue	Wed	Thu	Fri
Interval 1	0.0008678	-0.0002011	-0.0011766	-0.0014852	0.0022655
T-Stat	11.03	-3.39	-19.87	-25.62	30.89
Interval 2	0.0004161	-0.0004672	-0.001114	-0.0008978	0.0023366
T-Stat	7.02	-9	-22.23	-16.98	39.47
Interval 3	-0.0001519	-0.0002619	-0.0009974	-0.0011745	0.0027906
T-Stat	-2.44	-4.75	-18.49	-22.6	43.86
Interval 4	0.0008926	-0.0004007	-0.000498	-0.0019782	0.0024067
T-Stat	14.76	-7.69	-9.12	-37.4	39.55
Interval 5	0.0009114	0.000218	0.0001442	-0.0017217	0.0008352
T-Stat	15.12	4.08	2.67	-29.35	13.32
Interval 6	0.0006233	0.0005933	-0.0005696	-0.0014027	0.0010457
T-Stat	9.86	10.57	-10.47	-25.29	18.65
Interval 7	0.0012023	0.000134	-0.0010926	-0.0001064	0.0001168
T-Stat	19	2.52	-20.21	-1.86	2.21
Interval 8	0.0023501	-0.0000705	-0.0016229	-0.0014045	0.001174
T-Stat	34.72	-1.29	-30.61	-25.95	20.12
Interval 9	0.0009996	0.0002717	-0.0010488	-0.0010275	0.0011623
T-Stat	17.86	5	-19.99	-19.42	19.23
Interval 10	0.0005925	-0.0001845	-0.0002803	-0.000627	0.0008415
T-Stat	10.02	-3.64	-5.23	-11.95	14.01
Interval 11	0.0000666	0.0000531	0.0000373	-0.0005829	0.0005919
T-Stat	1.18	1.02	0.76	-11.73	10.79
Interval 12	-0.0001959	0.0002377	-0.0002809	-0.0007706	0.0011657

Table 2.4 - continued					
T-Stat	-3.94	5.33	-6.58	-17.78	23.87
Interval 13	0.0001462	-0.0000233	-0.0006042	-0.0004421	0.0011368
T-Stat	3.28	-0.52	-13.87	-8.71	24.59

2.7 Bid-Ask Spread in Stocks Followed by Analysts

Figure 2.8 shows the difference between firms that are followed and the ones that are not followed by analysts. There is a large and significant difference between the two groups. This is expected: firms that are not followed by analysts carry greater information risks, and therefore their trading is subject to more caution from market makers.

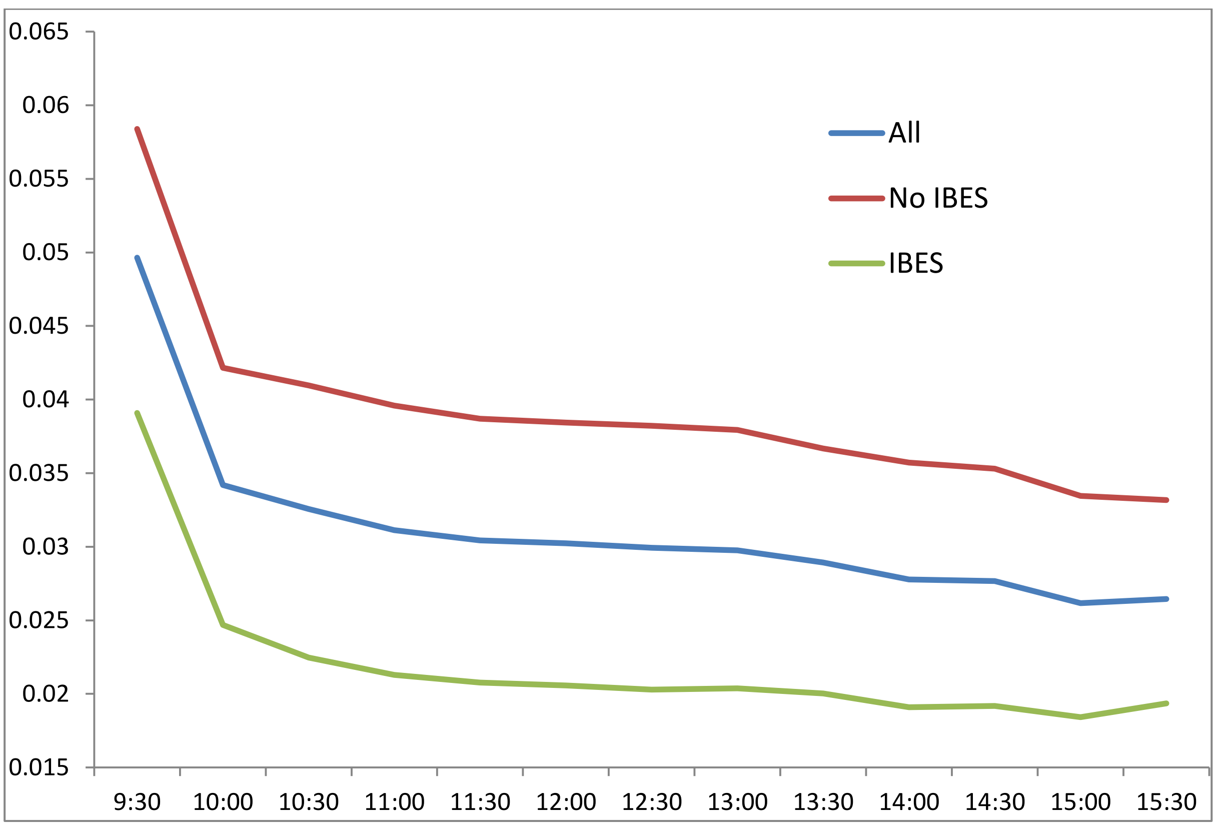

Figure 2.8 Bid-Ask Spread for Different Analyst Coverage

Table 2.5 simply proves what the graph was indicating. Both coefficients are highly significant. It is also interesting to see that the magnitude of the IBES coefficient is greater by almost 0.001 compared with the no IBES coefficient. That is more than a 10% difference between the two coefficients. We can infer, then, that being followed by analysts reduces the BAS to a greater extent than the risk increase when a stock is not on IBES. Thirty-minute intervals, in Table 2.6, are also consistent with the complete period differences.

Table 2.5 Bid-Ask Spread Differences for Analyst Coverage for the Complete Sample

	No IBES	IBES
Coefficient	0.0079853	-0.0091429
T-Stat	936.26	-899.65

Table 2.6 Bid-Ask Spread Differences for Analyst Coverage for 30-Minute Intervals

	No IBES	IBES
Interval 1	0.0028795	-0.0101652
T-Stat	79.88	-98.44
Interval 2	0.0023739	-0.0089773
T-Stat	196.85	-217.14
Interval 3	0.0025195	-0.0098873
T-Stat	206.92	-229.24
Interval 4	0.0025901	-0.0099682
T-Stat	205.8	-233.12
Interval 5	0.0026449	-0.0101729
T-Stat	213.26	-246.54
Interval 6	0.0025627	-0.0100706
T-Stat	219.93	-254.14
Interval 7	0.0026463	-0.0102061
T-Stat	216.25	-258.22
Interval 8	0.0025873	-0.0097715
T-Stat	208.02	-233.46
Interval 9	0.0024873	-0.092902
T-Stat	216.82	-244.28
Interval 10	0.0024632	-0.0091246
T-Stat	208.72	-240.86
Interval 11	0.0025556	-0.0094704
T-Stat	227.43	-257.21

Table 2.6 - continued		
Interval 12	0.002378	-0.0085237
T-Stat	235.3	-264.78
Interval 13	0.0023399	-0.0080029
T-Stat	227.23	-254.11

2.8 Panel Data Analysis

In order to understand intraday dynamics, I performed an analysis similar to McInish and Wood (1992). I therefore had to calculate intraday independent variables from the TAQ trading and quotes files for 2006.

2.8.1 Variables

This is the list of independent variables, grouped by their corresponding main characteristic. Scaled BAS is the dependent variable.

2.8.1.1 Activity

- **$Trades_{i,t}$.** This variable is the square root of the number of transactions for each stock i in Interval t. It is expected to have a negative relationship to BAS, since the more trades a stock has, the lower the uncertainty and therefore the BAS.
- **$Size_{i,t}$.** This variable is the square root of the average number of shares per trade for each stock i in Interval t. It is expect to have a negative relationship to BAS, since the larger the size of the trade, the lower the uncertainty and therefore the BAS.

2.8.1.2 Risk

- **Risk 1_i** and **Risk $2_{i,t}$.** Let $V_{i,t}$ be the standard deviation of the BAS for stock i interval t, M_i the mean of $V_{i,t}$ for stock i over time t, and S_i the standard deviation for $V_{i,t}$ for stock i over time t. **Risk 1_i** is M_i, and **Risk $2_{i,t}$** is $(V_{i,t}-M_i)/S_i$. The relationship of both variables to BAS is positive, since market makers will increase the difference when risk is perceived.

2.8.1.3 Information

- **Nsize$_{i,t}$.** The mean (X_i) and standard deviation (D_i) of the square root of the volume per trade (SIZE i,t). NSIZEi,t is SIZEi,t – Xi /Di. This variable shows the ffect of unusually large or small trades relative to the average size of trades. The more trades of a stock, the greater flow of this stock in the market. Therefore, I expect to see a negative relation between Nsize and BAS.

2.8.1.4 Competition

- **Regional$_{i,t.}$** This variable is the square root of the ratio of number of shares that were traded outside the NYSE, AMEX, or NASDAQ. The variable accounts for competition, that is, there is more competition if the stock is quoted in several exchanges. I expect to see a positive relationship, even close to zero, since most of these stocks are traded in the NASDAQ.
- **Price$_{i,t.}$** The final variable is the square root of average Price at interval t is included. Relationship is direct: the higher the price, the lower the BAS.

2.8.1.5 BAS

As previously defined, the scaled BAS is calculated by using the following formula for every quote in the data set:

$$BAS = \frac{(ask - bid)}{\frac{(ask + bid)}{2}}$$

2.8.2 Base Model

The base model for the panel data regression is the following:

$$BAS_{i,t} = b_0 + b_1 TRADES_{i,t} + b_2 SIZE_{i,t} + b_3 RISK1_i + b_4 RISK2_{i,t} + b_5 NSIZE_{i,t} + b_6 REGIONAL_{i,t} + b_7 PRICE_{i,t} + e_{i,t}$$

2.8.3 Density Functions

Part of my analysis is run on two subsamples: stocks that are on IBES and stocks that are not on IBES. This difference accounts for analyst coverage. In order to know more about the nature of the subsamples, I calculated a kernell density function for BAS and compared it with the normal distribution.

Figure 2.9 presents the distributions for stocks that are followed by analysts. It is interesting to note that this distribution is skewed to the left and fatter than the normal distribution, which implies that despite having lower values than the normal, the standard deviation is higher.

On the other hand, Figure 2.10 shows the distribution of stocks that are not followed by analysts. The average is greater than the one for followed stocks. There is also some skewedness to the left and a thinner graph, which implies that despite having greater values than the followed stocks, unfollowed stocks have a lower standard deviation.

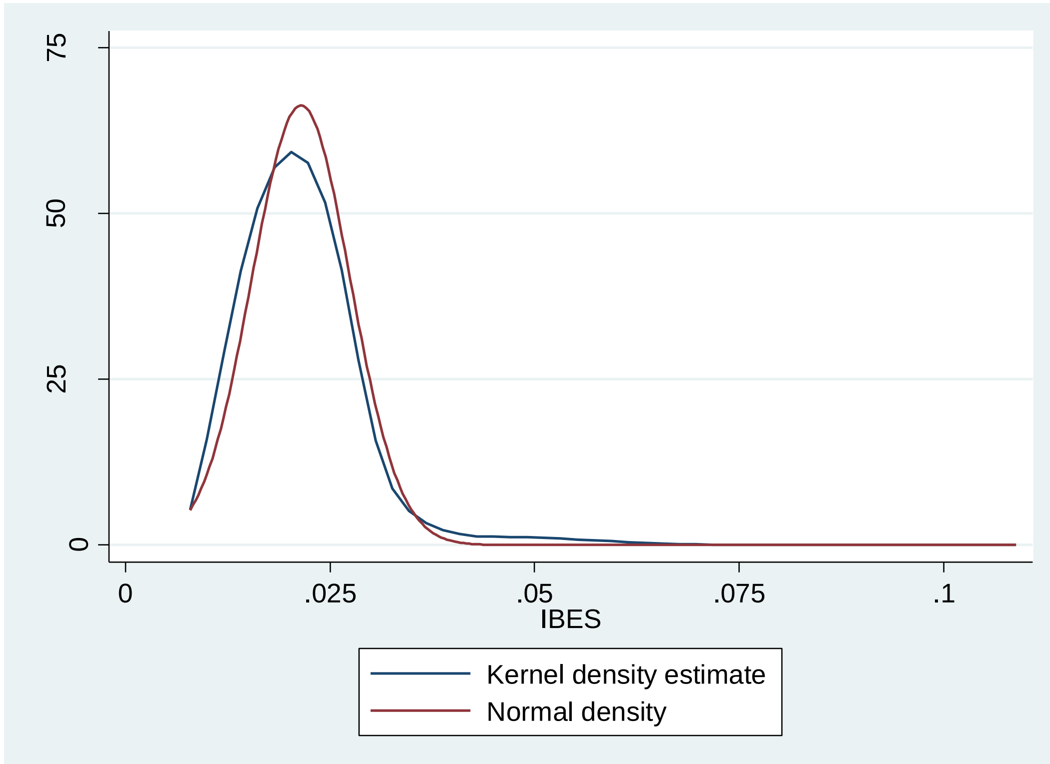

Figure 2.9 Kernell Density Distribution of Stocks That Are on IBES

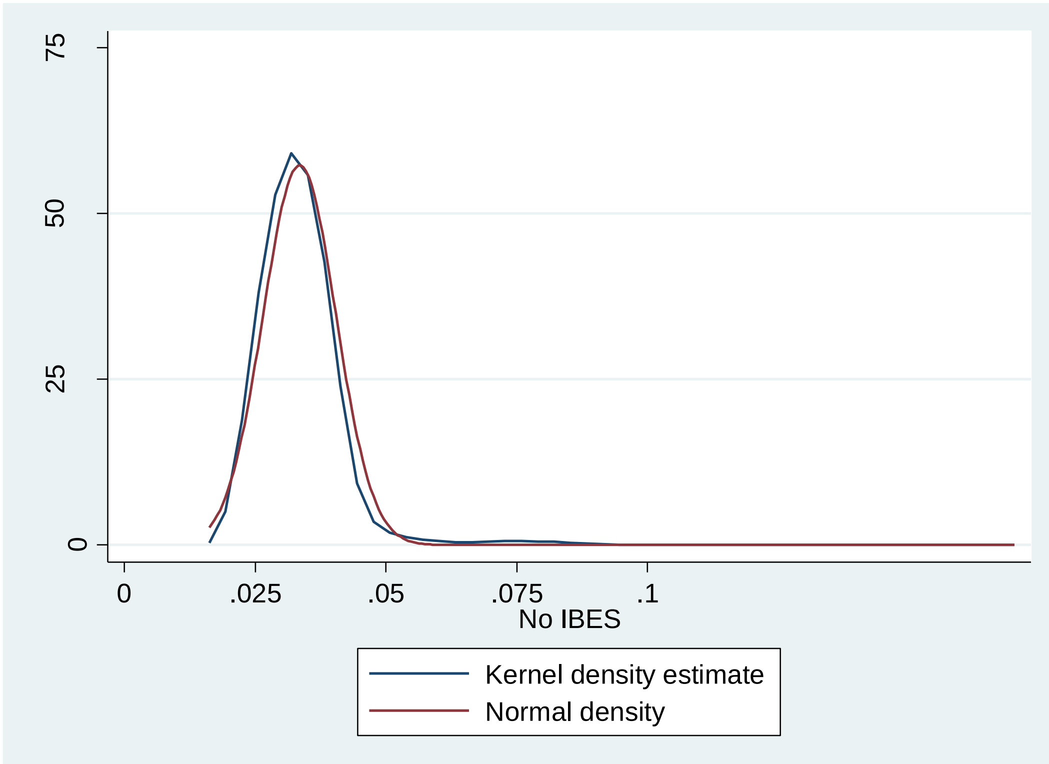

Figure 2.10 Kernell Density Distribution of Stocks That Are Not on IBES

2.8.4 Correlations

In order to have consistent results, it is important to evaluate the relationship among independent variables. I have calculated correlation matrices for the complete sample, the subsample that is not on IBES, and the subsample that is on IBES. For every table, the lower left triangle is Pearson's correlation, and the upper right triangle is Spearman's correlation.

2.8.4.1 Complete Sample

Correlations, in general, are low, as shown in Table 2.7. However, there is a very interesting relationship between the trade size and the regional variable that suggests that larger sizes are traded at larger stock exchanges. This makes sense for this sample, since most of the trading occurs on the NASDAQ. On the other hand, the correlation between Risk 1 and Trades has a greater coefficient when calculated through the Spearman method, indicating a nonlinear relationship.

Table 2.7 Correlation Matrix for the Complete Sample

	Trades	Size	Risk 1	Risk 2	Nsize	Regional	Price
Trades	1	0.1226	-0.5837	-0.0258	0.1391	0.0485	0.1290
Size	0.1047	1	0.1847	0.0145	0.3602	0.9450	-0.4388
Risk 1	-0.3873	0.2187	1	0.0200	-0.1053	0.1952	-0.3494
Risk 2	-0.0505	0.0042	0.0148	1	-0.0084	0.0128	-0.0095
Nsize	0.0735	0.4145	-0.0747	-0.0205	1	0.3670	-0.0140
Regional	0.0617	0.9568	0.224	0.0071	0.4151	1	-0.4437
Price	0.1524	-0.4823	-0.3608	0.0038	-0.0212	-0.4833	1

2.8.4.2 Stocks That Are Not on IBES

The differences in correlations between the complete sample and this subsample are not many. Table 2.8 shows that signs and magnitudes are consistent throughout the matrix. However, it is important to note some differences. The correlation between Regional and Trades more than doubled for the Spearman calculation, suggesting that firms that are not followed by analysts tend to be traded in regional exchanges. Another interesting correlation is the one between Price and Trades. It is negative in the Spearman calculation, close to zero, as opposed to positive for the complete sample. This implies that as price goes down, trades go up for the stocks that are not followed by analysts.

Table 2.8 Correlation Matrix for the Stocks That Are Not on IBES

	Trades	Size	Risk 1	Risk 2	Nsize	Regional	Price
Trades	1	0.1853	-0.5203	-0.0121	0.1265	0.1137	-0.0079
Size	0.1375	1	0.0787	0.0168	0.4289	0.9498	-0.4065
Risk 1	-0.3626	0.1398	1	0.0132	-0.1006	0.0950	-0.2952
Risk 2	-0.0437	-0.0038	0.0020	1	-0.0071	0.0150	-0.0038
Nsize	0.0614	0.4419	-0.0640	-0.0210	1	0.4346	-0.0567
Regional	0.1017	0.9599	0.1472	-0.0015	0.4420	1	-0.4028
Price	0.0884	-0.4505	-0.3011	0.0248	-0.0505	-0.4462	1

2.8.4.3 Stocks That Are on IBES

For the second subsample, we can observe in Table 2.9 that the correlation between Price and Trades is positive and greater in magnitude than in the complete sample. The correlation of Regional and Trades is quite similar to the complete sample, as well. This subsample behaves similarly to the complete sample.

Table 2.9 Correlation Matrix for the Stocks That Are on IBES

	Trades	Size	Risk 1	Risk 2	Nsize	Regional	Price
Trades	1	0.0916	-0.5814	-0.0576	0.1576	0.0258	0.1643
Size	0.0854	1	0.3472	0.0097	0.2390	0.9358	-0.4896
Risk 1	-0.3830	0.3757	1	0.0336	-0.1015	0.3345	-0.3376
Risk 2	-0.0615	0.0236	0.0362	1	-0.0105	0.0081	-0.0200
Nsize	0.0965	0.3430	-0.0919	-0.0159	1	0.2509	0.0402
Regional	0.0328	0.9467	0.3683	0.0272	0.3485	1	-0.4959
Price	0.1817	-0.5473	-0.3896	-0.0338	0.0298	-0.5519	1

2.8.5 Panel Data Regressions

This part of the study is similar to the one performed by McInish and Wood (1992). I regressed the following model:

$$BAS_{i,t} = b_0 + b_1 TRADES_{i,t} + b_2 SIZE_{i,t} + b_3 RISK1_i + b_4 RISK2_{i,t} + b_5 NSIZE_{i,t} + b_6 REGIONAL_{i,t} + b_1 PRICE_{i,t} + e_{i,t}$$

I utilized three approaches: pooled ordinary least squares (OLS), fixed effects, and random effects. I then performed a Hausman test to determine if fixed effects or random effects were better for the sample.

2.8.5.1 Pooled Ordinary Least Squares

This is the first complete model. I ran the regressions for the complete sample and for the two subsamples. It is interesting to see that all the variables are significant. The most impressive coefficient is the one for the Risk 1 variable. In order to avoid any potential bias, I reran the models without this variable.

Table 2.10 portrays the summary of the regressions. Trades are negative for the three subsamples, demonstrating that as trades increase, BAS goes down. The Size variable is also negative, also implying that as the size of the transaction increases, BAS goes down. The following variables are related to risk. Risk 1 is positive and has an important magnitude, which means that the average standard deviation of the BAS plays an important role in its determination. Risk 2 is also important but to a lesser extent.

Nsize, that is the standardized volume per trade, is negative. Regional is positive but with a very low magnitude. Price is also negative, implying that as price goes up, BAS goes down. All of the models have significant F statistics and R-squared.

Table 2.10 Pooled OLS Regressions

	Complete Sample	**No IBES**	**IBES**
Constant	0.045409	0.043264	0.042865
t-stat	79.32	56.46	52.71
Trades	-0.00206	-0.00198	-0.00247
t-stat	-29.16	-19.61	-28.52
Size	-0.00134	-0.00102	-0.00176
t-stat	-49.25	-27.62	-47.83
Risk 1	0.940745	0.979292	0.840706
t-stat	551.97	428.17	348.18
Risk 2	0.062453	0.061736	0.06573
t-stat	251.21	197.38	160.2
Nsize	-0.00475	-0.00562	-0.00479
t-stat	-13.84	-12.93	-8.66
Regional	0.001073	0.000777	0.001575
t-stat	38.87	20.98	41.7
Price	-0.02258	-0.02331	-0.01879
t-stat	-83.45	-62.56	-51.33
F	79857.94	44064.26	36637.95
	(7,190537)	(7,116881)	(7, 73648)
R squared	0.7458	0.7252	0.7769
Adjusted R2	0.7458	0.7252	0.7769

2.8.5.2 Fixed Effects

Fixed Effects regressions, shown in Table 2.11, account for individual factors of each cross section. These coefficients are more accurate than the ones from the pooled OLS version, since they are free of any cross-sectional bias. Size, for the IBES subsample, is the only variable that is not significant. However, despite being significant, size for the complete sample and for the no IBES subsample in terms of magnitude is really close to zero. This suggests that size, for my sample, is not a determinant variable.

The Trades variable, on the other hand, is negative and significant. This implies that the number of trades, regardless of size, affects the BAS. Behavior in the Risk and Nsize variables is similar to the one in the pooled OLS regressions. Regional is another variable whose value is really close to zero, suggesting a very limited relevance. Finally, price is relevant and negative, but its magnitude is almost half of pooled OLS. Regardless of this, price is one of the most important variables in determining the BAS.

Table 2.11 Fixed Effects Regressions

	Complete Sample	**No IBES**	**IBES**
Constant	0.025189	0.0256846	0.022965
t-stat	16.49	13.02	10.66
Trades	-0.00216	-0.0025948	-0.00131
t-stat	-13.18	-10.38	-7.73
Size	-6.5E-05	-0.0000776	**2.23E-05**
t-stat	-2.58	-2.26	**0.7**
Risk 1	0.867946	0.9111936	0.753502
t-stat	310.56	240.03	209.46
Risk 2	0.060077	0.059656	0.061698
t-stat	307.67	236.31	209.48
Nsize	-0.00284	-0.0033829	-0.00137
t-stat	-9.3	-8.48	-3.08
Regional	0.000096	0.0001042	0.000062
t-stat	4.01	3.18	2.06
Price	-0.01082	-0.011094	-0.0101
t-stat	-10.19	-7.8	-7.14
F	26467.51	15732.77	12162.21
	(7,190036)	(7,116571)	(7,73458)
R2 within	0.4937	0.4858	0.5368
between	0.8437	0.838	0.8373
overall	0.7403	0.7211	0.7657

2.8.5.3 Random Effects

Random Effects is another technique that accounts for cross-sectional differences. Coefficients and magnitudes in Table 2.12 are quite similar to the ones in Fixed Effects regression. Interpretations, therefore, are similar as well.

Table 2.12 Random Effects Regressions

	Complete Sample	**No IBES**	**IBES**
Constant	0.029178	0.029647	0.026196
t-stat	17.07	13.01	11.42
Trades	-0.00228	-0.00269	-0.00144
t-stat	-14.21	-11.03	-8.65
Size	-7.2E-05	-8.3E-05	**1.42E-05**
t-stat	-2.85	-2.42	**0.45**
Risk 1	0.871361	0.914394	0.756879
t-stat	315.48	243.72	212.48
Risk 2	0.060095	0.05967	0.06173
t-stat	307.61	236.29	209.38
Nsize	-0.00288	-0.00343	-0.00141
t-stat	-9.45	-8.6	-3.18
Regional	0.000102	0.000108	0.00007
t-stat	4.25	3.3	2.32
Price	-0.01269	-0.01289	-0.01165
t-stat	-12.87	-9.71	-8.9
Wald chi2(7)	188535.1	111981.7	86526.42
R2 within	0.4936	0.4858	0.5368
between	0.8442	0.8386	0.8376
overall	0.7409	0.7217	0.7664

2.8.5.4 Hausman Tests

Hausman tests prove if fixed effects or random effects regressions suit better for specific data sets. If the test is significant, it proves that fixed effects performs better than random effects. Tables 2.13, 2.14, and 2.15 show the tests for the complete sample and the two subsamples, and in the three cases fixed effects performs better.

Table 2.13 Hausman Test for the Complete Sample

	FE1	RE1	Difference	Sqrt
Trades	-0.0021585	-0.002279	0.0001205	0.0000339
Size	-0.0000648	-0.0000715	6.75E-06	1.33E-06
Risk 1	0.8679458	0.8713609	-0.003415	0.000437
Risk 2	0.0600766	0.0600945	-0.0000179	2.93E-06
Nsize	-0.0028417	-0.0028844	0.0000428	0.0000181
Regional	0.000096	0.0001017	-5.68E-06	8.31E-07
Price	-0.0108168	-0.0126871	0.0018703	0.0003939
chi2(7) =	227.16			
Prob>chi2 =	0			

Table 2.14 Hausman Test for No Analyst Coverage

	FE1	RE1	Difference	Sqrt
Trades	-0.0025948	-0.0026902	0.0000954	0.0000554
Size	-0.0000776	-0.0000829	5.22E-06	1.78E-06
Risk 1	0.9111936	0.9143936	-0.0032	0.00059
Risk 2	0.059656	0.0596696	-0.0000136	3.95E-06
Nsize	-0.0033829	-0.0034255	0.0000426	0.0000239
Regional	0.0001042	0.0001082	-4.05E-06	1.15E-06
Price	-0.011094	-0.0128891	0.0017952	0.0005098
chi2(7) =	113.48			
Prob>chi2 =	0			

Table 2.15 Hausman Test for Analyst Coverage

	FE1	RE1	Difference	Sqrt
Trades	-0.001307	-0.001442	0.0001345	3.02E-05
Size	0.0000223	0.0000142	8.11E-06	1.79E-06
Risk 1	0.7535018	0.7568793	-0.0033775	0.00053
Risk 2	0.0616982	0.0617304	-0.0000322	4.22E-06
Nsize	-0.001368	-0.001414	0.000046	2.44E-05
Regional	0.000062	0.00007	-7.90E-06	1.01E-06
Price	-0.010098	-0.01165	0.0015523	0.000541
chi2(7) =	170.07			
Prob>chi2 =	0			

2.8.5.5 Conclusions

The complete sample shows a big influence from Risk 1. It seems that this variable is determinant in pricing the BAS in penny stocks. The number of trades is an important activity variable that provides more information than trade size. Price is another very important variable; as price goes up, the BAS goes down. Hausman tests show that fixed effects regressions provide better explanations than random effects regressions.

2.8.6 Panel Data Regressions with No Risk 1 Variable

In order to avoid any bias from the Risk 1 variable, I reran the regressions without the variable (Table 2.16).

2.8.6.1 Pooled Ordinary Least Squares

R-squared dropped in a very important way. It is imperative to note the Risk 1 variable effect on the sample. It is definitely the most important variable in my sample. It is interesting to see that Size for the IBES subsample is positive. The magnitude of the coefficient, however, makes it rather irrelevant. Regional is another variable that is really close to zero. Risk 2 is positive and significant. Finally, Price became more important when Risk 1 is eliminated. That is, as the price reaches $5, the BAS tends to reduce. The magnitudes of Risk 2 and Price are quite similar.

Table 2.16 Pooled OLS Regressions with No Risk 1 Variable

	Complete Sample	**No IBES**	**IBES**
Constant	0.147592	0.166511	0.07559
t-stat	169.01	146.3	57.52
Trades	-0.01705	-0.01776	-0.01509
t-stat	-162.17	-117.93	-118.26
Size	-0.00018	-0.00038	0.000575
t-stat	-4.07	-6.46	9.75
Risk 2	0.061336	0.060164	0.065088
t-stat	153.04	120.03	97.52
Nsize	-0.03244	-0.02737	-0.04712
t-stat	-59.25	-39.52	-53.67
Regional	0.001001	0.000868	0.00138
t-stat	22.48	14.61	22.47
Price	-0.05136	-0.05517	-0.02799
t-stat	-120.02	-94.3	-47.13
F	16310.29	8118.95	8518.33
	(6,190538)	(6,116882)	(6, 73649)
R squared	0.3393	0.2942	0.4097
Adjusted R2	0.3393	0.2941	0.4096

2.8.6.2 Fixed Effects

This regression, as proved by the Hausman tests, is the best fit for the data. The biggest difference between this model and the OLS model is the change in the Price variable.

Magnitudes were similar between Risk 2 and Price in the previous regression. After accounting for cross-sectional differences, price is still statistically significant but has a low value. The Regional variable becomes negative, but its magnitude is also really low (Table 2.17).

Table 2.17 Fixed Effects Regressions with No Risk 1 Variable

	Complete Sample	**No IBES**	**IBES**
Constant	0.059507	0.072347	0.036747
t-stat	31.8	30.14	13.5
Trades	0.002897	0.002949	0.002637
t-stat	14.48	9.69	12.41
Size	0.000657	0.000566	0.000918
t-stat	21.41	13.55	22.98
Risk 2	0.057516	0.057304	0.058411
t-stat	240.11	185.84	157.14
Nsize	-0.00869	-0.00809	-0.01043
t-stat	-23.22	-16.62	-18.66
Regional	-0.0003	-0.00029	-0.00033
t-stat	-10.38	-7.12	-8.61
Price	-0.00891	-0.00933	-0.00825
t-stat	-6.84	-5.37	-4.61
F	9819.88	5857.51	4305.63
	(6,190037)	(6,116572)	(6,73459)
R2 within	0.2367	0.2316	0.2602
between	0.0564	0.0305	0.1184
overall	0.0998	0.0933	0.1336

2.8.6.3 Random Effects

Random effects regressions draw similar results to fixed effects regressions (Table 2.18). However, a fixed effects regression is preferred.

Table 2.18 Random Effects Regressions with No Risk 1 Variable

	Complete Sample	**No IBES**	**IBES**
Constant	0.06762	0.080204	0.043113
t-stat	25.8	22.67	12.38
Trades	0.002534	0.002529	0.002399
t-stat	12.74	8.37	11.34
Size	0.000664	0.00057	0.000928
t-stat	21.61	13.64	23.2
Risk 2	0.057522	0.057307	0.058427
t-stat	239.84	185.65	156.94
Nsize	-0.00887	-0.00823	-0.01066
t-stat	-23.68	-16.89	-19.04
Regional	-0.00031	-0.00029	-0.00033
t-stat	-10.38	-7.14	-8.58
Price	-0.01233	-0.01221	-0.01135
t-stat	-9.73	-7.21	-6.54
Wald chi2(6)	58823.42	35088.63	25794.75
R2 within	0.2366	0.2316	0.2601
between	0.0999	0.0636	0.1525
overall	0.1184	0.1067	0.1543

2.8.6.4 Conclusions

When eliminating the Risk 1 variable, significance in the complete model decreases. Nevertheless, coefficients and signs remain consistent with the ones calculated in the previous model. Size and Regional variables have a very low magnitude, suggesting that for this sample their relevance is very low.

2.8.7 Dummy Dependent Variable Regressions

Finally, I attempt to discover which factors affect the decision of analyst on whether to follow penny stocks. In order to deal with this issue, I ran several regressions with a dummy dependent variable, i.e., whether analysts follow the stock. Then, I utilized three different factors for the analyzed stocks: average 2006 market equity, total assets, and average price.

It is important to note that I used probit and logit models along with OLS to do my analysis. Coefficients in probit and logit cannot be interpreted per se but rather through marginal effects, the probabilities for the dependent variable to have a value of one if the independent variable has a mean value.

2.8.7.1 Market Equity

Table 2.19 shows the influence of market equity in the probability of a penny stock's being followed by analysts. Coefficients for market equity are positive and significant, meaning that there is indeed a relationship between market equity and a stock's being followed by analysts. Marginal effects are approximately 34%, implying that the average firm has a 34% opportunity of being followed.

Table 2.19 Analyst Coverage Based on Market Equity

	OLS	**Probit**	**Logit**
Constant	-0.87574	-3.92225	-6.40714
t-stat	-4.22	-6.3	-6.06
Log (ME)	0.111635	0.319899	0.523213
t-stat	5.93	5.73	5.53
Marginal effects	0.349112	0.340056	0.339294
dy/dx (ME)	0.111635	0.117222	0.11729
z-stat	5.93	5.76	5.59

2.8.7.2 Total Assets

Table 2.20 shows the relationship between total assets and the probability of a penny stock's being followed by analysts. Coefficients are significant but lower in magnitude, meaning that there needs to be a big change in assets to increase the likelihood of a stock's being followed. Differentials also demonstrate this point; a one-unit increase in assets increases the chance of being followed by only 5.3%, whereas for market equity, this difference was 11.7%. However, marginal effects are the highest, 36.6%.

Table 2.20 Analyst Coverage Based on Total Assets

	OLS	**Probit**	**Logit**
Constant	0.160085	-0.89424	-1.4498
t-stat	2.32	-4.74	-4.63
Log (TA)	0.05372	0.142202	0.231742
t-stat	3.22	3.17	3.12
Marginal effects	0.368286	0.365757	0.365484
dy/dx (TA)	0.05372	0.053487	0.053742
z-stat	3.22	3.17	3.12

2.8.7.3 Stock Price

Finally, Table 2.21 shows the relationship between stock price and the chance of a penny stock's being followed by analysts. Coefficients are positive and significant. However, for this sample, we know that the maximum price that a stock can have is $5. Marginal effects are the lowest (34%).

Table 2.21 Analyst Coverage Based on Stock Price

	OLS	**Probit**	**Logit**
Constant	0.245845	-0.72058	-1.19706
t-stat	8.29	-7.76	-7.29
Log (Price)	0.173572	0.52488	0.889552
t-stat	4.87	4.77	4.63
Marginal effects	0.349112	0.341529	0.338987
dy/dx (Price)	0.173572	0.192651	0.199326
z-stat	4.87	4.81	4.72

2.8.7.4 Market Equity and Total Assets

When combining market equity and total assets, we can see that total assets is subsumed by market equity. Table 2.22 shows that coefficients are insignificant and very low in magnitude. On the other hand, marginal effects are approximately 36%, greater than the one in the model that includes only total assets.

Table 2.22 Analyst Coverage Based on Market Equity and Total Assets

	OLS	**Probit**	**Logit**
Constant	-0.94087	-4.02647	-6.63454
t-stat	-3.6	-5.29	-5.09
Log (ME)	0.119588	0.335815	0.556777
t-stat	4.37	4.27	4.15
Log (TA)	-0.00201	-0.00783	-0.0196
t-stat	-0.1	-0.14	-0.2
Marginal effects	0.368286	0.3599	0.359144
dy/dx (ME)	0.119588	0.125622	0.128148
z-stat	4.37	4.29	4.18
dy/dx (TA)	-0.00201	-0.00293	-0.00451
z-stat	-0.1	-0.14	-0.2

2.8.7.5 Market Equity and Stock Price

Table 2.23 combines both market equity and stock price. As opposed to the previous model, both variables in this model are significant. However, marginal effects go down to approximately 35.5%. Despite this fact, the model is a better fit than the previous on since both variables are significant. We can also see that the price variable plays an important role since it has a greater differential than the market equity variable. The conclusion is that price plays a more important role in a penny stock's being followed by analysts than market equity.

Table 2.23 Analyst Coverage Based on Market Equity and Stock Price

	OLS	**Probit**	**Logit**
Constant	-0.69053	-3.34358	-5.58027
t-stat	-2.85	-4.65	-4.58
Log (ME)	0.086837	0.240712	0.399237
t-stat	3.84	3.61	3.57
Log (Price)	0.173734	0.541405	0.951268
t-stat	3.89	3.81	3.81
Marginal effects	0.368286	0.354483	0.349258
dy/dx (ME)	0.086837	0.089569	0.090737
z-stat	3.84	3.61	3.57
dy/dx (Price)	0.173734	0.201456	0.216201
z-stat	3.89	3.83	3.87

2.8.7.6 Market Equity, Total Assets, and Stock Price

Finally, I include the three variables in the regression. Table 2.24 demonstrates, once again, that total assets is subsumed by the other two variables. Marginal effects are also approximately 35.5%, and the variables behave in a fashion similar to that shown in the previous tables. However, the previous model is a better model, since it is more parsimonious.

Table 2.24 Analyst Coverage Based On Market Equity, Total Assets, and Stock Price

	OLS	**Probit**	**Logit**
Constant	-0.75484	-3.54974	-6.0102
t-stat	-2.9	-4.59	-4.52
Log (ME)	0.097313	0.273698	0.465534
t-stat	3.54	3.4	3.38
Log (TA)	-0.01385	-0.04329	-0.08364
t-stat	-0.67	-0.73	-0.83
Log (Price)	0.178179	0.557279	0.984142
t-stat	3.94	3.87	3.87
Marginal effects	0.368286	0.353998	0.348212
dy/dx (ME)	0.097313	0.101793	0.105658
z-stat	3.54	3.41	3.39
dy/dx (TA)	-0.01385	-0.0161	-0.01898
z-stat	-0.67	-0.73	-0.84
dy/dx (Price)	0.178179	0.207262	0.223361
z-stat	3.94	3.89	3.95

2.8.7.7 Conclusions

Dummy dependent variable models demonstrate that a firm with average values for market equity and price has a 35.5% chance of being followed by analysts. Market equity is an important factor, but price is a more determinant factor for making analysts follow a penny stock. On the other hand, total assets, by itself, had the highest marginal effects, but it became irrelevant once it was regressed with the other variables.

2.9 Conclusions

- As with McInish and Wood (1992), the scaled BAS for penny stocks follows a similar pattern. It is really high at the beginning of the session, then settles down, and peaks toward the end. The overall magnitude is greater for this sample than for McInish and Wood's sample.
- When comparing the average yearly BAS to an individual month's BAS, it was interesting to see that July and August had a statistically significant greater BAS and November and December had a lower BAS. Thirty-minute intervals are consistent with every month's pattern, except for January and May.
- The days of the week told a similar story: Thursdays had a statistically lower BAS, whereas Fridays had a higher BAS. Thirty-minute intervals were also consistent. Tuesdays were the days that behaved like the mean.
- The comparison of IBES against no IBES demonstrated what I was expecting: lower BAS for firms that are followed and higher BAS for neglected firms. This is consistent with the financial literature: since less information is available concerning neglected firms, they carry greater risk.
- When running panel data regressions, Risk 1 was the most important variable in the analysis. Price and Trades were also important. A fixed effects model is a better fit for the needs of the data. I reran the model without the Risk 1 variable, and the results held. However, the overall significance of the model decreases.
- Finally, through dummy dependent variable models, I determined that market equity and price were the most important variables in determining whether analysts follow a stock. Total assets is subsumed when regressed with the other variables.

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