Assessing the Effects of Earnings Surprise on Returns and Volatility with High Frequency Data

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I. Introduction

A company's earnings play a key role in the valuation of its stock, and thus earnings estimates, as well as earnings announcements, are always carefully scrutinized—sometimes to the point where they may matter more than actual performance. In the third quarter of 2006, Alcoa reported it was experiencing the best year in its entire history, generating more profit in the first nine months than any previous year in over a century. Despite its exceptional performance, Alcoa's shares fell six percent in the extended trading period after the results were posted. Its fault was missing Wall Street's estimates (Mandaro 2006). Although earnings announcements are reported only four times a year, in conjunction with analyst estimates, their potentially significant effects on stock prices suggest that analyzing price behavior on earnings announcement dates can yield important insights on how the market uses the information from these numbers.

According to the Gordon Growth Model, the basic fundamental method of valuing stocks, a stock's current price P depends on the expected earnings D_e, the growth rate of the dividend g, and the required rate of return for the investor k such that

$$P = \frac{D_e}{k - g}$$

The efficient-markets hypothesis asserts that investors constantly update the stock price as they receive new information. In relation to the Gordon Growth Model, new information affects D, k, and/or g, and the fundamental price has to be adjusted to reflect all current information. Small adjustments in one of these figures can result in huge readjustments of stock price—suppose for example, a stock's dividend is 1.25 dollars, k=.06, and the growth rate is estimated at four percent, or .04. The price should then be 50 dollars. If new information suggests that the growth rate is actually one percent slower than previously expected, and g=.03, the price drops to 33.33 dollars. The earnings announcements provided every quarter are crucial bits of information that provide a benchmark for company performance, which are scrutinized not only to determine the health of a firm, but also to be compared to analyst estimates. A difference in forecasted earnings and the actual earnings reported that results in a revaluation of key figures could thus have a significant impact on shares.

Empirical research on the informational value of earnings announcements dates back to the work of Beaver (1968). Using annual earnings report data, he found that the volatility of returns increases around earnings announcement days. Landsman and Maydew (2001) extend his research using more recent data and quarterly earnings reports, and find similar results. There has also been a good deal of research examining "earnings surprise", or the difference between analyst estimates and the reported earnings data. Bamber (1987) finds that as the magnitude of the unexpected earnings increases, the magnitude of the trading volume reaction increases. Kinney et al. (2002) observe the manner in which earnings surprise materializes in stock returns, and find that although some small negative surprises accompany large negative returns and some small positive surprises accompany large positive returns, consistent with anecdotes from the press, 43% to 45% of firms' surprises are associated with returns of the opposite sign.

This paper seeks to add to the current literature on earnings surprises in relation to a stock's return and volatility through its use of high frequency financial data, and various tools that have emerged from its availability. First, more data points allow for the use of more precise definitions of returns. In previous papers analyzing the effect of earnings surprise on returns, the earlier papers typically use daily close-to-close returns. With high frequency data, a distinction can be made between overnight returns, that is, the difference between the market opening prices with the closing prices from the previous day, and the within-day returns, or the returns from market open to market close of the same day. Examination of the relationship between earnings surprises and these two kinds of returns can provide a more in-depth look into the effect of quarterly earnings announcements and estimates on returns.

Second, high frequency data also allows for the calculation of realized variance (RV). The RV is has become an important and accurate estimate for a stock's volatility because it has been shown to be consistent with integrated variance, and is relatively simple to calculate (Anderson and Bollerslev 1998). One volatility model that has emerged using the RV is the heterogeneous autoregressive realized variance (HAR-RV) model, as developed by Corsi (2003). This model has been shown by Anderson et. al (2003) to be better at predicting variance than traditional GARCH models that do not take advantage of high frequency data, and it provides a different approach to analyzing the relation between earnings announcements and volatility. An expanded version of the HAR-RV model will be used to determine the effect of earnings surprise on volatility.

Finally, the relationships between earnings surprise will be further analyzed by exploring the impacts negative surprises have on stock prices versus those of positive surprises, the effect of using indicator variables of earnings surprise versus variables of magnitude (i.e. the difference between using indicator for a firm's earnings beating analyst estimates rather than using the percentage the earnings beat estimates), and accounting for the dispersion of analyst estimates.

The rest of this paper proceeds as follows. Section 2 contains a discussion of the model of volatility used in this paper. Section 3 describes the regression methods, including an explanation of the HAR-RV model, and how it will be expanded for the purposes of this paper. Section 4 explains in detail the data used in this paper, and section 5 will explain the results. Finally, Section 6 concludes the paper.

2. A Model of Volatility

2.1 Core Model: Stochastic Volatility Model

A common method of estimating the underlying volatility of a given stock using high frequency data is to calculate what is called the realized variance. The foundation for using realized variance derives from stochastic volatility models, the standard model of which is given by the differential equation

$$dp(t) = \mu(t)dt + \sigma(t)dW(t), \tag{1}$$

where the movement of a stock's log-price $dp(t)$ is a function of a time-varying drift component $\mu(t)dt$ and a time-varying volatility component $\sigma(t)dW(t)$, in which $W(t)$ is a standard Brownian motion (Merton 1971). In essence, the model treats the underlying security's volatility as a random process. The volatility from time t to time $t+1$ would then be given by the integral of the volatility component, and the integrated variance is defined as

$$IV_{t+1} = \int_t^{t+1} s^2\,(t)dt. \tag{2}$$

2.2 Realized Variance

In practice, one cannot continuously observe asset prices, which makes it infeasible to directly calculate the integrated variance. However, with high frequency data, one can get a close estimate using realized variance. Calculating the realized variance is simple and intuitive. Consider a set of prices observed at a discrete time interval. The intraday geometric returns is defined as

$$r_{t,j} = p(t-1+\frac{j}{M}) - p(t-1+\frac{j-1}{M}), \quad (3)$$

Where p is the log of the stock price, t represents the day, M is the frequency the prices are sampled at, and j = 1, 2, … , M. The realized variance can then be calculated as

$$RV_t = \sum_{j=1}^{M} r^2{}_{t,j} \ . \quad (4)$$

Anderson and Bollerslev have shown that as the frequency approaches infinity (i.e. the time between observations reaches zero), the realized variance converges to the integrated variance (1998) and can thus serve as a good measure for volatility.

2.3 Market Microstructure Noise

According to theory then, the estimation error of the realized variance decreases as the sampling frequency increases. However, a problem occurs with sampling at increasingly small intervals. Due to characteristics built into the market, such as the bid-ask bounce or rounding errors, the observed price is not always equal to the fundamental price of the stock as would be expected by the Gordon Growth Model, as described in the introduction (i.e. $p = \frac{D_e}{k-g}$). That is to say,

$$p^*(t) = p(t) + \varepsilon_t \quad (5)$$

Where $p^*(t)$ is the observed price, $p(t)$ is the fundamental price, and ε_t is the microstructure noise. As $p^*(t)$ is observed, not $p(t)$, as the sampling frequency increases, the microstructure noise becomes more pronounced and the estimate becomes more biased.

The distortive nature of microstructure noise can be visually represented by a tool developed by Anderson, Bollerslev, Diebold and Labys (1999) called the volatility signature plot. The volatility signature plot graphs the relationship of sampling frequency with mean volatility, and two sample signature plots are given in Figure 1. Without microstructure noise, the mean volatility should be roughly constant as the sampling frequency increases (i.e. intervals become smaller). However, with microstructure noise, as the interval becomes smaller, mean volatility becomes increasingly biased toward infinity. To avoid this problem, many authors choose to sample the data at intervals ranging from 5 to 30 minutes (Zhang et al. 2005).

2.3.1 Sub-sampling

Another approach to reducing the bias caused by microstructure noise is through "sub-sampling." A problem with sampling by itself is that it requires large portions of data to be thrown out. For example, the commonly used 15 minute sampling interval for minute-by-minute price data from 9:35 A.M. to 3:59 P.M. means throwing out 360 of the 385 data points. In order to use all of the data available, one could "sub-sample" the data by sampling at a set interval starting from the first observation (i.e., 9:35, 9:50, 10:05, etc.) and calculate RV, then sampling again at the interval starting at the second observation (i.e., 9:36, 9:51, 10:06, etc.) and calculate RV, and so on, and then taking the average of these results. This method ensures that all of the data points are used while avoiding the problem of microstructure noise. It also seems to have the added benefit of making the calculations of realized variance more consistent. Preliminary research found that sampling at a 10 minute interval versus sampling at a 15 minute interval to calculate RV can produce inconsistent results during the regressions (e.g. independent variables were significant at one frequency but not significant at another frequency), but this problem disappears when using sub-sampling.

3. Regression Methods

3.1 Model of Earnings Surprise with Returns

3.1.1 Definitions

To examine the relationship between earnings surprise and returns, the concepts need to be defined. First, define overnight returns as

$$r_t^{ON} = p_{o,t} - p_{c,t-1} , \tag{6}$$

where $p_{o,t}$ is the opening log price of the share on day t and $p_{c,t-1}$ is the closing log price of the previous day,[1] and the within-day returns as

$$r_t^{WD} = \sum_{j=1}^{M} r_{t,j} , \tag{7}$$

where $r_{t,j}$ refers to the intraday return. Note that the within-day return ends up being just the difference between the opening log price of a share and the closing log price on the same day.

[1] In this paper, the price of the stock at 9:35 AM serves as the opening price. Varying the opening price time to see if the market needs additional time to adjust to earnings announcements shows there is little effect on the results. The results of this paper, which will be detailed later, suggest that the market adjusts to earnings surprises fairly quickly after the announcement, and using 9:35 AM as the opening time suffices for this research.

Simply using the returns as calculated however could result in misleading results, due to the tendency of volatility to cluster. During a period of high volatility, returns that are relatively large in magnitude are not surprising, regardless of whether or not there was an earnings surprise the day before. Furthermore, returns for a stock that is characterized by high volatility would be expected to be larger in magnitude than for a stock that tends to be fairly stable, so direct comparisons of different stocks' reactions to earnings surprises may not be very useful. Standardizing returns allows for the determination of the reaction of the stock prices to earnings surprises that are greater than usual; thus standardize both the overnight and within-day returns by the weekly volatility to get

$$r_t^{standardized} = \frac{r_t}{\sqrt{RV_{t-5,t}/5}}, \quad (8)$$

where $RV_{t\text{-}5,t}$ refers to the averaged realized variance from the preceding week. Keane (2008) also uses weekly volatility to standardize the returns, as she finds that using weekly volatility is flexible enough to allow the value to evolve over time, without being skewed by the volatility based off of one day's results.

Since the purpose of this paper is to determine the effect of an earnings surprise on a stock's returns, define the regressor "earnings surprise" as

$$SURPRISE_t = \frac{EPS_{actual,t} - EPS_{estimate,t}}{EPS_{estimate,t}} * 100 \quad (9)$$

where $EPS_{actual,t}$ is the earnings per share reported on earnings announcement day *t,* and $EPS_{estimate,t}$ is the earnings per share estimated for that day *t.* Two points should be clarified. First, $EPS_{estimate,t}$ refers to the average of EPS estimates across earnings forecasters; most estimates are the average of the estimates of 20 to 30 analysts. Second, a distinction needs to be made between earnings announcements that are made before the market opens and those that are made after the market closes. The data is aligned such that the earnings surprise variable always pertained to the subsequent trading period. In this way, the earnings surprise can be consistently analyzed in relation to the trading period following the earnings announcement. If day *t* does not have an earnings announcement, $SURPRISE_t$ is equal to 0.

To refine the earnings surprise variable, separate the positive and negative earnings surprises. This is motivated by the asymmetry of the news impact curve (Engle and Ng 1993), a measure of how news impacts stock volatility. The news impact curve shows that negative news causes more volatility than positive news. Separating positive and negative earnings surprises and running a sign-split regression allows observation of different reactions of the market to positive and negative earnings surprises. Thus, separate $SURPRISE_t$, and designate POS_t as positive earnings surprises, and NEG_t as negative earnings surprises.

3.1.2 Regressions

The first model is now defined as the regression of overnight returns on POS_t and NEG_t, as

$$r_t^{ON} = \beta_0 + \beta_P POS_t + \beta_N NEG_t + \varepsilon_t \tag{10}$$

and the second model is similarly a regression of within-day returns on the same variables,

$$r_t^{WD} = \beta_0 + \beta_P POS_t + \beta_N NEG_t + \varepsilon_t \ . \tag{11}$$

Of course, it may not be the case that the market responds according to the magnitude of the earnings surprise; it may be that the market responds to the fact that there *is* a surprise. To account for this possibility, define the indicator variables: $BEAT_t$, to indicate days when the announced earnings beat analyst estimates, and $MISS_t$, to indicate the days when the earnings miss analyst estimates. In order to determine if no earnings surprise days have an effect on returns, define a final indicator variable $MEET_t$ to indicate the days when the firm meets exactly the analyst estimates. The third and fourth models can then be defined as

$$r_t^{ON} = \beta_0 + \beta_B BEAT_t + \beta_M MISS_t + \beta_T MEET_t + \varepsilon_t \tag{12}$$

and

$$r_t^{WD} = \beta_0 + \beta_B BEAT_t + \beta_M MISS_t + \beta_T MEET_t + \varepsilon_t \ . \tag{13}$$

3.2 Model of Earnings Surprise with Volatility

3.2.1 HAR-RV Model

The heterogeneous autoregressive realized variance (HAR-RV) model, developed by Corsi (2003), uses realized variance, and taking advantage of the fact that volatility tends to cluster in financial markets, provides a venue for forecasting the variance by using past values of realized variance, averaged at different periods of time. The model as outlined by Corsi uses lagged averages over 1, 5, and 22 days, to represent the average realized variance from the preceding day, week, and month, respectively. These averages can be defined as

$$RV_{t,t+h} = h^{-1}(RV_{t+1} + RV_{t+2} + \ldots + RV_{t+h}) \tag{4}$$

The HAR-RV regression can then be expressed as

$$RV_{t,t+h} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \varepsilon_{t+1} \qquad (5)$$

The simplicity of the model, as well as its ability to better forecast variance than other models such as the generalized autoregressive heteroskedasticity (GARCH) model, makes it an ideal one to use in order to determine the relation between volatility and earnings surprise.

3.2.2 Regressions

To examine the relationship between earnings surprise and volatility[2], add the same two sets of regressors from the previous section to the original HAR-RV model. That is, models five and six can be defined as:

$$RV_{t,t+h} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_P POS_t + \beta_N NEG_t + \varepsilon_t \qquad (14)$$

and

$$RV_{t,t+h} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_B BEAT_t + \beta_M MISS_t + \beta_T MEET_t + \varepsilon_t. \qquad (15)$$

The rationale for using these sets of variables is the same as it was for examining the relationship between earnings surprise and returns—a split-sign regression allows for positive and negative earnings surprises to have different effects on the independent variable, and indicator variables allow for the possibility that investors react not so much to the magnitude of the earnings surprises, but the fact that there *was* an earnings surprise.

Another factor that can be analyzed is the degree to which analysts disagree with one another on earnings estimate. The more analysts disagree, the less information the market has, as there is no coherent and reliable measure to base decisions on. As such, one could expect the earnings surprise to have an even larger effect on volatility if there was a great deal of dispersion in analyst estimates. As such, the final model is developed accounting for such dispersion, using interacting dispersion with the three different regressors as such:

$$RV_{t,t+h} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_B POS_t + \beta_M NEG_t + \beta_T MEET_t + \beta_{Disp} DISP_t + \beta_{DP} DISP_t * POS_t + \beta_{DN} DISP_t * NEG_t + \beta_{DM} DISP_t * MEET_t + \varepsilon_t. \qquad (16)$$

[2] In the following three models, the annualized realized variation is expressed in terms of log annualized volatility. That is, $\sqrt{252 \times RV} \times 100$ is used to express volatility.

$DISP_t$ refers to the standard deviation in analyst estimates, across all earnings forecasters, for an earnings announcement day t, and similar to $SURPRISE_t$, it is zero when t is not an earnings announcement day. Due to the problem of perfect multicollinearity if indicator variables were used (the three interaction terms added together would equal the dispersion regressor), POS_t and NEG_t are used instead of their equivalent indicator variables.

4. The Data

This paper uses high frequency financial data obtained from price-data.com, focusing on 30 stocks in the S&P 100 Index with the largest market capitalization at the end of 2008, excluding Google, Phillip Morris International, and Oracle, due to the limited data available for these three stocks. The stocks analyzed are: ExxonMobil (XOM), Proctor and Gamble (PG), General Electric (GE), AT&T (T), Johnson & Johnson (JNJ), Chevron (CVX), Microsoft (MSFT), Amazon (AMZN), Wal-Mart (WMT), JP Morgan (JPM), IBM (IBM), Hewlett-Packard (HPQ), Wells Fargo (WFC), Verizon Wireless (VZ), Cisco Systems (CSCO), the Coca-Cola Company (KO), Pepsi (PEP), Abott Laboratories (ABT), Intel (INTC), Apple (AAPL), Bank of America (BAC), McDonald's (MCD), Merck (MRK), Amgen (AMGN), Qualcomm (QCOM), United Parcel Service (UPS), United Technologies (UTX), Goldman Sachs (GS), Schlumberger (SLB), and Wyeth (WYE).

Each dataset contains observations recorded at the one-minute frequency from 9:35 AM to 3:59 PM, for a total of 385 observations per day. Each dataset contains data for varying periods, with most data observed from the period of 4/9/1997 to 1/7/2009 (the shortest period is that of Wyeth, which begins on 5/10/2002). As mentioned in section 3.3, the data is subsampled at various frequencies, depending on the stock, but most stocks are subsampled at the 10 minute interval.

The analyst estimates, actual earnings reported, and dispersion were obtained from the I/B/E/S database that is available at the Wharton Research Database Service (WRDS). As previously mentioned, the mean of analyst estimates are used for the purpose of this paper. The timing of the earnings reports were not available from the I/B/E/S, as such, the timing of the announcement—whether the earnings announcement was made before the market opens, or after the market closes—was verified from earnings.com. The earnings report dates are adjusted so the surprises are always used in a predictive sense to explain increases/decreases in volatility and returns.

5. Results

The results of the five different tests are separated into three tables. Table 1 gives the regression of earnings surprise with overnight returns, Table 2 gives the regression of earnings surprise with intraday returns, and Table 3 gives the regression of earnings surprise with volatility. Table 4 summarizes the three tables by giving the percent of firms for which a particular regressor was significant for a given dependent variable. Because some firms have very limited days when they either miss earnings estimates or hit them exactly (for example, Cisco Systems only missed earnings estimates once out of 44 earnings reports observed), it may not be as informative to interpret the regression results pertaining to days such firms miss/meet earnings. As such, my analysis of negative surprises and days of no surprises will be limited to all firms have at least 7 or more days of the type of earnings surprise being analyzed. Due to the arbitrary nature of this cutoff point, I will include the number of days that each company experienced each type of earnings surprise on the tables so that readers can make their own decision on which cutoff makes the most sense if they disagree. The key findings can be summarized as follows.

5.1 The Relationship of Earnings Surprise and Returns

Table 1, which focuses on overnight returns, suggests that in 25 out of the 30 firms, positive earnings surprises are significantly correlated with positive overnight returns. The number of significant variables is roughly the same whether or not indicator variables are used in place of the magnitude of earnings surprise. Similar results can be derived from observing the firms with at least seven negative earnings surprise dates—in 10 out of the 12 such firms, a negative earnings surprise was followed systematically by negative overnight returns. As for the firms that had at least seven earnings announcement days of just hitting analyst estimates, five out of 14 were found to have some correlation between overnight returns and days of meeting estimates.

In contrast, Table 2, which focuses on within-day returns, shows that only in 10 firms were the within-day returns statistically significant with positive earnings surprises, and when they were significant, it was not clear which direction the earnings surprise was correlated with the within-day returns. Only four out of the 12 firms had correlations between negative surprises and within-day returns, and when there was a statistically significant correlation, the relationship was positively correlated for two firms and negatively correlated for two firms. Of the 14n firms with at least seven earnings announcement days with no earnings surprise, four showed correlations between within-day returns and days of just hitting analyst expectations.

These results suggest that quarterly earnings surprises tend to be correlated with returns in the expected directions, but only with overnight returns. That is, the market adjusts to earnings announcements fairly quickly within the trading periods surrounding the announcement, and after it has adjusted, the earnings surprise loses its informative value. When the firm meets analyst estimates exactly, the surprise, or lack thereof, tends to have no real correlation with either the overnight returns or the within-day returns.

5.2 The Relationship of Earnings Surprise and Volatility

Table 3 shows that out of the 30 firms, the relationship between positive earnings surprise percentage and log annualized volatility was statistically significant and positively correlated for 20 of the firms. In other words, for 20 firms, a positive earnings surprise was followed systematically by an increase in volatility the trading period immediately after the earnings announcement. If the indicator variable for beating estimates is used instead of the magnitude of surprise, all but four firms show a positive correlation with positive earnings surprise days and volatility.

For the 12 firms that had at least seven days in which analyst estimates were missed for that quarter, five out of the 12 show a negative correlation between negative surprises and volatility. Negative surprises are also followed by an increase in volatility. If an indicator is used for missing estimates is used, the number of firms in which the relationship becomes statistically significant jumps to 10. These results suggest that the market reacts more to the fact that there *is* a surprise, not the magnitude of the surprise.

An interesting and somewhat surprising result is that for the 14 firms that have at least seven earnings announcement dates in which the earnings just met the analyst estimates, 12 of these firms showed systematic increases in volatility the trading period after the announcement. In other words, there seems to be an increase in market activity even if there is no surprise. It may be the case that analyst estimates are discounted as not being very accurate. However, looking at the regressions of earnings surprise on returns suggests this is not the case. Another reason could be the fact that even if the actual announced earnings are exactly what analysts predicted, the earnings announcement is still news to someone. Not everyone agrees with the estimates, and the degree to which analysts disagree could in theory effect the volatility. This is accounted for in the seventh model developed in this paper.

5.3 Dispersion

Accounting for the dispersion produces mixed results. The regressions of the model including dispersion reveal that dispersion has a significant effect for 15 of the firms. However, there is no systematic relation that is easily apparent. For some firms, the dispersion matters for positive surprises only. For others, it is only relevant with negative surprises, or with negative and no surprises, etc. While increased dispersion of analyst estimates does suggest a larger increase in volatility, there does not seem to be a general result, other than the limited suggestion that dispersion matters in some cases.

5.4 Negative versus Positive Surprises

The final finding of this paper concerns the different effects negative surprises have on stocks in comparison to positive surprises. As previously noted, research suggests that markets react differently to surprises depending on the direction of the surprise. Furthermore, a common view with regards to earnings surprises and firms is that a company's management has the incentives to avoid negative earnings surprises (Matsumoto). If this is the case, negative surprises should have a larger impact on stock price behavior, as positive surprises are relatively more "expected" in such an environment. The findings of this paper support this claim. Out of the 12 firms that had at least seven negative surprise days, beating estimates and missing estimates were both significantly correlated with increases in volatility in nine firms. Of these nine, seven of the firms exhibited overall larger increases in volatility after missing estimates in comparison to when they beat estimates. In terms of overnight returns, eight out of ten firms displayed this trait. These findings support the claim that negative surprises tend to have larger effects than positive surprises.

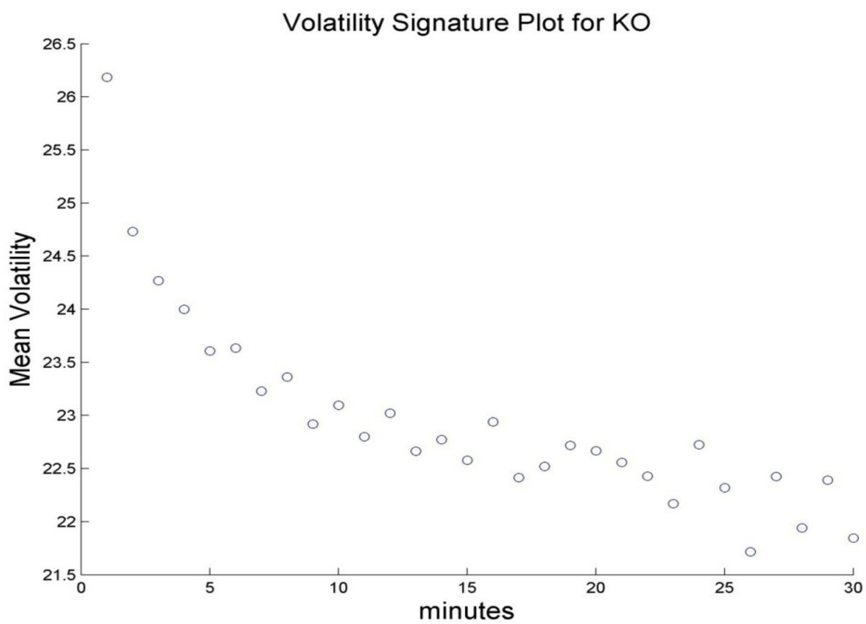
5.5 Review of the Evidence and Explanation

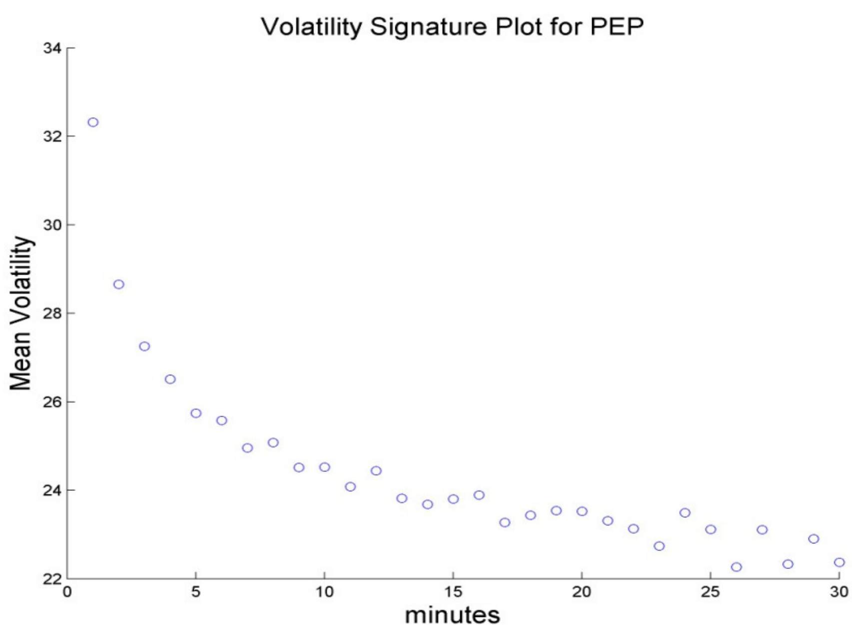
The previous results suggest that earnings surprise do tend to be significantly correlated with stock price behavior, at least in relation to overnight returns and realized volatility. The fact that an earnings surprise tends to be significantly correlated with realized volatility while it is not with within-day returns is interesting, however, because both the realized volatility and within-day returns are calculated using intraday returns (as previously defined). The within-day returns are the sum of the log intraday returns, while the realized volatility is the sum of the squares of log intraday returns. A possible explanation for this difference is that while the market adjusts fairly quickly in the expected direction to reflect a given earnings surprise, frequently occurring before the market opens, there is a brief period of uncertainty. Shares exchange hands more often as investors and analysts debate over the significance of a particular earnings surprise, but there is no systematic bias in the direction share prices move.

6. Conclusion

The aim of this paper was to explore the ways that the market quarterly earnings announcements and analyst estimates to adjust stock prices by looking at the relationship between earnings surprise and returns, as well as earnings surprise and volatility. Using high frequency data and models such as the HAR-RV that take advantage of the availability of such data indicates that the market does use the information provided by estimates and quarterly earnings reports, and at least in the short run, the earnings surprise is significantly correlated with regards to volatility and overnight returns. Furthermore, there appears to be an increase in volatility in the trading period after earnings are announced, but there is no systematic bias that indicates which direction prices will go in that period. This paper also finds the surprising result that even when the quarterly earnings reported is equal to what the analysts predicted, the announcement is followed by an increase in volatility in the trading period immediately after the announcement is made. Accounting for analyst estimate dispersion could provide an explanation for why stocks react even if there is no earnings surprise: the average of earnings estimates may equal the actual announced earnings, but if analysts widely disagreed in their estimates, that information was less meaningful to the market. However, the data are not very informative about the effects, as dispersion seems to be significant in some cases but not in others, and there is no pattern to when the dispersion is significant. Nevertheless, the findings taken together reveal the importance of earnings on equity price valuation, and suggest that it could prove beneficial to explore further the mechanisms through which the markets process this information.

Figure 1. Volatility Signature Plots for Coca-Cola (KO) and Pepsi (PEP)





Without microstructure noise, the mean volatility should be roughly constant as the sampling frequency increases (i.e. intervals become smaller). However, with microstructure noise, as the interval becomes smaller, mean volatility becomes increasingly biased toward infinity.

Table 1. Regression Results, Earnings Surprise with Overnight Returns

Any coefficient not significant at the 10% level was omitted for simplification. * indicates significance at the 5% level, ** at the 1% level

Firm	**# of Est Days**			**Magnitude of Surprise**		**Indicator Variables for Surprise**		
Firm	*Pos*	*Neg*	*Meet*	*Positive*	*Negative*	*Beat*	*Miss*	*Meet*
XOM	30	12	2	.03**	.03*	0.48**	-0.96**	-
PG	31	2	10	-	-	-	-	-
GE	10	6	27	.18**	.25**	.54**	-	-
T	35	6	2	.02**	.04**	.34*	-2.38**	-
JNJ	30	6	7	.27**	-	.57**	-	0.41
CVX	12	13	1	.05**	.04**	.64**	-.60**	-
MSFT	32	5	6	.09**	.70**	.43**	-1.98**	-
AMZN	14	23	5	.03**	.01**	1.92**	-1.93**	-.933*
WMT	28	6	10	.10**	.62**	.63**	-2.16**	-
JPM	26	14	2	.03**	.02*	.46**	-	-0.79
IBM	30	5	8	.30**	.12**	.80**	-.83*	-1.96**
HPQ	17	2	4	.26**	.55**	1.84**	-9.54**	1.28**
WFC	13	17	13	.12*	.02**	.38*	-.71**	-
VZ	16	3	12	-	-	-	-	-0.31
CSCO	35	1	8	-	.69**	.57**	-3.57**	-2.07
KO	27	6	10	.19**	-	.78**	-	-.48*
PEP	24	8	11	.25**	-	.91**	.63**	-
ABT	10	3	30	-	-	-	-	-
INTC	28	10	5	.02	.26**	.37*	-2.83**	-
AAPL	37	4	2	.01**	-	.83**	-	-
BAC	31	7	4	.05**	.05**	.30*	-1.32**	-.93**
MRK	17	7	19	.07**	.09	.73**	-2.20**	-
AMGN	31	7	5	.13**	.37**	.33*	-1.12**	-
QCOM	34	5	3	.04**	-	.63**	-	-
MCD	14	10	19	-	.10*	-	-	-
UPS	19	5	9	.10**	.24**	.65**	-3.19**	-
UTX	40	1	2	.15**	-	.62**	-	-
GS	32	3	1	.01**	-.07**	-	.93**	1.63**
SLB	24	13	6	.03**	.06**	.20	-.73**	-
WYE	16	6	1	-	.53**	.64**	-3.24**	-
# signif.	***n/a***	***n/a***	***n/a***	***24***	***21***	***25***	***19***	***10***

Table 2. Regression Results, Earnings Surprise with Within-Day Returns

Any coefficient not significant at the 10% level was omitted for simplification. * indicates significance at the 5% level, ** at the 1% level

Firm	**# of Est Days**			**Magnitude of Surprise**		**Indicator Variables for Surprise**		
Firm	*Pos*	*Neg*	*Meet*	*Positive*	*Negative*	*Beat*	*Miss*	*Meet*
XOM	30	12	2	-	-	-	-	-
PG	31	2	10	.16*	-.51*	.46**	1.24	-.6*
GE	10	6	27	-.26*	-	-.76*	-	-0.35
T	35	6	2	-.02**	.02**	-.42*	-	-
JNJ	30	6	7	-	-	-	-	-
CVX	12	13	1	-	0.03	-	-	-
MSFT	32	5	6	-.03	-	-	-	-
AMZN	14	23	5	.02**	-	.66*	-0.38	-
WMT	28	6	10	.06	-	-	-	-
JPM	26	14	2	-.02**	-	-	-	-
IBM	30	5	8	-.08*	.11**	-0.31	-0.76	-
HPQ	17	2	4	-	-	-.54*	-	-1.06*
WFC	13	17	13	-	-	0.47	0.43	-
VZ	16	3	12	-	-	-	-	-
CSCO	35	1	8	-	-	-	-	-
KO	27	6	10	-	-.19**	-0.36	1.10**	-0.58
PEP	24	8	11	-	-	-.52**	.73*	-
ABT	10	3	30	-	-	-	-	-
INTC	28	10	5	-.02*	-	-	-	-
AAPL	37	4	2	-	-	-	-	-
BAC	31	7	4	-	-.04**	-	-	-
MRK	17	7	19	.07**	-	1.00**	-.93*	.54*
AMGN	31	7	5	.05*	-	-	-	-
QCOM	34	5	3	-	-.35*	-	1.16**	-
MCD	14	10	19	-	-	-	-	-
UPS	19	5	9	-	-.19**	-	1.25**	-
UTX	40	1	2	-	-	-	-	-
GS	32	3	1	-	-.09*	-	-	-
SLB	24	13	6	-	-	-	-	-
WYE	16	6	1	-	-	-	-	-
# signif.	***n/a***	***n/a***	***n/a***	***11***	***10***	***10***	***9***	***5***

Table 3. Regression Results, Earnings Surprise with Volatility

Note: coefficients from the original HAR-RV model will be omitted for simplification.

Any coefficient not significant at the 10% level was omitted for simplification. * indicates significance at the 5% level, ** at the 1% level

Firm	**# of Est Days**			**Magnitude of Surprise**		**Indicator Variables for Surprise**		
Firm	*Pos*	*Neg*	*Meet*	*Positive*	*Negative*	*Beat*	*Miss*	*Meet*
XOM	30	12	2	-	-	2.77*	5.14*	6.16**
PG	31	2	10	3.11**	-2.52**	7.96**	7.13**	6.43*
GE	10	6	27	1.42**	-	3.84**	-	4.54*
T	35	6	2	.27**	-.42**	9.81**	25.19*	4.58*
JNJ	30	6	7	1.46**	-1.85	6.51**	5.80*	6.91*
CVX	12	13	1	-	-	-	7.03**	-2.06**
MSFT	32	5	6	-	1.11	-	-4.33*	-
AMZN	14	23	5	-	-	13.57**	10.54**	8.24
WMT	28	6	10	0.57	-	2.79*	4.83**	-
JPM	26	14	2	0.22	-.28**	8.51**	9.54**	5.77**
IBM	30	5	8	.38**	-	2.18**	-	-
HPQ	17	2	4	.94**	-.56**	9.09**	-	8.46**
WFC	13	17	13	1.13	-	4	6.31**	4.11**
VZ	16	3	12	-	1.34*	2.98	-	8.37*
CSCO	35	1	8	-	-.49**	-	2.65**	8.21**
KO	27	6	10	.60**	-.91**	4.88**	6.20**	6.21**
PEP	24	8	11	1.32**	-	7.19**	6.13*	11.45
ABT	10	3	30	1.92**	-1.44*	8.87**	2.94*	7.43**
INTC	28	10	5	.23**	-	5.71**	-	17.49**
AAPL	37	4	2	-	-.02**	6.39**	9.65**	-
BAC	31	7	4	-	-1.20**	2.46	20.93	5.73**
MRK	17	7	19	-	-.83**	2.72	10.32**	5.44**
AMGN	31	7	5	.60*	-	-	-	4.37**
QCOM	34	5	3	.42**	-	8.95**	-	-
MCD	14	10	19	0.53	-2.34	12.47**	17.70**	8.92**
UPS	19	5	9	1.13**	-1.32**	7.97**	11.78**	13.13**
UTX	40	1	2	2.24**	-.34**	9.50**	16.28**	-
GS	32	3	1	.21**	-	9.01**	-	-
SLB	24	13	6	.50**	-.94**	8.10**	12.13**	-
WYE	16	6	1	.58**	-2.37	7.82**	12.38	9.70**
# signif.	***n/a***	***n/a***	***n/a***	***21***	***18***	***26***	***22***	***22***

Table 4. Percent of Firms for which Regressor was Significant

	Magnitude		**Indicator Var.**		
Dependent Var.	*Positive*	*Negative*	*Beat*	*Miss*	*Meet*
Volatility	70%	60%	87%	73%	73%
Overnight Return	80%	70%	83%	63%	33%
Intraday Return	37%	33%	33%	30%	17%

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