Does Beta Move with News?
Systematic Risk and Firm-Specific Information Flows*

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Abstract

This paper studies time-varying patterns in the systematic risk (or "beta") of individual stocks during firm-specific information flows. We show that systematic risk increases by an economically and statistically significant amount on news announcement days, before reverting to its average level two to five days later. We employ intra-daily data and recent advances in econometric theory to obtain firm-level estimates of daily changes in beta for all constituents of the S&P 500 index over the period 1995-2006, and estimate the behavior of beta around the dates of over 22,000 quarterly earnings announcements. We find that the increase in beta is larger for more liquid and more visible stocks, and for announcements with bigger information content and higher ex-ante uncertainty. We also find strong variations in beta changes across industries. A simple model of investors' expectations formation using intermittent earnings announcements helps explain our empirical findings: changes in beta may be generated by investors learning about profitability across different firms.

Keywords: CAPM, beta, realized volatility, earnings announcements.

J.E.L. codes: G14, G12, C32.

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1 Introduction

Does the systematic risk of a stock change during the release of firm-specific information? According to the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), a stock's expected return is proportional to its systematic risk, or "beta", which represents the sensitivity of the stock's returns to the market portfolio returns.

Early empirical applications of the CAPM assume a constant beta, whereas more recent studies allow for time variation in a stock's systematic risk. An extensive literature in asset pricing finds evidence that betas change over time with variables describing the business cycle (see Ferson, Kandel, and Stambaugh (1987), Shanken (1990), Ferson and Schadt (1996), among others). Other papers estimate time-varying betas without the need to specify a given set of state variables (Lewellen and Nagel (2006)). Another strand of the literature departs from the assumption of a constant CAPM beta by estimating separate components of beta that reflect different types of market risk (Campbell and Mei (1993), Campbell and Vuolteenaho (2004)). In all these approaches, variations in systematic risk occur at low frequencies, typically quarterly or monthly.

In this paper we study variations in systematic risk (as captured by the CAPM beta) during times of firm-specific information flows. There is no empirical evidence on time-varying systematic risk in relation to the release of firm-specific information. We allow for a stock's beta to vary at the daily frequency, and study how variations in beta are affected by firm-specific information disclosures. This question has important implications for studies of the efficiency of financial markets, and for asset pricing more generally.

To better understand the dynamics of changes in betas around news announcements, we decompose a stock's beta into a "variance component" and a "covariance component". This decomposition enables us to separately estimate changes in beta due to changes in a stock's own volatility, and changes in beta attributable to movements in the average covariance of a stock with the remaining assets in the market portfolio.

We analyze time variations in beta around firm-specific information flows by focusing on quarterly earnings announcements. These represent regular and well-documented information disclosures, and are thus well-suited for a study of many stocks over a long time period. Our sample consists of all constituents of the S&P 500 index over the period 1995-2006, and includes 22,575 earnings announcements for a set of 810 distinct stocks.

We employ a new methodology to construct *firm-level* estimates of *daily* betas starting from intra-daily return data. This methodology draws from recent econometric advances in the estimation of risk from high frequency data (see Andersen, *et al.* (2003) and Barndorff-Nielsen and Shephard (2004)), which enable the estimation of the variances and covariances of daily returns by using information in intra-daily returns and computing the "realized covariance" matrix. We then compute a stock's "realized beta" as the ratio between its realized covariance with the market return and the realized variance of the market return. We choose a sampling frequency of 25 minutes, as in Bollerslev, *et al.* (2008) among others, to balance the desire to reduce measurement error and the need to avoid microstructure biases arising at the highest frequencies. Our results are robust to using alternative methods for the estimation of a stock's realized beta.[1]

Using panel data techniques, we estimate changes in beta over windows of 21 days around a stock's earnings announcements. We first examine the entire sample of stocks to test for the presence of a pervasive pattern in beta during information flows. We then analyze cross-sectional differences in the behavior of betas, to test whether changes in betas are related to specific stocks characteristics or to the information environment surrounding earnings announcements.

Our results show strong evidence that betas increase during information flows, by a statistically and economically significant amount. Pooling across all stocks, we find that average betas increase by 0.08 on earnings announcement days, with over 80% of this change coming from the covariance component of beta. Betas decline sharply on the post-announcement day, and then slowly revert to their average level, about two to five days after the announcement.

We find significant cross-sectional differences in the behavior of beta during news announcements. Changes in beta increase with a stock's turnover (from 0.03 to 0.11), and vary substantially with the information content of earnings announcements: Beta increases by 0.08 during the release of bad news, by 0.13 during good news, and by only 0.04 when the earnings surprise is close to zero. We also find that changes in beta are more pronounced in the presence of a higher dispersion in analyst forecasts of earnings, a variable capturing investors' uncertainty or disagreement about future news. Our results suggest that larger increases in betas on announcement days are characterized by a stronger movement in the covariance component of beta. In contrast, we do not find

[1] We test the robustness of our results by estimating betas from 5-minute returns, and by using the estimator proposed by Hayashi and Yoshida (2005) (see Section 5). Our results are relatively insensitive to both of these changes.

any significant patterns linked to a stock's market capitalization or book-to-market ratio.

Our industry analysis reveals strong differences in the behavior of betas across different sectors of the economy: the increase in beta is largest for High Tech stocks (around 0.10, with a t-statistic of 4.10) and lowest for stocks in the Health sector (-0.07 and not statistically significantly different from zero). The differences across industry are even more important when observed separately for the earlier and the later part of our sample period (1995 to 2000 and 2001 to 2006). We find that changes in betas for High Tech stocks are particularly large during the first half of our sample (which includes the technology bubble period) than during the second half of the sample.

Why should we expect beta to change during firm-specific information flows? A simple theoretical model of investors' expectations formation helps explain our empirical findings. Stock prices are related to future earnings through a simple present-value model, and log-earnings evolve as a random walk with drift. Earnings announcements are made intermittently. Investors' expectations about the future earnings of a given firm are based both on that firm's past announcements, and on more recent announcements by other firms. In this model, the correlated nature of earnings across firms and the fact that announcements are made only intermittently, generate covariances and betas that spike upwards on announcement days. As in our empirical results, the spike in beta is upwards regardless of whether the earnings announcement represents good news or bad news. This change in beta is the result of investors updating their expectations about future earnings for the announcing firm and for all other firms: good (bad) news for the announcing firm is interpreted as partial good (bad) news for other firms, causing the prices on all these stocks to move in the same direction. This raises the average covariance between the return on the announcing firm and the returns on the other firms, thus causing an increase in the announcing firm's market beta (where the market is defined as a weighted average of all individual stock returns).

Our paper is related to a number of empirical studies in the asset pricing and accounting literature. The behavior of betas around earnings announcements is also analyzed in Ball and Kothari (1991), who estimate cross-sectional regressions of daily returns and obtain a cross-sectional daily estimate of beta. The authors find that the average beta increases by 0.067 over a three-day window around earnings announcements. By utilizing intra-day returns we are able to obtain estimates of betas for individual stocks rather than estimates of average betas. We can thus link the behavior of betas to firm-specific characteristics.

As in Lewellen and Nagel (2006), we estimate time-varying betas from returns measured at higher frequencies. While Lewellen and Nagel use daily returns to estimate quarterly and semi-annual betas, we use intra-daily returns to estimate daily betas. Our focus, however, is different, as we are not interested in testing the conditional CAPM but in analyzing the behavior of beta during firm-specific information flows.

Our paper is also related to recent studies that document an increase in a stock's beta following additions to the S&P 500 index (see Vijh (1994) and Barberis, Shleifer, and Wurgler (2005)). These papers, however, examine changes in beta occurring during a single event in the life of a stock and estimated over long horizons, and their findings are explained by market frictions or investor sentiment.[2]

The question of changes in systematic risk during firm-specific information flows has not been directly addressed in the theoretical literature. However, the studies by Epstein and Turnbull (1980) and Shin (2006) consider issues that are related to this question.

The remainder of the paper is structured as follows. In Section 2 we review the econometrics literature that allows us to estimate firm-specific daily betas from high frequency data. Section 3 describes our sample, and Section 4 describes our estimation method and presents our empirical results. Section 5 contains robustness tests performed using alternative measures of beta. Section 6 presents a model of investors' earnings expectations formation from intermittent earnings announcements, which helps explain our empirical results. Section 7 concludes.

2 The theory of realized betas

Our empirical work employs recent advances in the econometrics of risk measurement using high frequency data (see Andersen, *et al.* (2003) for applications involving volatility, and Barndorff-Nielsen and Shephard (2004) for applications involving covariances, correlations and betas.[3] This theory enables us to obtain an estimate of beta for an individual stock and on each day. We can thus analyze the dynamic behavior of beta with greater accuracy and at a higher frequency than

[2] In a related paper, Greenwood (2008) finds that stocks that are overweighted in the Nikkei 225 index have higher betas than other stocks in the index. He focuses on cross-sectional differences in betas due to correlated shocks in investor demand rather than on event-driven changes in beta.

[3] Andersen, *et al.* (2006a) and Barndorff-Nielsen and Shephard (2007) provide recent surveys of this research area.

has been so far possible.[4] The cost of this empirical approach is computational, since obtaining estimates of betas means handling large amounts of high frequency data. We describe our data set and the construction of our variables in Section 3.

2.1 Theory and estimation of realized betas

The framework of Barndorff-Nielsen and Shephard (2004) (BNS, henceforth), is based on a general multivariate stochastic volatility diffusion process for the $N \times 1$ vector of returns on a collection of assets, denoted $d \log \mathbf{P}(t)$:

$$\begin{aligned} d \log \mathbf{P}(t) &= d\mathbf{M}(t) + \Theta(t)\, d\mathbf{W}(t) \\ \Sigma(t) &= \Theta(t)\, \Theta(t)' \end{aligned} \tag{1}$$

where $\mathbf{M}(t)$ is a $N \times 1$ term capturing the drift in the log-price, and $\Sigma(t)$ is the $N \times N$ instantaneous or "spot" covariance matrix of returns. The quantity of interest in our study is not the instantaneous covariance matrix (and the corresponding "instantaneous betas") but rather the covariance matrix for the daily returns, a quantity known as the "integrated covariance matrix":

$$ICov_t = \int_{t-1}^{t} \Sigma(\tau)\, d\tau. \tag{2}$$

As in standard analyses, the beta of an asset is computed as the ratio of its covariance with the market return to the variance of the market return, and can thus be computed from the integrated covariance matrix:

$$I\beta_{it} \equiv \frac{ICov_{imt}}{IV_{mt}}, \tag{3}$$

where $ICov_{ijt}$ is the (i, j) element of the matrix $ICov_t$, $IV_{mt} = ICov_{mmt}$ the integrated variance of the market portfolio, $ICov_{imt}$ is the integrated covariance between asset i and the market, and $I\beta_{it}$ is the "integrated beta" of asset i. The integrated covariance matrix can be consistently estimated

[4] Work on time-varying systematic risk using lower frequency data or alternative methods includes Robichek and Cohn (1974), Ferson, Kandel and Stamabugh (1987), Shanken (1990), Ball and Kothari (1991), Ferson and Harvey (1991), Andersen, *et al.* (2006b), Lewellen and Nagel (2006), among others. Previous research employing high frequency data to estimate betas includes that of Bollerslev and Zhang (2003), Bandi, *et al.* (2005), Todorov and Bolerslev (2007), and Ghosh (2008), though the focus and coverage of those papers differ from ours.

(as the number of intra-daily returns diverges to infinity) by the "realized covariance" matrix:

$$
\begin{aligned}
RCov_t^{(S)} &= \sum_{k=1}^{S} \mathbf{r}_{t,k}\mathbf{r}'_{t,k} \\
&\xrightarrow{p} ICov_t \quad \text{as } S \to \infty,
\end{aligned}
\tag{4}
$$

where $\mathbf{r}_{t,k} = \log \mathbf{P}_{t,k} - \log \mathbf{P}_{t,k-1}$ is the $N \times 1$ vector of returns on the N assets during the k^{th} intra-day period on day t, and S is the number of intra-daily periods. The individual elements of this covariance matrix can be written as:

$$
RV_{it}^{(S)} = \sum_{k=1}^{S} r_{i,t,k}^2 \tag{5}
$$

$$
RCov_{ijt}^{(S)} = \sum_{k=1}^{S} r_{i,t,k} r_{j,t,k} \tag{6}
$$

where $r_{i,t,k}$ is the i^{th} element of the return vector $\mathbf{r}_{t,k}$.

An important contribution of BNS is a central limit theorem for the realized covariance estimator:

$$
\sqrt{S}\left(RCov_t^{(S)} - ICov_t\right) \xrightarrow{D} N\left(0, \Omega_t\right) \quad \text{as } S \to \infty, \tag{7}
$$

where Ω_t can be consistently estimated using intra-daily returns[5].

Combining the above distribution theory with the "delta method" yields the asymptotic distribution of realized beta for a given stock i :

$$
\sqrt{S}\left(R\beta_{it}^{(S)} - I\beta_{it}\right) \xrightarrow{D} N\left(0, W_{i,t}\right), \text{ as } S \to \infty \tag{8}
$$

When the sampling frequency is high (S is large), but not so high as to lead to problems coming from market microstructure effects (discussed in detail below), the above results suggest that we may treat our estimated realized betas as noisy but unbiased estimates of the true integrated betas:

$$
\begin{aligned}
R\beta_{it}^{(S)} &= I\beta_{it} + \epsilon_{it}, \\
\text{where } \epsilon_{it} &\overset{a}{\sim} N\left(0, W_{i,t}/S\right).
\end{aligned}
\tag{9}
$$

Betas can then be treated as noisy estimates of true betas, and inference on these can be conducted using standard OLS regressions (though with autocorrelation and heteroskedasticity-robust standard errors). Thus we can use more standard "long span" asymptotics ($T \to \infty$) rather than the "continuous record" asymptotics (i.e., $S \to \infty$) of BNS.

[5] Recent extensions of the theory presented by BNS include Bandi and Russell (2005), Barndorff-Nielsen, *et al.* (2008) and Donovon, *et al.* (2008).

One advantage of the regression-based approach is that it allows for the inclusion of different control variables in the model specification, so that it is easy to control for the impact of changes in the economic environment (such as market liquidity or the state of the economy) or for the effect of various firm characteristics (such as return volatility or trading volume).

2.2 Dealing with market microstructure effects

At very high frequencies, market microstructure features can lead the behavior of realized variance and realized beta to differ from that predicted by the theory. For example, estimating the beta of a stock which trades only infrequently can lead to a bias towards zero, known as the "Epps effect" (see Epps (1979), Scholes and Williams (1977), Dimson (1979) and Hayashi and Yoshida (2005)). One simple approach to avoid these effects is to use returns that are not sampled at the highest possible frequency (which is one second for US stocks) but rather at a lower frequency, for example 5 minutes or 25 minutes. By lowering the sampling frequency we reduce the impact of market microstructure effects, at the cost of reducing the number of observations and thus the accuracy of the estimator. This is the approach taken in Todorov and Bollerslev (2007) and Bollerslev *et al.* (2008), and is the one we follow in our empirical analysis. We construct betas from 25-minute returns, and check the robustness of our results to using betas that are constructed from 5-minute returns.

An alternative approach is to use an estimator of betas that is designed to be robust to market microstructure effects. One such estimator is the Hayashi and Yoshida (2005) estimator, (henceforth HY) which is designed to handle the problems introduced by non-synchronous trading.[6] This estimator is more difficult to implement, but it is generally expected to perform better for less frequently-traded stocks. Griffin and Oomen (2006) note that, although the HY estimator is robust to non-synchronous trading, it is not robust to other microstructure effects, and so it too may benefit from lower-frequency sampling. In the robustness section of the paper we construct an alternative measure of beta using the HY estimator. We follow the suggestion of Griffin and Oomen (2006) and consider a wide set of sampling frequencies, ranging from one second to approximately 30 minutes.

[6] The HY estimator is similar to the familiar Scholes and Williams (1977) estimator, although it is adapted to high frequency data and is based on an alternative statistical justification.

2.3 "Variance" and "covariance" components of beta

The goal of our study is to understand the dynamics of beta during firm-specific information flows. Given that the firms we study are constituents of the index we use as the market portfolio (the S&P500 index), an increase in the variance of a given stock's return will mechanically increase its beta with the market. Further, since it is well-known that the volatility of stock returns are higher than average on announcement dates, an apparent increase in beta coming solely from an increase in the volatility of the stock's return would not be very surprising or very interesting.

To overcome this, we decompose the beta of a stock into two components: one related to the volatility of the individual stock, and the other related to the average covariance of an individual stock with all other constituents of the market index. With this decomposition, we are able to study changes in "total" beta and to identify the source of the change: a change in the variance of the stock, or a change in its covariance with other stocks. To make things concrete, consider a market index made up as a weighted-average of N individual stocks, with return is described by:

$$r_{mt} = \sum_{j=1}^{N} \omega_{jt} r_{jt}. \tag{10}$$

Then any individual firm's market beta can be decomposed into two terms:

$$\begin{aligned} \beta_{it} &\equiv \frac{Cov\left[r_{it}, r_{mt}\right]}{V\left[r_{mt}\right]} \\ &= \omega_{it} \frac{V\left[r_{it}\right]}{V\left[r_{mt}\right]} + \sum_{j=1, j\neq i}^{N} \omega_{jt} \frac{Cov\left[r_{it}, r_{jt}\right]}{V\left[r_{mt}\right]}. \end{aligned} \tag{11}$$

Note that if firm i is not a constituent of the market index, then $\omega_{it} = 0$ and so the beta is purely related to covariance terms. We label the first term above the "variance" component, and the second term the "covariance" component of beta.[7]

[7] These definitions are justified to the extent that both $V[r_{it}]$ and $Cov[r_{it}, r_{jt}]$ have a negligible impact on $V[r_{mt}]$. This will be true if the weight of any individual stock in the index is small, as the impact of $V[r_{it}]$ and $Cov[r_{it}, r_{jt}]$ on the market variance is of the order of the weight squared, i.e., a lower order of magnitude. Note that the corresponding decomposition for the *covariance* of a stock with the market holds exactly.

A corresponding result also holds for realized beta:

$$
\begin{aligned}
R\beta_{it} &\equiv \frac{RCov_{imt}}{RV_{mt}} \\
&= \omega_{it}\frac{RV_{it}}{RV_{mt}} + \sum_{j=1,j\neq i}^{N} \omega_{jt}\frac{RCov_{ijt}}{RV_{mt}} \\
&\equiv R\beta_{it}^{(var)} + R\beta_{it}^{(cov)}.
\end{aligned} \tag{12}
$$

Thus changes in realized betas can be caused by changes in a stock's own volatility, or by changes in the stock's average covariance with other stocks in the index. Given the weights of each firm in the market portfolio, we can estimate these two components of realized beta given just three simple-to-compute quantities: RV_{it}, RV_{mt} and $RCov_{imt}$. In our empirical analysis we study changes in total realized beta, $R\beta_{it}$, and changes in the covariance component, $R\beta_{it}^{(cov)}$.

3 Data

The sample used in this study includes all stocks that were constituents of the S&P 500 index at some time between January 1995 and December 2006, a total of 810 companies. We compute daily realized betas using high frequency prices from the TAQ database. Data on daily returns, volume and market capitalization are from the CRSP database, book-to-market ratios are computed from COMPUSTAT, and analyst forecasts are from IBES.

As described in Section 2, and in line with the CAPM framework, we compute realized betas as the ratio between the realized covariance of a stock's returns with the returns of the market, and the realized variance of the market returns:

$$
R\beta_{it} = \frac{RCov_{imt}}{RV_{mt}} \tag{13}
$$

For each stock, we use prices from the TAQ database between 9:45am and 4:00pm, sampled every 25 minutes, to compute high frequency returns, and combine these with the overnight return, defined as the return between 4:00pm the previous day and 9:45am on the current day.[8] We choose a 25-minute frequency to measure returns so that we can balance the need to reduce measurement error relative to using lower frequency returns, and the need to avoid the microstructure biases that arise

[8] The start of the trade day is 9:30am, but to handle stocks that begin trading slightly later than this we take our first observation as at 9.45am.

at the highest frequencies (see Epps (1979), Hayashi and Yoshida (2005) and Griffin and Oomen (2006)). In the robustness section we analyze betas that are computed from 5-minute returns and betas that are obtained using the Hayashi-Yoshida (2005) estimator.

The prices we use are the national best bid and offer prices (NBBO), computed by examining quote prices from all exchanges offering quotes on a given stock.[9] The market return for our analysis is the Standard & Poor's Composite Index return (S&P 500 index). We use the exchange traded fund tracking the S&P 500 index (SPDR, traded on Amex with ticker SPY) to measure the market return, as in Bandi *et al.* (2006) and Todorov and Bollerslev (2007) (see Elton, *et al.* (2002) and Hasbrouck (2003) for studies of this asset). This fund is very actively traded and, since it can be redeemed for the underlying portfolio of S&P 500 stocks, arbitrage opportunities ensure that the fund's price does not deviate from the fundamental value of the underlying index. The prices of the SPDR are available on the TAQ database.

We identify quarterly earnings announcements using the announcement dates recorded in COMPUSTAT and IBES. Announcement dates do not always coincide across the two databases. For the companies in our sample, COMPUSTAT and IBES announcement dates agree in about 86% of the cases. In case of disagreement, we take the earlier date to be the announcement date.[10] In order to identify announcement dates as accurately as possible and limit the possibility of errors in the identification of the announcement date, we only consider quarterly announcements for which

[9] Using national best bid and offer (NBBO) prices rather than transaction prices or quotes from a single exchange has the benefit that almost all data errors are identified during the construction of the NBBO. Such data errors are not uncommon in high frequency prices, given the thousands of price observations per day for each stock. The cost of using NBBO prices is the computational difficulty in constructing them, given the need to handle quotes from all exchanges and maintain a rolling best NBBO pair of quotes.

[10] DellaVigna and Pollet (2008) analyze discrepancies in annoucement dates reported in COMPUSTAT, IBES, and business newswires (obtained from a search on Lexis-Nexis) for a random sample of 2601 earnings announcements occurring between January 1984 and December 2002. They consider earnings announcements where the difference between COMPUSTAT and IBES dates is at most 5 days. They find that, for the post-1995 period, the earlier of the two COMPUSTAT and IBES announcement dates corresponds to the newswires date (the "correct" announcement date) in 95.8% of the cases for Friday announcements and in 97% of the cases for non-Friday announcements. They conclude that the choice of the earlier date between COMPUSTAT and IBES announcement dates represents an accurate criterion for the identification of earnings announcement dates. We identify 178 earnings announcements in our sample that are also present in the random sample used by DellaVigna and Pollet (2008). We find that our announcement dates always correspond to the dates reported by business newswires.

the distance between COMPUSTAT and IBES dates is no greater than two days.

Our combination of IBES and COMPUSTAT databases provide only the day of the announcement, not the time. We use close-to-close returns, and so the initial reaction to an earnings announcement will appear as occurring on "event day 0" if the announcement was between midnight and 4pm, and on "event day 1" if the announcement was between 4pm and midnight. Bagnoli, *et al.* (2005) use the Reuters Forecast Pro database, which contains both the date and time of an earnings announcement though for a shorter span of time (2000-2003), in their study of strategic announcement times. Using their Table 1, we are able to compute that 76% of their sample of around 4000 firms announce between midnight and 4pm, with the remaining 24% announcing between 4pm and midnight.

We include in the sample firms with valid price and return data obtained from CRSP and with book-to-market information obtained from COMPUSTAT. Information on actual earnings and on earnings forecasts is obtained from the IBES Detail file.

The final sample includes 810 different firms and a total of 22,575 earnings announcements. The number of firm-day observations used in the empirical analysis is 1,492,404. Table 1, Panel A, shows descriptive statistics of our sample. The statistics are calculated as daily cross-sectional means or medians, and are then averaged within a given year. Panel B shows the composition of our sample with respect to a five-industry classification. We use 4-digit SIC codes to identify the following sectors: Consumer, Manufacturing, High Tech, Health, and a residual category for the remaining unclassified companies.[11]

4 Empirical evidence on changes in beta

4.1 Changes in beta around news announcements: an illustration

Before describing the estimation procedure and analyzing the results from our regression analysis, we illustrate here an example of the sorts of patterns in systematic risk around information flows that characterize two of the stocks in our sample. In Figure 1 we plot estimates of the change in market beta for Microsoft and Merck on each of 21 days around quarterly earnings announcement dates, relative to days outside this 21-day window. The estimates and confidence intervals are based

[11] The industry definitions are obtained from Kenneth French's webiste: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

on the theoretical work of Barndorff-Nielsen and Shephard (2004). As in our main analysis, we use the overnight return and intra-daily prices sampled every 25 minutes, over the period January 1995 to December 2006.

If systematic risk is unaffected by stock-specific information flows then we would expect the estimated changes to be approximately zero, and the confidence intervals to include zero. For Merck, in the lower panel of Figure 1, we see that this is roughly correct: the estimated changes in beta vary in the range -0.25 to +0.25, and the confidence intervals include zero on almost every date. We observe an increase in beta on the earnings announcement date (event date 0) of 0.21, which is significant at the 10% level but not at the 5% level (the t-statistic is 1.77).

The results for Microsoft are very different: here we observe a change in beta of 1.12 on event day 1,[12] which is both strongly statistically significant (t-statistic of 3.92) and economically important: Microsoft's average beta over this sample period is 1.18 and so this change represents almost a doubling of its systematic risk. This large change is interesting from both and asset pricing and a hedging perspective: According to the CAPM, this doubling of beta implies a doubling of the risk premium for Microsoft on its announcement dates. Further, a large change in the covariance of Microsoft with the market index implies that portfolio replication strategies and hedging strategies may break down on such dates.

We turn now to the panel regression estimation for all stocks in our sample.

4.2 Estimation method and specification

We estimate changes in realized betas by using a panel regression approach. We estimate a panel regression of realized betas on event day dummies and control variables, according to the following specification:

$$\begin{aligned} R\beta_{it} &= \delta_{-10}I_{t-10} + ... + \delta_0 I_t + ... + \delta_{10}I_{t+10} \\ &\quad +\gamma_{i1}D_{1t} + \gamma_{i2}D_{2t} + ... + \gamma_{i12}D_{12t} + \boldsymbol{\gamma}\mathbf{X}_{it} + \varepsilon_{it}, \end{aligned} \tag{14}$$

where $R\beta_{it}$ is the realized beta of stock i on day t, I_t are dummy variables defined over a 21-day event window around earnings announcements: $I_t = 1$ if day t is an announcement date, $I_t = 0$ else.

[12] For Microsoft and several other tech stocks announcements appear to take place after 4pm, while for other stocks, such as Merck, they appear to take place before 4pm.

D_{1t} to D_{12t} are dummy variables for each of the 12 years in the sample (1995 to 2006). We allow for firm and year fixed effects in realized betas, so that average betas may differ across stocks, and so that the beta of a given stock may differ across years.

$\mathbf{X}_t = \left[R\beta_{it-1},\ Volume_{it},\ \widehat{RV_{it}}\right]'$ is a vector of control variables including the lagged realized beta $R\beta_{it-1}$, the trading volume of stock i on day t, and the volatility of stock i on day t, $\widehat{RV_{it}}$, instrumented using lagged volatility and the event-day dummies. We include lagged realized betas in the regression to account for autocorrelation in realized betas (see Andersen, *et al.* (2006b) for example). As we discuss in Section 2, there is evidence that non-synchronous trading can cause a downward bias in realized covariances. Since non-synchronous trading is less important on days with high trading intensity, and given that earnings announcement dates are generally characterized by greater than average trading volume, it is crucial to account for the possibility that an observed increase in realized beta on announcement dates may be due to a decrease in the bias related to non-synchronous trading. We control for this effect by including a stock's trading volume in our regression specification. We include a control for volatility, given existing empirical evidence that volatility can affect covariance estimates (Forbes and Rigobon (2002)).

We estimate the panel regression by allowing the observations to be clustered on any given day, following Wooldridge (2002, 2003) and Petersen (2008). The estimation of panel data with clusters yields standard errors that are robust to heteroskedasticity and to any form of intra-cluster correlation. This procedure is flexible and allows for different cluster sizes, as is the case in our unbalanced sample. Moreover, the estimation procedure yields consistent standard errors when the number of clusters (days) is large relative to the number of intra-cluster observations (firm/days). This is a feature of our sample, which consists of 500 firms per day over a sample period of about 3,000 days.[13]

From our regression specification, we can detect changes in betas during times of news an-

[13] We check the robustness of our results to different methods for computing standard errors. We obtain similar results when we estimate standard errors that are clustered by firm, thus allowing for arbitrary correlation across time. We also adopt the two-way clustering technique proposed by Petersen (2008) and Thomson (2006) and cluster the residuals by firm and year, obtaining negligible differences in the estimated standard errors. We also find similar results when we compute Newey-West (1987) standard errors.

nouncements by testing the following hypotheses:

$$
\begin{aligned}
& H_0^{(j)} \quad : \quad \delta_j = 0 \\
\text{vs.} \quad & H_a^{(j)} \quad : \quad \delta_j \neq 0, \ \text{ for } j = -10, -9, ..., 10.
\end{aligned}
$$

We also test whether cross-sectional differences in the behavior of betas around earnings announcements are related to stock characteristics or to the information environment surrounding earnings announcements. Specifically, we estimate separate pooled regressions for sub-samples of stocks that are sorted into quintiles based on the following characteristics:

1. Market capitalization, measured 10 trading days before the earnings announcement day. We use this measure to test whether changes in betas around earnings announcements exhibit different patterns for large and small stocks.

2. The book-to-market ratio, measured 10 trading days before the earnings announcement day. We use this measure to test whether value and growth stocks experience changes in betas to different degrees during periods of earnings announcements.

3. Average daily turnover, computed during the two months that precede the earnings announcement month. This variable captures the liquidity characteristics of a stock in the absence of announcement events and can be a proxy for the speed of incorporation of new information into prices.

4. Residual analyst coverage, defined as a stock's analyst coverage othogonalized with respect to its market capitalization. We consider the number of analysts that issue an earnings forecast for firm i within an interval of 90 days before the earnings announcement date t. Since the number of analysts following a stock is positively correlated with a stock's market capitalization, we estimate the following cross-sectional regression:

$$\ln(1 + na_{i,t}) = \alpha_t + \beta_t \ln(cap_{i,t}) + \varepsilon_{i,t},$$

where $na_{i,t}$ is analyst coverage and $cap_{i,t}$ is market capitalization. Given estimates of the parameters α_t and β_t, we obtain estimates of $\varepsilon_{i,t}$, the residual number of analysts. This variable is a proxy for the amount of information available about a stock, controlling for size, and can be seen as a measure of the speed of incorporation of information into prices.

5. Earnings surprise, defined as the standardized difference between actual and expected earnings:
$$sur_{i,t} = \frac{e_{i,t} - E_{t-1}\left[e_{i,t}\right]}{p_{i,t-10}},$$
where $e_{i,t}$ is the earnings per share of company i announced on day t, and $E_{t-1}\left[e_{i,t}\right]$ is the expectation of earnings per share, measured by the consensus analyst forecast. We define the consensus analyst forecast as the mean of all analyst forecasts issued during a period of 90 days before the earnings announcement date. If analysts revise their forecasts during this interval, we use only their most recent forecasts. The earnings surprise is standardized by the stock price measured 10 days before the announcement date to allow for cross-sectional comparisons. We use this variable to test whether changes in betas around earnings announcements vary with the sign and the magnitude of the earnings news. By grouping stocks into quintiles of earnings surprise, we can test for the impact of good news, bad news, and no news on realized betas.

6. The dispersion of analyst forecasts, measured by the coefficient of variation of analysts' forecasts of earnings:
$$disp_{i,t} = \frac{\sqrt{V_{t-1}\left[e_{i,t}\right]}}{\left|E_{t-1}\left[e_{i,t}\right]\right|},$$
where $V_{t-1}\left[e_{i,t}\right]$ is the variance of all the forecasts of earnings that analysts issue for company i within an interval of 90 days before the announcement date t. This variable captures investors' ex-ante uncertainty or disagreement about the future news announcement.

7. Industry, identified on the basis of a stock's 4-digit SIC code. We identify five sectors: Consumer, Manufacturing, High Tech, Health, and "Other" (as detailed in Section 3) and analyze cross-sectional differences in the behavior of beta among stocks that belong to different sectors of the economy.

4.3 Results for the entire sample

In Table 2 and Figure 2 we present estimated changes in beta during a 21-day event window around quarterly earnings announcement dates, relative to the average beta outside this window, using the panel estimation methods described in the previous section. Realized betas are computed using 25-minute intra-daily returns and the overnight return. In the final column of Table 2 we present estimates of the change in beta attributable to changes in the *covariance* component of beta, $R\beta_{it}^{(cov)}$, defined in Section 2.3.

The coefficient estimates on the event window dummy variables show no evidence of changes in beta during the first eight days of the event window (day -10 to day -3): none of the coefficient estimates are significantly different from zero. Betas experience a sharp increase of 0.08 (with a t-statistic of 8.03) on day 0, the announcement date, and an immediate drop on day 1, to 0.02. Beta then continues to decrease on day 2, to -0.03. Over the next few days beta reverts back to its non-event average and the estimated coefficients are not significantly different from zero. Our estimate of the change in beta on day 0 is comparable to that of Ball and Kothari (1991), who estimate average daily betas from cross-sectional regressions of stock excess returns on market risk premia. Using a sample of 1,550 firms during the period 1980-1988, the authors find that, on average, beta increases by 0.067 over a 3-day window around earnings announcements (relative to the average beta computed over the previous 9 days). Their estimate, however, is much less precise than ours.

How much of this increase in beta is attributable to comovement among stock prices during earnings announcements rather than to an increase in the return volatility of announcing companies? The analysis of the covariance component suggests that the change in realized beta is mostly driven by comovement: the covariance component increases to 0.07 on announcement days, accounting for over 80% of the total change in beta. In Section 6 below we suggest that this finding can be explained by learning: when a given firm announces its earnings, investors can learn about the future earnings of non-announcing stocks.

4.4 A more detailed look at the empirical results

Our results for the entire sample of firms reveal that a stock's beta experiences an average increase of 0.08 on earnings announcement days, with around 80% of that change coming from an increase in the average covariance with other stocks, and the remaining 20% being attributable to an increase in the stock's volatility. Our estimation method allows us to analyze changes in betas around news announcements for each individual stock in our sample. The illustration of the patterns in beta observed for two stocks in our sample (Microsoft and Merck) is just an example of the great degree of heterogeneity that we find across different stocks. To be able to summarize our disaggregated findings in a meaningful way, we examine changes in betas for separate groups stocks that share similar characteristics. We ask how the behavior of beta around news announcements changes with stock characteristics and with characteristics of the earnings announcement. We pursue this analysis in this section.

We consider two types of variables to use for breaking firms into groups. The first includes standard stock characteristics, such as market capitalization, the book-to-market ratio, the industry to which the firm belongs, and the average turnover of the stock. The second type of variables are those that characterize the "information environment" of the earnings announcement, such as the degree of analyst coverage of the stock, the size and sign of the earnings "surprise" (measured with respect to the consensus of analyst forecasts of earnings) and the degree of ex-ante uncertainty or disagreement about the earnings figure (measured as the dispersion of analyst forecasts).

4.4.1 Results by characteristics of the firm

Table 3 and Figure 3 present the results for stocks classified according to market capitalization. The regression estimates show that the effect of new information is stronger for large stocks than for small stocks, with an increase in beta of 0.10 and 0.08, respectively. Notice, however, the difference in the behavior of the variance and covariance components: While the covariance component accounts for about one half of the total increase in beta for large stocks (46% of total change in beta), the change in beta for small stocks is almost entirely due to the covariance component, which accounts for 95% of the total increase in beta on day 0. This difference is not so surprising, as the S&P 500 index is value-weighted, and the variance component of realized betas for small cap stocks will thus be lower than for large cap stocks (see equation 12). It is noteworthy, however, that small cap announcements still lead to substantial changes in covariances, reflected in the changes in beta.

Growth and value stocks do not show substantial differences in the behavior of total beta around news announcement (around 0.08 for growth stocks and 0.09 for value stocks), as shown in Table 4 and Figure 4, however differences are present in the covariance component of beta are substantial: 0.05 for growth stocks and 0.08 for value stocks, suggesting that comovement is the main determinant of the change in beta for value stocks.

Next , we study the differential behavior of beta during information flows across different sectors of the economy. We group stocks into five sectors based on their 4-digit SIC codes: Consumer, Manufacturing, High Tech, Health, and "Other" (as detailed in Section 3). Table 5 and Figure 5 indicate that there are remarkable differences across industries in the reaction of beta to earnings announcements. Changes in betas are particularly large in the High Tech sector, where beta increases by about 0.10 on day 0 and 0.13 on day +1 of the announcement window (with t-statistics of 4.10 and 3.70 respectively). For the Manufacturing sector increases in beta are smaller but still significant (0.08 on day 0 with a t-statistic of 4.17), while betas do not show any significant change for the Health sector. The final five columns in Table 5 show that these patterns are largely driven by changes in the covariance component of beta, suggesting that news about a company's earnings has an impact on a broader set of stocks in the market, thus increasing the average covariance in the returns of these stocks.[14] This interpretation is consistent with the numerous references to "bellwether stocks" in the financial press. These stocks are closely watched by investors, as news about them is taken to provide information on other stocks in the economy.[15]

Finally, Table 6 and Figure 7 presents estimation results for changes in beta across stocks with different levels of turnover, used as a measure of the liquidity of a stock on non-announcement days. Turnover is strongly associated with changes in beta. Low turnover stocks show a much smaller increase in beta (0.03, with a t-statistic of 1.92) than stocks characterized by high and medium turnover (0.09 and 0.10, with t-statistics of 4.36 and 3.65 respectively). These findings are consistent with the intuition that illiquid stocks, or stocks with low trading volume, incorporate information slowly and thus react less to news. The same pattern is reflected in the covariance component of beta, suggesting that announcements by illiquid stocks lead to lower changes in average covariances than more liquid stocks.

4.4.2 Results by characteristics of the information environment

Next we study changes in beta across different features of the information environment of the earnings announcement. Firstly, we consider the degree of analyst coverage of a stock. Analyst coverage is often used in the finance literature as a measure of a stock's visibility or the amount of information available about a company. We test whether changes in betas upon news releases are associated with residual analyst coverage (analyst coverage orthogonalized with respect to market

[14] In a follow-up paper we are studying in greater detail the dynamics of changes in beta around information flows both within and across different sectors of the economy.

[15] Consider, for example, this exerpt from a Financial Times article (20 January 2005) titled "Sentiment sullied by lacklustre guidances from bellwethers": *Wall Street stocks were lower yesterday afternoon as uninspiring earnings and guidances from several bellwether companies sullied market sentiment in spite of economic data that were at worst benign.*

capitalization). The estimates in Table 7 and Figure 8 suggest that stocks with low analyst coverage experience the lowest changes in beta during earnings announcements. The change in beta increases with analyst following in a monotonic way until the fourth quintile of analyst coverage, and drops for stocks with the highest analyst following. This drop is however compensated by the substantial increase observed the day after the announcement (event day +1). The coefficient estimates show that the change in beta is mostly driven by a change in the covariance component.

Next, we determine whether changes in betas during information flows are affected by the sign and the size of new information. To answer this question we sort stocks into quintiles based on standardized earnings surprise. Table 8 and Figure 9 report estimates of changes in betas for quintiles of stocks with different earnings news: from very bad news (large and negative surprise, quintile 1), to no news (quintile 3), to very good news (large and positive surprise, quintile 5). The results show that changes in betas are stronger in the presence of "big" news (positive or negative) than following relatively uninformative news releases. Changes in beta are, on average, 0.08 for bad news, 0.04 for no news, and 0.13 for good news (with t-statistics of 3.04, 1.96, and 4.92 respectively). It is worth noting that the contribution of the covariance component of beta is lowest for the quintile of stocks reporting no news (63%), and increases for announcements with larger earnings surprises (reaching 89% for large positive surprises). Our results also show evidence of an asymmetric pattern in beta changes − good news has a stronger impact on beta than bad news. This finding is suggestive of the idea that "bad news travels slowly", documented in the empirical literature using low frequency returns (see for example Hong, Lim, and Stein, (2000), and Hou (2007)).

Finally, we analyze cross-sectional differences in beta changes related to ex-ante uncertainty about earnings. We measure investors' uncertainty or disagreement about the prospects of a firm by the dispersion in analyst forecasts of earnings before the announcement date. We find strong evidence that the positive change in beta on announcement days increases with forecast dispersion, as can be seen from Table 9 and Figure 10. Stocks with low dispersion of forecasts experience an increase in betas of 0.05, while stocks with large forecast dispersion show a change in beta that exceeds 0.10. Moreover, the contribution of the covariance component explains an increasing fraction of changes in beta as uncertainty becomes larger (this fraction increases monotonically from 65% to 89%).[16]

[16] These results are confirmed if we use an alternative measure of uncertainty about earnings. We estimate the

Taken together, these findings suggest that the positive change in beta observed on earnings announcement days is larger when the announcement has a stronger information content (regardless of whether it represents good news or bad news), and when there is more ex-ante uncertainty about the future announcement. In these scenarios, the changes in beta are mostly explained by an increase in the covariance component of beta.

4.5 Sub-period analysis

To see whether the behavior of beta around firm-specific news announcements exhibits any variation across time, we study changes in beta in two sub-samples of our sample period: 1995-2000 and 2001-2006. Importantly, the first sample includes the technology bubble, and the second sample includes the post-bubble period. The analysis of these separate samples, and in particular the study of changes in beta across different industries, may then shed further light on the link between information disclosures and systematic risk.

Table 10 and Figure 11 report changes in realized beta and changes in the covariance component of beta for the full sample of stocks in the two sample periods. When looking at the full sample of stocks, the results reveal only limited changes across the two sub-periods: changes in beta on day 0 are more pronounced during the second half of the sample period, however changes on day +1 are greater in the first sub-period, and if we average across these two event days we find essentially no change across the sub-samples.

The sub-sample analysis of stocks sorted by industry yields much more interesting results, see Table 11 and Figure 12. There is evidence of important differences in the behavior of beta across industries over the two sample periods. During the first part of the sample the change in realized beta is particularly strong for the High Tech sector, which experiences an increase in beta around news announcements of 0.13 and 0.19 on event days 0 and +1, for an average increase in realized beta of 0.16 (see Panel A of Table 11). In comparison, the change in beta for the corresponding two-day window during the post-bubble period is only half as large (0.08), though still economically important. In contrast, the stocks in the other sectors (except for the residual category) experience a decrease in the change in beta on day 0 going from the first half to the second half of the sample

standard deviation of a stocks' growth rate of earnings, and use this measure as a proxy for investors' uncertainty about a firm's earnings process. We find that, as the earnings process becomes more difficult to predict, the release of information leads to larger positive changes in beta, increasingly explained by the covariance component.

period, and only the manufacturing sector shows an increase in realized beta over time for a two-day event window, from 0.03 to 0.05. A similar pattern can be observed from Panel B of Table 11, which reports changes in the covariance component of beta across industry and over time.

Overall, our study of the 1995-2000 and 2001-2006 sub-periods shows that changes in beta generated by an earnings announcement do not show substantial variation on average, but they vary in significant ways within certain industries. Most noteworthy is the large increase in covariances sparked by an earnings announcement from a firm in the High Tech sector during the 1995-2000 period (which includes the tech bubble), and its subsequent reduction in the 2001-2006 sub-period.

5 Robustness tests

In this section we test the robustness of our results to alternative measures of realized beta. In particular, we check the sensitivity of our results to the choice of sampling frequency and to the methodology used in constructing realized betas.

5.1 Higher frequency beta

In our main set of empirical results we follow earlier research on estimating covariances and betas from high frequency data, see Todorov and Bollerslev (2007) and Bollerslev *et al.* (2008) for example, and use a sampling frequency of 25 minutes. This choice reflects a trade-off between using all available high frequency data and avoiding the impact of market microstructure effects, such as infrequent trading or non-synchronous trading. In Table 12 we present results based on realized betas computed from 5-minute intra-daily prices, and the overnight return, following the same estimation methodology adopted in Table 2 for 25-minute betas. These results reveal that the behavior of 5-minute betas is very similar to the patterns observed for 25-minute betas, although the estimated changes in 5-minute betas are slightly smaller. The proportion of changes explained by the covariance component of beta are also very similar to those for 25-minute betas. The similarity of our results for 5-minute and 25-minute betas is likely to be related to our focus on *changes* in systematic risk rather than on the *level* of systematic risk, which provides some built-in protection against biases arising from market microstructure effects.

5.2 An alternative estimator of beta

We next analyze changes in betas around earnings announcements using a measure of beta developed by Hayashi and Yoshida (2005) to handle the problem of non-synchronous trading. Non-synchronous trading leads realized covariances to be biased towards zero, and motivates the use of lower frequency data. The HY estimator of the covariance takes into account the non-synchronous nature of high frequency data and corrects this bias. Griffin and Oomen (2006) note that while the HY estimator corrects for problems stemming from non-synchronous trading, it does not correct for other forms of market microstructure effects, which also appear in the data. This suggests using the HY estimator on a slightly lower sampling frequency. We computed the HY estimator on 16 different sampling frequencies, ranging from 1 second to 30 minutes. For each firm, we chose the sampling frequency that generated a HY covariance that had an average value closest in absolute value to the covariance computed from daily returns (i.e., the one that minimized the bias in the HY estimator). This was almost always *not* the highest frequency, consistent with Griffin and Oomen (2006). We combined our "optimal" HY estimator of the covariance with the realized variance of the market using 5-minute prices, and used these HY-betas in the same estimation methodology adopted in Table 2 for 25-minute betas. The results are presented in Table 12. The estimated coefficients on the dummy variables that define the event window are remarkably similar to those obtained from the basic regression using 25-minute betas. Total betas increase slightly relative to our main empirical results (0.086 versus 0.084 on day 0, for example), but not uniformly or substantially. Thus, similar to our use of 5-minute price data, we thus conclude that our initial results using 25-minute betas are not much changed by using a more sophisticated estimator of beta.

6 Earnings announcements and expectations formation

Having documented statistically and economically meaningful changes in systematic risk around earnings announcements, we now develop a simple model to understand how these changes are generated. The firms studied in Section 4, like most U.S. companies, announce their earnings only quarterly, roughly every 66 trading days. If stock prices are linked to expectations about future earnings, then between earnings announcements investors must update their expectations using other sources of information, such as, in the first instance, earnings announcements by other firms. In this section we present a simple model of investors' expectations formation processes when earnings announcements occur only intermittently.

Before describing the model that links expected future dividends and earnings to current stock prices, we specify the dynamics of dividends and earnings. Following an extensive literature in finance (see Kleidon (1986) and Mankiw, *et al.* (1991) for example), we assume that log-dividends follow a random walk with drift:

$$\log D_{it} = g_i + \log D_{i,t-1} + w_{it}, \tag{15}$$

where $t = 1, 2, ..., T$ represents trade days and $i = 1, 2, ..., N$ represents different firms. To link dividends and earnings, we use an assumption related to Kormendi and Lipe (1987) and Collins and Kothari (1989), which posits that the dividend paid at time t is a fixed proportion of the earnings at time t :

$$\begin{aligned}
D_{it} &= \lambda_i X_{it} && (16)\\
\text{so} \quad \log X_{it} &= \log D_{it} - \log \lambda_i \\
&= g_i + (\log X_{it} + \log \lambda_i) + w_{it} - \log \lambda_i \\
&= g_i + \log X_{it} + w_{it} \\
\text{and} \quad \Delta \log X_{it} &= g_i + w_{it} && (17)
\end{aligned}$$

and thus log-earnings also follow a random walk, which is linked to work in financial accounting, see Ball and Watts (1972) and Kothari (2001) for example. We write the process in log-differences so that the left-hand side variable is stationary[17].

To allow for correlated changes in earnings we decompose the innovation to the earnings process into a common component, Z_t, and an idiosyncratic component, u_{it}:

$$w_{it} = \gamma_i Z_t + u_{it} \tag{18}$$

where γ_i captures the importance of the common component for stock i.[18]

[17] Kothari (2001) reviews the accounting and finance literature on models for earnings and notes that several researchers have documented a transitory predictable component in earnings growth. For simplicity, we use the standard random walk model.

[18] This structure for the innovations to log-earnings leads directly to a CAPM-style model for individual earnings innovations as a function of "market" earnings innovations, related to recent work by Da and Warachka (2008).

Next, we consider the variable that measures the information released on announcement dates. Ignoring for now the fact that earnings announcements only occur once per quarter, consider an earnings announcement, y_{it}, which is made *every day* and reports the (overlapping) growth in earnings over the past M days:

$$y_{it} = \sum_{j=0}^{M-1} \Delta \log X_{i,t-j} + \eta_{it} \tag{19}$$

The earnings announcement is thus expressed as a growth rate over the past M days, simplifying our subsequent calculations. The presence of the measurement error, η_{it}, in the above equation allows for the feature that earnings announcements may only imperfectly represent the true earnings of a firm, due to numerical or accounting errors, or perhaps due to manipulation. Of course, earnings are *not* reported every day, and we next consider earnings announcements that occur only intermittently.

6.1 Allowing for intermittent earnings announcements

We now incorporate into our model the distinctive feature of the earnings announcement environment, namely that earnings announcements are only made once per quarter. Following Sinopoli *et al.* (2004), we adapt the above framework to allow y_{it} to be observed only every M days. Thus the earnings announcement simply reports the earnings growth since the previous announcement, M days earlier. We accomplish this by setting the measurement error variable, η_{it}, to have an extreme form of heteroskedasticity:

$$V\left[\eta_{it}|I_{it}\right] = \sigma^2_{\eta i} \cdot I_{it} + \sigma^2_I \left(1 - I_{it}\right) \tag{20}$$

where $I_{it} = 1$ if day t is an announcement date and $I_{it} = 0$ else, and $\sigma^2_I \to \infty$. If day t is an announcement date, then quarterly earnings $\sum_{j=0}^{M-1} \Delta \log X_{i,t-j}$ are observed with only a moderate amount of measurement error, whereas if day t is not an announcement date then quarterly earnings are observed with an infinitely large amount of measurement error, i.e., they are effectively not observed at all.

Stacking the above equations for all N firms we thus obtain the equations for a state space model for all stocks:

$$\Delta \log \mathbf{X}_t = \mathbf{g} + \boldsymbol{\gamma} Z_t + \mathbf{u}_t \tag{21}$$

$$\mathbf{y}_t = \sum_{j=0}^{M-1} \Delta \log \mathbf{X}_{t-j} + \boldsymbol{\eta}_t \tag{22}$$

Extending the approach of Sinopoli *et al.* (2004) to the multivariate case is straightforward, and the heteroskedasticity in $\boldsymbol{\eta}_t$ becomes:

$$V\left[\boldsymbol{\eta}_t | \mathbf{I}_t\right] = R \cdot \Gamma_t + \sigma_I^2 \left(I_N - \Gamma_t\right) \tag{23}$$

where $R = diag\left\{\sigma_{\eta 1}^2, \sigma_{\eta 2}^2, ..., \sigma_{\eta N}^2\right\}$, I_N is a $N \times N$ identity matrix, and Γ_t is a $N \times N$ matrix of zeros with a 1 in the (i,i) element if y_{it} is observable on day t.

Expectations of future (and past) earnings can be estimated in this framework using a standard Kalman filter, see Hamilton (1994) for example, where the usual information set is extended to include both lags of the observed variable, $\mathbf{y}_t$, and lags of the indicator vector for announcement dates, $\mathbf{I}_t$, so $\mathcal{F}_t = \sigma\left(\mathbf{y}_{t-j}, \mathbf{I}_{t-j}; j \geq 0\right)$. The Kalman filter enables us to easily compute expectations of earnings of stock i for each day in the sample: $\hat{E}\left[X_{it} | \mathcal{F}_t\right]$. This estimate will be quite accurate on earnings announcement dates (depending on the level of $\sigma_{\eta i}^2$), and in between announcement dates the estimate will efficiently combine information from earlier announcements for this stock, and from announcements for other stocks.

Note that our model assumes that investors are able to process announcements from several firms and update their expectations about future earnings fully efficiently. Recent work by Hirshleifer *et al.* (2007) provides evidence that investors react less to earnings announcements when there are a number of other announcements made on the same day. Our simulation results below can be interpreted as what might be expected in a market populated with fully efficient, attention *un*constrained, investors. The extension to allow for attention constraints, or other behavioral features, is left for future work.

6.2 Linking earnings expectations to stock prices

There are numerous models for linking expectations about future dividends and earnings to stock prices, see Campbell, *et al.* (1997) for a review. For simplicity, we consider a standard present-value relation for stock prices:

$$\begin{aligned} P_{it} &= \sum_{j=1}^{\infty} \frac{E_t\left[D_{i,t+j}\right]}{(1+r_i)^j} \qquad (24) \\ &= \sum_{j=1}^{\infty} \frac{\lambda_i E_t\left[X_{i,t+j}\right]}{(1+r_i)^j}, \text{ assuming } D_{it} = \lambda_i X_{it} \ \forall t \end{aligned}$$

where $D_{i,t+j}$ is the dividend paid at time $t+j$ by firm i, and r_i is the discount rate. Given our model for the evolution of earnings, X_{it}, we have:

$$E_t\left[\log X_{i,t+j}\right] = jg_i + \log X_{it},$$

and from the Kalman filter:

$$\hat{E}_t\left[\log X_{i,t+j}\right] = jg_i + \hat{E}_t\left[\log X_{it}\right],$$

where $\hat{E}_t\left[\log X_{it}\right]$ is the "nowcast" of $\log X_{it}$, that is, the best estimate of $\log X_{it}$ given all information up to time t. In the absence of measurement errors, and if announcements were made every day, the nowcast would simply be $\log X_{it}$ itself. Next we obtain multi-step predictions[19]:

$$\begin{aligned} \hat{E}_t\left[X_{i,t+j}\right] &\approx \exp\left\{\hat{E}_t\left[\log X_{i,t+j}\right] + \frac{1}{2}\hat{V}_t\left[\log X_{i,t+j}\right]\right\} \qquad (25) \\ &\approx \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\} \exp\left\{jg_i + \frac{1}{2}j\sigma_{wi}^2\right\} \end{aligned}$$

Substituting the above into our pricing equation, we obtain:

$$\begin{aligned} P_{it} &= \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\} \sum_{j=1}^{\infty} \frac{\lambda_i \exp\left\{jg_i + \frac{1}{2}j\sigma_{wi}^2\right\}}{(1+r_i)^j} \qquad (26) \\ &= \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\} \frac{\lambda_i \exp\left\{g_i + \frac{1}{2}\sigma_{wi}^2\right\}}{1 + r_i - \exp\left\{g_i + \frac{1}{2}\sigma_{wi}^2\right\}} \end{aligned}$$

With this expression we thus find that daily returns correspond to the change in the nowcast of the log-earnings process:

$$\begin{aligned} R_{i,t+1} &\equiv \log P_{i,t+1} - \log P_{it} \qquad (27) \\ &= \hat{E}_{t+1}\left[\log X_{it+1}\right] - \hat{E}_t\left[\log X_{it}\right] \end{aligned}$$

[19] In addition to $j\sigma_{wi}^2$, $\hat{V}_t\left[\log X_{i,t+j}\right]$ includes a term related to the number of days between time t and the most recent announcement for firm i. This term adds a small deterministic component to returns as defined in equation (27), which has precisely no effect on our numerical results and so we do not report it here.

6.3 Numerical results and analysis

The nature of the state space model presented above does not enable us to derive analytical results for market betas. To overcome this difficulty, we use simulation methods to obtain estimates of how market betas change around earnings announcements. In our simulations we use parameter values that are realistic and close to the values that we observe in the data.

We set the number of firms (N) to 100 and the number of days between earnings announcements (M) to 25.[20] In all cases we simulate $T = 1000$ days, and we assume that earnings announcements are evenly distributed across the sample period. Given that the variance of the common component, σ_z^2, is not separately identifiable from the loadings on the common component, γ_i, we fix $\gamma_i = 1 \;\forall\; i$ for all of our simulations. We use our sample of 810 firms over the period 1995-2006 to obtain reasonable parameter values for the simulation study. From our sample the volatility of the innovation to quarterly earnings, σ_w, has a median (across firms) of 0.33, and 25% and 75% quantiles of 0.15 and 0.62. We use $\sigma_w^2 = 0.3^2/66$ as our value for the *daily* variance of earnings innovations in our base scenario, and vary it between $0.15^2/66$ and $0.6^2/66$ across simulations. We set the proportion of σ_w^2 attributable to the common component, $R_z^2 \equiv \sigma_z^2/\sigma_w^2$, to 0.05, and vary it between 0 and 0.10 to study the impact of learning – a higher value for R_z^2 means more of the variability of the earnings innovation can be learned from other firms' earnings announcements. In unreported simulation results we find only limited evidence of changes in beta reactions from changes in the rate of growth in earnings (g) or the variance of measurement errors on reported earnings $\left(\sigma_\eta^2\right)$, and so we set both of these parameters to zero for simplicity. To allow for daily returns being driven by liquidity traders or by other features not related to changes in expectations about future earnings, we also introduce a noise term for stock returns, and set

$$\tilde{R}_{it} = R_{it} + \varepsilon_{it} \tag{28}$$

where $\varepsilon_{it} \sim iid\ N\left(0, \sigma_\varepsilon^2\right)$ and R_{it} is as given in equation (27) above. We set σ_ε^2 so that the ratio $V\left[R_{it}\right]/V\left[\tilde{R}_{it}\right]$ equals 0.02 in our base simulation, implying that 2% of the variability in observed

[20] We are forced to use values for N and M that are smaller than in our empirical application by computational limitations, however these are representative of realistic values. Using a smaller N means that each firm has a higher weight in the "index" (1/100 rather than around 1/500) which will inflate the impact of "own variance" around earnings announcements. Using a smaller M will make the estimates of betas outside our event window (of 21 days, as in our empirical application) less accurate, but does not otherwise affect our results.

returns is explained by changes in expectations about future earnings. We vary it between 0.01 and 0.04 in comparative statics[21].

In Figure 13 we present the changes in beta for our base case scenario. This figure qualitatively matches several of the features observed in our empirical results: relative to betas outside our announcement period (the announcement date ±10 days), betas spike upwards on event dates, then drop on the day immediately after the event date, and then slowly return to their non-announcement average level. Figure 13 reveals that part of the spike on the event date is driven by the "variance" effect, but the majority (around 70%) is driven by an increase in the average covariance between the announcing firm and other firms. This increase in average covariances is a result of learning: when firm i has an announcement that represents good (bad) news, its price moves up (down). In the absence of an announcement for firm j, for example, expectations about earnings for firm j are updated using the information contained in the announcement of firm i, and so its price will move in the same direction as firm i. This leads to an increase in the covariance between the returns on stock i and stock j on firm i's announcement date. (Of course, a corresponding case holds when firm j has an announcement and firm i does not.)

The drop in beta immediately after the announcement date, and its slow increase on subsequent dates, are also the result of learning: the day after an earnings announcement for firm i, investors are reasonably sure about the level of earnings for firm i, and have observed only few other earnings announcements (namely, those that announced on day +1). Thus they do not revise their nowcasts for firm i in a substantial way. As time progresses, firm i's earnings announcement is further in the past, and more announcements from other firms are observed: the nowcasts are then less precise, and more open to revisions from day to day. While the reaction in beta to earnings announcements presented in Figure 13 is reminiscent of work on stock market overreactions, these (optimal) revisions of expectations are what drives the increase in beta, its subsequent drop, and its slow increase over the following days.

To investigate the impact of the various parameters of our simple model, we now present some comparative statics varying the four main parameters in our model. In Figure 14 we consider varying R_z^2, the proportion of earnings innovations w_{it} that come from the common component,

[21] Straightforward calculations, available upon request, reveal that the impact of ε_{it} on the estimates of changes in beta is a simple shrinkage of these changes towards zero. That is, the *shape* of the changes in beta through the event window do not change for $\sigma_\varepsilon^2 > 0$, but the magnitudes brought closer to zero for larger values of σ_ε^2.

Z_t, which effectively controls the degree of learning possible in the model. In the base scenario this is set to 0.05. In the left panel of Figure 14 we set this to zero, eliminating learning from the model, while in the right panel we set it to 0.10. In the left panel we see that beta spikes sharply on day 0 (the announcement date) but this spike is purely due to an increase in the variance of the announcing firm's stock returns; the "covariance" component of beta is essentially zero on all days, including day 0. The magnitude of the change in beta (around 0.4 in this simulation) follows from the magnitude of the change in return volatility on that date. When R_z^2 is increased to 0.10, we observe a much larger spike in beta (around 1.4) with the majority of this spike being driven by the covariance component of beta. Thus, more correlated earnings processes lead to more learning, and larger responses in betas to earnings announcements.

In Figure 15 we change the variance of the innovations to the earnings process, σ_w^2, with the motivation that a more variable earnings process implies a greater resolution of uncertainty on announcement dates. In our base scenario we set this parameter close to the median value in our sample of firms, $0.3^2/66$, and in Figure 15 we consider the 25^{th} and 75^{th} quantiles of our data, $0.15^2/66$ and $0.6^2/66$. In the left panel, with low variance of the earnings innovation process, we see a small change in beta on announcement dates, around 0.25, with the majority of this change being attributable to the covariance component of beta. In the right panel, with a high value for the earnings innovation variance, we observe a much larger spike in beta, around 2.4, with the majority being attributable to an increase in the variance of the announcing firm's stock returns. Thus more volatile earnings processes lead to larger spikes in beta, with a substantial fraction (though not all) coming from the mechanical increase in beta due to the increase in variance.

Finally, in Figure 16 we present the results from changing the amount of variation in returns that is explained by variation in earnings expectations. In the base scenario this is set to 0.02, and in Figure 16 we vary it between 0.01 and 0.04. In the left panel, with a low value of noise, we observe a larger spike in beta on announcement dates, around 1.8 in this simulation. This is not so surprising: with daily returns being better explained by changes in expectations about future earnings, the large updates in investors' expectations are more revealed in the observed prices. Conversely, when noise is high and returns are less well explained by changes in expectations about future earnings, the response of beta to earnings announcements is smaller, around 0.6 in this simulation.

The scenarios considered in Figures 13 to 16 reveal that with just a few parameters our simple model of investor expectations is able to generate a range of patterns in betas around earnings announcement dates: the changes in beta can be large or small; they can be due entirely to the increase in a stock's return variance, entirely to the increase in average covariances with other stocks' returns, or to a mixture of the two effects; and the drop in beta immediately following an announcement date can either be pronounced, moderate, or essentially absent. All of these features are related to the intermittent nature of earnings announcements, to the degree of correlation between the earnings of different firms, and to investors' efforts to update their expectations about future earnings.

7 Conclusions

In this paper we analyze the behavior of a firm's beta during times of firm-specific information flows. We focus on regular and well-documented information flows represented by earnings announcements, and use recent advances in the econometrics of high frequency data to obtain accurate estimates of the beta for individual firms on a daily basis. Previous studies assume that a stock's systematic risk remains constant during information flows, or varies at low frequencies with variables following the business cycle.

Using intra-daily data for all companies in the S&P 500 index over the period 1995-2006 (a total of 810 distinct firms), we find that beta generally increases on announcement days by a statistically and economically significant amount, and declines on post-announcement days before reverting to its long-run average level. Changes in beta are greatest for firms with high turnover and analyst coverage, suggesting a larger effect of news on beta for liquid and visible companies where information is quickly incorporated into prices. The increase in beta is also substantially larger for companies releasing strong news (positive or negative) than for companies whose earnings announcement has smaller information content. Furthermore, the increase in beta around news announcements is stronger when investors' ex-ante uncertainty, measured by analyst forecast dispersion, is higher. We also find important cross-sectional differences in changes in beta around news announcements across different industries: stocks in the High Tech sector experience large increases in beta, whereas stocks in the Health sector show almost no change in beta during news releases.

By decomposing a stock's systematic risk into a "variance" component and a "covariance" component, we find that the covariance of the announcing stock returns with the returns of other stocks in the market index increases significantly on announcement dates. A simple model of investors' expectations formation using intermittent earnings announcements helps explain this finding: good (bad) news for the announcing firm is interpreted as partial good (bad) news for related firms, causing the prices on all stocks to move in the same direction. This raises the average covariance of the return on the announcing firm with the returns on the other firms, which translates into a higher market beta.

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Table 1, Panel A: Descriptive statistics

This table presents descriptive statistics for the data used in this study. The sample includes all firms that were constituents of the S&P500 during the period 1995-2006, a total of 810 different firms and 22,575 earnings announcements. The following statistics are computed as daily cross-sectional means or medians and averaged over time during each sample year. Cap is the average market capitalization, measured 10 trading days before the earnings announcement day. Med cap is the median of market capitalization. B/M is average book-to-market, measured 10 trading days before earnings announcement. Turnover is a stock's average daily turnover (volume of trade/shares outstanding) measured over the two months that precede the earnings announcement month. Ret is a stock's average daily return. Sur is a stock's earnings surprise, measured as the difference between actual earnings and consensus forecast, standardized by share price. The consensus forecast is computed as the mean of all quarterly forecasts issued by analysts within 60 days before the earnings announcement day. Med Sur is the median earnings surprise. N. anlst is the number of analysts following a firm during the 60-day interval before the earnings announcement day.

Year	Cap ($ Bn)	Med cap ($ Bn)	B/M	Turnover (%)	Ret (%)	Sur (%)	Med Sur (%)	N. anlst
1995	7.92	4.16	0.57	0.35	0.116	-0.002	0.009	6.76
1996	9.99	5.05	0.52	0.36	0.076	0.016	0.006	6.80
1997	13.19	6.09	0.46	0.40	0.106	0.022	0.009	6.68
1998	16.83	7.26	0.43	0.43	0.057	-0.001	0.012	7.01
1999	21.22	7.88	0.44	0.46	0.051	0.032	0.020	6.84
2000	24.10	7.61	0.53	0.56	0.048	0.040	0.020	6.55
2001	21.21	7.94	0.49	0.65	0.016	0.049	0.021	9.16
2002	18.10	7.49	0.54	0.73	-0.056	0.023	0.027	8.29
2003	17.69	7.55	0.60	0.69	0.146	0.032	0.032	7.68
2004	20.85	9.32	0.52	0.65	0.067	0.053	0.039	8.18
2005	22.37	10.84	0.47	0.68	0.033	0.025	0.035	7.73
2006	24.47	12.35	0.46	0.75	0.064	0.070	0.052	7.78
Average	18.16	7.80	0.50	0.56	0.06	0.03	0.02	7.45

Table 1, Panel B: Industry classification

This table reports the composition of the firms in our sample with respect to five industry categories based on 4-digit SIC codes. The table reports the average number of firms (n) and the fraction of firms (%) belonging to each industry over the sample period. The industries are defined as follows: 1. Consumer (Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)); 2. Manufacturing (Manufacturing, Energ, and Utilities); 3. High Tech (Business Equipment, Telephone and Television Transmission, computer programming and data processing, Computer integrated systems design, computer processing, data prep, computer facilities management service, computer rental and leasing, computer maintanence and repair, computer related services, R&D labs, research, development, testing labs); 4. Health (Healthcare, Medical Equipment, and Drugs); 5. Other (Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance).

Industry definition	**n**	**%**
Consumer	153	18.89
Manufacturing	221	27.28
High-Tech	157	19.38
Health	55	6.79
Other	224	27.65
Total	810	100.0

Tables 2-12: Changes in beta around information flows

Description of Tables

Table 2 reports coefficient estimates from a panel regression of daily betas on dummy variables for each of 21 days around quarterly earnings announcements (where event day 0 is the earnings announcement day), controlling for a stock's volume, lagged beta, and volatility, and including firm and year fixed effects. The table reports the coefficient estimates for regressions of realized betas and for regressions of the covariance component of realized beta. t-statistics are computed from standard errors that are robust to heteroskedasticity and to arbitrary intra-day correlation.

Tables 3 to 12 present coefficient estimates for changes in realized betas and changes in the covariance component of beta around earnings announcements for quintiles of stocks grouped by different characteristics. The characteristics analyzed in the tables are as follows: Table 3: market capitalization; Table 4: book-to-market; Table 5: Industry; Table 6: Turnover; Table 7: Residual analyst coverage; Table 8: Earnings surprise; Table 9: Analyst forecast dispersion. All variables are defined in Table 1. The coefficients are estimated from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements (where event day 0 is the earnings announcement day), controlling for a stock's volume, lagged beta, and volatility, and including firm and year fixed effects. t-statistics are computed from standard errors that are robust to heteroskedasticity and to arbitrary intra-day correlation.

Tables 10 and 11 present coefficient estimates for changes in realized beta and changes in the covariance component of beta around earnings announcements estimated during two sub-periods: 1995-2000 and 2001-2006. Table 10 reports results for all stocks in the sample; Table 11 reports results for stocks grouped into 5 industries. The industry classification is defined in Table 1. The coefficients are estimated from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements (where event day 0 is the earnings announcement day), controlling for a stock's volume, lagged beta, and volatility, and including firm and year fixed effects. t-statistics are computed from standard errors that are robust to heteroskedasticity and to arbitrary intra-day correlation.

Table 12 reports coefficient estimates for changes in realized beta and changes in the covariance component of beta during a 21-day window around earnings announcements. 5-minute beta is a stock's realized daily beta computed from 5-minute returns. HY beta is a stock's daily beta computed with the Hayashi-Yoshida (2005) method, where the tick frequency is optimized for individual stocks. The coefficients are estimated from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements (where event day 0 is the earnings announcement day), controlling for a stock's volume, lagged beta, and volatility, and including firm and year fixed effects. t-statistics are computed from standard errors that are robust to heteroskedasticity and to arbitrary intra-day correlation.

Table 2: Changes in beta around information flows, pooled sample

Event day	Realized beta	Covariance component
-10	-0.001	-0.001
	(-0.20)	(-0.21)
-9	0.000	0.000
	(-0.04)	(-0.01)
-8	0.004	0.004
	(0.53)	(0.51)
-7	0.008	0.008
	(1.11)	(1.12)
-6	-0.005	-0.005
	(-0.71)	(-0.67)
-5	0.011	0.012
	(1.69)	(1.69)
-4	0.006	0.007
	(0.93)	(0.97)
-3	0.012	0.012
	(1.67)	(1.61)
-2	0.019	0.018
	(2.63)	(2.51)
-1	0.010	0.009
	(1.45)	(1.26)
0	0.084	0.068
	(8.03)	(6.53)
1	0.021	0.005
	(2.14)	(0.54)
2	-0.028	-0.027
	(-3.93)	(-3.82)
3	-0.027	-0.027
	(-3.90)	(-3.90)
4	-0.017	-0.016
	(-2.46)	(-2.37)
5	-0.010	-0.009
	(-1.39)	(-1.26)
6	-0.011	-0.009
	(-1.61)	(-1.44)
7	0.000	0.001
	(0.06)	(0.17)
8	0.000	0.001
	(0.07)	(0.10)
9	-0.004	-0.004
	(-0.63)	(-0.58)
10	-0.002	-0.002
	(-0.38)	(-0.29)

Table 3: Changes in beta by Market Capitalization

Day	Realized beta					Covariance component				
	Market capitalization quintile					Market capitalization quintile				
	1(small)	2	3	4	5(big)	1(small)	2	3	4	5(big)
−10	0.005	-0.002	0.003	-0.003	-0.012	0.005	-0.002	0.003	-0.003	-0.012
	(0.35)	(-0.15)	(0.20)	(-0.21)	(-0.93)	(0.33)	(-0.13)	(0.22)	(-0.22)	(-0.97)
−9	0.007	0.001	-0.003	0.001	-0.008	0.007	0.000	-0.003	0.001	-0.008
	(0.46)	(0.04)	(-0.25)	(0.10)	(-0.67)	(0.47)	(0.04)	(-0.23)	(0.11)	(-0.66)
−8	0.017	0.015	-0.009	-0.012	0.008	0.017	0.014	-0.009	-0.013	0.008
	(1.00)	(1.07)	(-0.66)	(-0.87)	(0.68)	(1.00)	(1.04)	(-0.67)	(-0.92)	(0.71)
−7	0.022	0.002	0.000	0.031	-0.020	0.022	0.002	0.000	0.030	-0.019
	(1.38)	(0.18)	(0.02)	(2.39)	(-1.66)	(1.38)	(0.16)	(0.03)	(2.35)	(-1.58)
−6	-0.041	0.001	0.006	0.006	0.002	-0.041	0.001	0.006	0.006	0.003
	(-2.63)	(0.10)	(0.45)	(0.44)	(0.18)	(-2.63)	(0.11)	(0.47)	(0.44)	(0.23)
−5	0.002	0.024	-0.001	0.033	-0.002	0.002	0.024	-0.001	0.033	-0.003
	(0.13)	(1.86)	(-0.07)	(2.59)	(-0.18)	(0.14)	(1.88)	(-0.06)	(2.63)	(-0.25)
−4	0.004	-0.016	0.017	0.019	0.003	0.005	-0.016	0.017	0.019	0.003
	(0.28)	(-1.20)	(1.26)	(1.46)	(0.23)	(0.29)	(-1.20)	(1.29)	(1.48)	(0.29)
−3	-0.011	0.002	0.017	0.030	0.023	-0.011	0.002	0.017	0.030	0.022
	(-0.74)	(0.16)	(1.24)	(2.26)	(1.87)	(-0.73)	(0.15)	(1.22)	(2.27)	(1.75)
−2	0.000	0.033	0.022	0.033	0.005	0.000	0.033	0.022	0.032	0.002
	(0.02)	(2.38)	(1.63)	(2.26)	(0.41)	(0.02)	(2.36)	(1.59)	(2.24)	(0.17)
−1	0.002	0.004	-0.004	0.029	0.017	0.002	0.003	-0.004	0.028	0.013
	(0.13)	(0.26)	(-0.29)	(2.06)	(1.32)	(0.12)	(0.23)	(-0.31)	(2.00)	(0.98)
0	0.078	0.089	0.047	0.100	0.099	0.074	0.084	0.038	0.084	0.053
	(3.24)	(4.31)	(2.26)	(4.72)	(4.88)	(3.09)	(4.05)	(1.84)	(4.01)	(2.64)
1	0.033	0.020	0.012	0.020	0.010	0.030	0.014	0.005	0.009	-0.039
	(1.46)	(0.98)	(0.60)	(1.07)	(0.57)	(1.33)	(0.69)	(0.28)	(0.51)	(-2.01)
2	-0.019	-0.028	-0.038	-0.023	-0.032	-0.019	-0.028	-0.038	-0.022	-0.028
	(-1.15)	(-1.88)	(-2.85)	(-1.67)	(-2.65)	(-1.16)	(-1.89)	(-2.85)	(-1.63)	(-2.36)
3	-0.019	-0.022	-0.016	-0.031	-0.047	-0.019	-0.022	-0.016	-0.031	-0.047
	(-1.18)	(-1.60)	(-1.20)	(-2.45)	(-3.96)	(-1.18)	(-1.61)	(-1.20)	(-2.49)	(-4.01)
4	-0.011	-0.012	-0.004	-0.016	-0.040	-0.011	-0.012	-0.004	-0.016	-0.037
	(-0.69)	(-0.86)	(-0.29)	(-1.24)	(-3.56)	(-0.69)	(-0.85)	(-0.30)	(-1.24)	(-3.39)
5	-0.007	-0.008	-0.001	0.002	-0.032	-0.007	-0.008	-0.001	0.002	-0.029
	(-0.45)	(-0.60)	(-0.09)	(0.12)	(-2.84)	(-0.44)	(-0.59)	(-0.07)	(0.16)	(-2.61)
6	-0.021	-0.017	-0.005	0.003	-0.012	-0.021	-0.017	-0.005	0.003	-0.008
	(-1.43)	(-1.38)	(-0.43)	(0.25)	(-1.05)	(-1.43)	(-1.35)	(-0.39)	(0.25)	(-0.69)
7	0.003	0.018	0.004	-0.004	-0.020	0.003	0.018	0.005	-0.004	-0.017
	(0.18)	(1.29)	(0.35)	(-0.33)	(-1.67)	(0.18)	(1.30)	(0.39)	(-0.33)	(-1.47)
8	0.000	0.007	0.002	-0.007	-0.002	0.001	0.007	0.002	-0.007	0.000
	(0.03)	(0.49)	(0.15)	(-0.52)	(-0.15)	(0.03)	(0.50)	(0.11)	(-0.56)	(-0.04)
9	-0.011	-0.013	0.001	0.002	0.001	-0.011	-0.012	0.001	0.003	0.001
	(-0.70)	(-0.94)	(0.09)	(0.19)	(0.05)	(-0.70)	(-0.92)	(0.11)	(0.21)	(0.07)
10	0.014	0.005	0.006	-0.021	-0.017	0.014	0.006	0.006	-0.020	-0.016
	(0.91)	(0.42)	(0.49)	(-1.75)	(-1.58)	(0.92)	(0.43)	(0.50)	(-1.72)	(-1.45)

Table 4: Changes in beta by Book-to-Market Ratio

Day	Realized beta						Covariance component				
	Book-to-Market quintile						Book-to-Market quintile				
	1(low)	2	3	4	5(high)		1(low)	2	3	4	5(high)
-10	-0.010	0.009	-0.001	0.009	-0.010		-0.010	0.010	-0.002	0.009	-0.010
	(-0.72)	(0.70)	(-0.11)	(0.67)	(-0.74)		(-0.70)	(0.73)	(-0.18)	(0.69)	(-0.73)
-9	-0.023	0.004	0.003	-0.002	0.008		-0.023	0.003	0.004	-0.001	0.008
	(-1.73)	(0.29)	(0.25)	(-0.13)	(0.57)		(-1.71)	(0.24)	(0.27)	(-0.10)	(0.60)
-8	0.027	-0.009	-0.010	0.016	-0.010		0.026	-0.010	-0.009	0.016	-0.010
	(1.80)	(-0.65)	(-0.74)	(1.11)	(-0.68)		(1.78)	(-0.70)	(-0.71)	(1.12)	(-0.68)
-7	0.012	0.014	0.014	-0.003	0.005		0.013	0.014	0.014	-0.003	0.005
	(0.86)	(0.98)	(1.03)	(-0.22)	(0.37)		(0.90)	(1.00)	(1.03)	(-0.22)	(0.36)
-6	-0.024	0.011	0.010	0.003	-0.023		-0.023	0.012	0.010	0.003	-0.022
	(-1.74)	(0.82)	(0.79)	(0.21)	(-1.66)		(-1.71)	(0.85)	(0.74)	(0.22)	(-1.61)
-5	-0.010	0.031	-0.005	0.010	0.034		-0.010	0.031	-0.005	0.009	0.034
	(-0.73)	(2.21)	(-0.37)	(0.76)	(2.39)		(-0.71)	(2.23)	(-0.37)	(0.70)	(2.40)
-4	-0.004	0.016	0.036	-0.008	-0.008		-0.002	0.017	0.036	-0.009	-0.007
	(-0.28)	(1.19)	(2.77)	(-0.59)	(-0.53)		(-0.16)	(1.23)	(2.79)	(-0.66)	(-0.52)
-3	0.025	0.047	0.004	-0.011	0.010		0.023	0.046	0.004	-0.011	0.010
	(1.73)	(3.37)	(0.30)	(-0.81)	(0.72)		(1.63)	(3.31)	(0.32)	(-0.81)	(0.72)
-2	0.013	0.008	0.014	0.028	0.033		0.012	0.007	0.014	0.028	0.032
	(0.92)	(0.60)	(0.99)	(2.12)	(2.22)		(0.83)	(0.52)	(0.97)	(2.09)	(2.21)
-1	0.008	-0.006	0.016	0.010	0.015		0.006	-0.008	0.016	0.009	0.015
	(0.56)	(-0.43)	(1.24)	(0.72)	(1.01)		(0.39)	(-0.56)	(1.18)	(0.66)	(0.98)
0	0.077	0.119	0.067	0.075	0.089		0.050	0.100	0.050	0.064	0.081
	(3.38)	(5.15)	(3.26)	(3.59)	(4.29)		(2.23)	(4.34)	(2.47)	(3.04)	(3.91)
1	0.007	0.048	0.023	0.007	0.024		-0.031	0.030	0.015	-0.002	0.019
	(0.32)	(2.21)	(1.13)	(0.37)	(1.33)		(-1.30)	(1.35)	(0.73)	(-0.08)	(1.06)
2	-0.052	-0.044	-0.032	-0.026	0.014		-0.049	-0.044	-0.031	-0.026	0.014
	(-3.72)	(-3.02)	(-2.25)	(-1.95)	(0.98)		(-3.57)	(-2.99)	(-2.23)	(-1.95)	(0.99)
3	-0.049	-0.026	-0.023	-0.015	-0.017		-0.048	-0.026	-0.023	-0.015	-0.017
	(-3.61)	(-1.86)	(-1.68)	(-1.12)	(-1.20)		(-3.56)	(-1.89)	(-1.69)	(-1.14)	(-1.19)
4	-0.026	-0.048	-0.020	-0.014	0.019		-0.025	-0.047	-0.020	-0.013	0.019
	(-1.90)	(-3.68)	(-1.57)	(-1.11)	(1.36)		(-1.86)	(-3.60)	(-1.55)	(-1.04)	(1.35)
5	-0.033	-0.005	-0.014	0.004	0.005		-0.031	-0.004	-0.013	0.004	0.005
	(-2.54)	(-0.41)	(-1.04)	(0.28)	(0.36)		(-2.44)	(-0.33)	(-1.00)	(0.30)	(0.38)
6	-0.023	-0.019	-0.012	-0.009	0.008		-0.021	-0.018	-0.011	-0.010	0.008
	(-1.79)	(-1.56)	(-0.96)	(-0.72)	(0.57)		(-1.63)	(-1.42)	(-0.87)	(-0.73)	(0.61)
7	0.003	-0.011	-0.007	0.005	0.000		0.005	-0.010	-0.007	0.005	0.000
	(0.19)	(-0.73)	(-0.50)	(0.35)	(-0.02)		(0.38)	(-0.68)	(-0.49)	(0.35)	(-0.01)
8	-0.003	-0.012	-0.002	0.012	0.005		-0.003	-0.012	-0.003	0.012	0.005
	(-0.24)	(-0.92)	(-0.18)	(0.87)	(0.39)		(-0.19)	(-0.87)	(-0.23)	(0.88)	(0.35)
9	-0.002	-0.009	-0.007	-0.007	0.008		-0.002	-0.008	-0.007	-0.007	0.008
	(-0.15)	(-0.67)	(-0.53)	(-0.50)	(0.61)		(-0.16)	(-0.62)	(-0.53)	(-0.49)	(0.63)
10	-0.007	-0.008	0.010	-0.017	0.010		-0.007	-0.007	0.010	-0.017	0.011
	(-0.52)	(-0.63)	(0.76)	(-1.29)	(0.78)		(-0.50)	(-0.58)	(0.80)	(-1.28)	(0.85)

Table 5: Changes in beta by industry

Day	Realized beta					Covariance component				
	Industry					Industry				
	Cnsmr	Manuf	HiTec	Hlth	Other	Cnsmr	Manuf	HiTec	Hlth	Other
-10	-0.001	0.002	0.028	-0.021	-0.025	-0.001	0.002	0.028	-0.021	-0.025
	(-0.06)	(0.14)	(1.46)	(-0.96)	(-1.93)	(-0.05)	(0.16)	(1.48)	(-0.99)	(-1.98)
-9	0.000	-0.012	0.030	-0.048	0.003	0.000	-0.012	0.030	-0.049	0.003
	(-0.03)	(-1.02)	(1.61)	(-1.93)	(0.26)	(0.02)	(-0.99)	(1.65)	(-2.02)	(0.27)
-8	0.003	-0.008	0.008	-0.025	0.020	0.003	-0.008	0.008	-0.025	0.020
	(0.24)	(-0.60)	(0.41)	(-1.18)	(1.55)	(0.22)	(-0.59)	(0.42)	(-1.19)	(1.55)
-7	0.005	0.001	0.025	-0.017	0.010	0.006	0.001	0.025	-0.016	0.010
	(0.40)	(0.08)	(1.25)	(-0.76)	(0.75)	(0.44)	(0.10)	(1.25)	(-0.74)	(0.76)
-6	-0.010	-0.014	0.037	-0.070	-0.003	-0.010	-0.014	0.037	-0.068	-0.003
	(-0.81)	(-1.13)	(1.77)	(-3.20)	(-0.20)	(-0.82)	(-1.07)	(1.78)	(-3.15)	(-0.21)
-5	0.028	0.001	0.038	-0.020	-0.004	0.027	0.001	0.038	-0.019	-0.004
	(2.19)	(0.05)	(1.86)	(-0.88)	(-0.31)	(2.17)	(0.11)	(1.87)	(-0.86)	(-0.33)
-4	0.003	0.007	0.034	-0.064	0.003	0.003	0.007	0.035	-0.063	0.002
	(0.22)	(0.54)	(1.68)	(-2.88)	(0.25)	(0.24)	(0.58)	(1.77)	(-2.81)	(0.18)
-3	0.008	-0.004	0.031	-0.013	0.024	0.008	-0.004	0.030	-0.014	0.023
	(0.66)	(-0.31)	(1.57)	(-0.55)	(1.75)	(0.62)	(-0.27)	(1.51)	(-0.57)	(1.73)
-2	0.024	0.023	0.030	-0.027	0.010	0.023	0.023	0.029	-0.026	0.009
	(1.84)	(1.75)	(1.54)	(-1.21)	(0.72)	(1.75)	(1.74)	(1.47)	(-1.20)	(0.65)
-1	0.007	-0.009	0.043	0.000	0.008	0.007	-0.009	0.038	0.001	0.008
	(0.57)	(-0.73)	(2.06)	(-0.01)	(0.60)	(0.52)	(-0.75)	(1.86)	(0.03)	(0.55)
0	0.026	0.077	0.104	-0.007	0.077	0.008	0.064	0.087	-0.028	0.065
	(1.19)	(4.17)	(4.10)	(-0.19)	(3.87)	(0.35)	(3.51)	(3.48)	(-0.75)	(3.30)
1	-0.031	0.011	0.127	-0.061	-0.009	-0.035	0.006	0.067	-0.067	-0.017
	(-1.75)	(0.70)	(3.70)	(-1.70)	(-0.57)	(-1.99)	(0.41)	(1.92)	(-1.87)	(-1.04)
2	-0.021	-0.012	-0.052	-0.039	-0.045	-0.021	-0.012	-0.048	-0.035	-0.045
	(-1.71)	(-0.99)	(-2.57)	(-1.85)	(-3.50)	(-1.68)	(-0.98)	(-2.37)	(-1.64)	(-3.49)
3	-0.019	-0.002	-0.094	-0.020	-0.021	-0.019	-0.001	-0.094	-0.020	-0.021
	(-1.58)	(-0.13)	(-4.89)	(-0.88)	(-1.68)	(-1.55)	(-0.12)	(-4.94)	(-0.89)	(-1.66)
4	-0.006	-0.012	-0.029	-0.012	-0.025	-0.006	-0.011	-0.027	-0.013	-0.025
	(-0.49)	(-0.97)	(-1.49)	(-0.60)	(-2.15)	(-0.47)	(-0.93)	(-1.40)	(-0.61)	(-2.10)
5	-0.015	0.002	-0.039	0.001	-0.004	-0.015	0.002	-0.036	0.002	-0.003
	(-1.18)	(0.13)	(-2.14)	(0.07)	(-0.33)	(-1.17)	(0.17)	(-1.97)	(0.08)	(-0.27)
6	-0.027	0.013	-0.066	0.000	0.010	-0.026	0.013	-0.062	0.000	0.011
	(-2.30)	(1.12)	(-3.48)	(-0.02)	(0.83)	(-2.20)	(1.17)	(-3.34)	(-0.01)	(0.89)
7	-0.007	0.026	-0.033	-0.001	-0.001	-0.006	0.026	-0.031	0.000	0.000
	(-0.58)	(2.18)	(-1.83)	(-0.06)	(-0.05)	(-0.54)	(2.18)	(-1.72)	(0.01)	(0.00)
8	0.001	0.027	-0.028	0.001	-0.011	0.001	0.026	-0.026	0.001	-0.011
	(0.04)	(2.16)	(-1.49)	(0.03)	(-0.88)	(0.08)	(2.11)	(-1.44)	(0.05)	(-0.87)
9	-0.004	0.012	-0.025	0.001	-0.010	-0.003	0.012	-0.025	0.003	-0.011
	(-0.30)	(1.02)	(-1.33)	(0.06)	(-0.87)	(-0.29)	(1.05)	(-1.32)	(0.14)	(-0.87)
10	-0.018	0.010	0.014	0.011	-0.020	-0.017	0.010	0.015	0.011	-0.019
	(-1.47)	(0.91)	(0.72)	(0.46)	(-1.70)	(-1.41)	(0.93)	(0.78)	(0.47)	(-1.62)

Table 6: Changes in beta by Turnover

Day	Realized beta					Covariance component				
	Turnover quintile					Turnover quintile				
	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
−10	-0.004	-0.004	0.017	-0.010	-0.008	-0.004	-0.004	0.017	-0.010	-0.008
	(-0.39)	(-0.34)	(1.38)	(-0.70)	(-0.46)	(-0.31)	(-0.38)	(1.37)	(-0.73)	(-0.46)
−9	-0.003	0.007	-0.008	-0.004	0.010	-0.002	0.007	-0.009	-0.004	0.010
	(-0.23)	(0.63)	(-0.64)	(-0.35)	(0.56)	(-0.20)	(0.65)	(-0.66)	(-0.31)	(0.55)
−8	0.011	-0.004	0.011	-0.002	-0.001	0.012	-0.004	0.011	-0.002	-0.001
	(0.96)	(-0.33)	(0.88)	(-0.17)	(-0.04)	(1.01)	(-0.32)	(0.85)	(-0.18)	(-0.07)
−7	-0.005	0.002	0.004	0.016	0.018	-0.004	0.002	0.004	0.017	0.017
	(-0.42)	(0.17)	(0.33)	(1.23)	(0.91)	(-0.35)	(0.17)	(0.31)	(1.27)	(0.90)
−6	-0.002	-0.005	-0.011	-0.011	0.007	-0.002	-0.004	-0.012	-0.011	0.007
	(-0.21)	(-0.45)	(-0.88)	(-0.85)	(0.37)	(-0.19)	(-0.38)	(-0.90)	(-0.81)	(0.38)
−5	0.005	0.001	-0.004	0.028	0.025	0.005	0.001	-0.004	0.028	0.025
	(0.40)	(0.06)	(-0.36)	(1.98)	(1.31)	(0.46)	(0.05)	(-0.34)	(2.00)	(1.29)
−4	-0.029	0.001	0.008	-0.007	0.050	-0.028	0.002	0.008	-0.007	0.050
	(-2.37)	(0.11)	(0.63)	(-0.50)	(2.56)	(-2.31)	(0.16)	(0.63)	(-0.47)	(2.58)
−3	0.020	-0.009	-0.003	0.039	0.013	0.020	-0.010	-0.003	0.038	0.011
	(1.65)	(-0.79)	(-0.27)	(2.80)	(0.68)	(1.64)	(-0.81)	(-0.26)	(2.80)	(0.61)
−2	0.005	0.015	0.027	0.004	0.043	0.005	0.014	0.027	0.003	0.042
	(0.45)	(1.28)	(2.17)	(0.24)	(2.13)	(0.42)	(1.15)	(2.12)	(0.18)	(2.11)
−1	0.003	0.009	-0.007	0.021	0.018	0.003	0.008	-0.009	0.020	0.017
	(0.29)	(0.75)	(-0.54)	(1.46)	(0.98)	(0.23)	(0.66)	(-0.66)	(1.41)	(0.92)
0	0.033	0.046	0.091	0.109	0.100	0.016	0.031	0.076	0.095	0.086
	(1.92)	(2.37)	(4.36)	(4.80)	(3.65)	(0.92)	(1.61)	(3.67)	(4.21)	(3.17)
1	0.013	0.004	0.009	0.024	0.022	-0.004	-0.010	-0.003	0.012	0.005
	(0.84)	(0.24)	(0.46)	(1.17)	(0.81)	(-0.26)	(-0.54)	(-0.14)	(0.59)	(0.18)
2	-0.011	-0.048	-0.045	-0.039	-0.011	-0.008	-0.047	-0.045	-0.039	-0.010
	(-0.97)	(-3.87)	(-3.38)	(-2.69)	(-0.57)	(-0.76)	(-3.83)	(-3.35)	(-2.63)	(-0.55)
3	-0.027	-0.017	-0.019	-0.036	-0.038	-0.026	-0.016	-0.019	-0.036	-0.039
	(-2.17)	(-1.32)	(-1.51)	(-2.51)	(-2.13)	(-2.06)	(-1.30)	(-1.50)	(-2.53)	(-2.17)
4	0.000	-0.026	-0.015	-0.039	-0.005	0.001	-0.025	-0.015	-0.038	-0.005
	(-0.04)	(-2.22)	(-1.27)	(-2.63)	(-0.30)	(0.06)	(-2.14)	(-1.28)	(-2.57)	(-0.26)
5	-0.021	-0.021	-0.014	-0.015	0.018	-0.019	-0.020	-0.013	-0.014	0.019
	(-1.83)	(-1.77)	(-1.11)	(-1.13)	(1.00)	(-1.68)	(-1.69)	(-1.04)	(-1.05)	(1.04)
6	-0.002	-0.005	-0.017	-0.021	-0.015	-0.001	-0.005	-0.016	-0.020	-0.014
	(-0.22)	(-0.49)	(-1.47)	(-1.68)	(-0.81)	(-0.05)	(-0.42)	(-1.39)	(-1.57)	(-0.75)
7	0.017	-0.008	-0.015	0.003	0.005	0.017	-0.007	-0.015	0.003	0.006
	(1.45)	(-0.67)	(-1.15)	(0.20)	(0.32)	(1.53)	(-0.60)	(-1.13)	(0.25)	(0.38)
8	0.006	-0.013	-0.001	-0.002	0.018	0.006	-0.012	-0.001	-0.001	0.017
	(0.48)	(-1.14)	(-0.07)	(-0.13)	(1.00)	(0.51)	(-1.06)	(-0.09)	(-0.10)	(0.98)
9	0.006	-0.004	-0.013	-0.006	-0.004	0.006	-0.004	-0.013	-0.005	-0.004
	(0.48)	(-0.37)	(-1.07)	(-0.48)	(-0.25)	(0.51)	(-0.29)	(-1.13)	(-0.43)	(-0.25)
10	0.008	-0.028	-0.005	0.022	-0.007	0.009	-0.027	-0.004	0.023	-0.007
	(0.71)	(-2.52)	(-0.40)	(1.63)	(-0.41)	(0.81)	(-2.44)	(-0.36)	(1.66)	(-0.41)

Table 7: Changes in beta by Residual Analyst Coverage

	Realized beta					**Covariance component**				
Day	Residual coverage quintile					Residual coverage quintile				
	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	-0.010	0.005	-0.007	0.007	-0.005	-0.010	0.005	-0.008	0.006	-0.004
	(-0.86)	(0.43)	(-0.54)	(0.48)	(-0.32)	(-0.85)	(0.39)	(-0.59)	(0.43)	(-0.24)
-9	0.004	-0.006	-0.003	0.002	-0.002	0.005	-0.006	-0.004	0.002	-0.001
	(0.36)	(-0.49)	(-0.27)	(0.17)	(-0.09)	(0.43)	(-0.48)	(-0.34)	(0.17)	(-0.05)
-8	0.017	0.002	0.012	0.013	-0.024	0.018	0.002	0.011	0.014	-0.025
	(1.34)	(0.14)	(0.90)	(0.87)	(-1.44)	(1.39)	(0.13)	(0.88)	(0.89)	(-1.52)
-7	0.020	0.012	0.012	-0.003	-0.008	0.021	0.013	0.012	-0.003	-0.007
	(1.52)	(0.94)	(1.00)	(-0.23)	(-0.49)	(1.54)	(0.96)	(0.95)	(-0.23)	(-0.46)
-6	0.017	-0.007	-0.017	-0.022	0.011	0.017	-0.007	-0.017	-0.022	0.011
	(1.35)	(-0.60)	(-1.34)	(-1.63)	(0.67)	(1.36)	(-0.57)	(-1.32)	(-1.59)	(0.65)
-5	0.006	0.015	0.003	-0.001	0.033	0.007	0.015	0.004	-0.001	0.033
	(0.50)	(1.17)	(0.27)	(-0.05)	(2.11)	(0.56)	(1.18)	(0.29)	(-0.10)	(2.09)
-4	-0.004	-0.012	-0.005	0.010	0.036	-0.003	-0.012	-0.006	0.011	0.036
	(-0.31)	(-0.92)	(-0.38)	(0.75)	(2.19)	(-0.25)	(-0.88)	(-0.45)	(0.81)	(2.20)
-3	0.023	0.012	0.008	0.016	0.008	0.023	0.011	0.008	0.016	0.008
	(1.84)	(0.91)	(0.56)	(1.24)	(0.48)	(1.83)	(0.83)	(0.57)	(1.18)	(0.46)
-2	0.004	0.011	0.007	0.051	0.015	0.003	0.011	0.006	0.050	0.014
	(0.34)	(0.86)	(0.51)	(3.55)	(0.89)	(0.20)	(0.84)	(0.46)	(3.51)	(0.83)
-1	-0.016	0.001	0.017	0.005	0.038	-0.017	0.000	0.016	0.004	0.036
	(-1.21)	(0.12)	(1.31)	(0.34)	(2.35)	(-1.28)	(0.01)	(1.23)	(0.26)	(2.23)
0	0.052	0.070	0.080	0.117	0.073	0.035	0.053	0.063	0.102	0.061
	(2.54)	(3.46)	(3.75)	(5.51)	(3.15)	(1.72)	(2.62)	(2.96)	(4.86)	(2.62)
1	0.006	0.020	0.000	0.005	0.051	-0.001	0.001	-0.013	-0.011	0.031
	(0.32)	(1.01)	(0.02)	(0.26)	(2.04)	(-0.07)	(0.07)	(-0.71)	(-0.53)	(1.27)
2	-0.034	-0.027	-0.033	-0.036	-0.011	-0.034	-0.025	-0.032	-0.035	-0.010
	(-2.40)	(-2.14)	(-2.57)	(-2.61)	(-0.63)	(-2.39)	(-1.98)	(-2.54)	(-2.53)	(-0.59)
3	-0.029	-0.009	-0.049	-0.008	-0.035	-0.028	-0.008	-0.049	-0.008	-0.034
	(-2.23)	(-0.73)	(-3.87)	(-0.56)	(-2.09)	(-2.19)	(-0.64)	(-3.92)	(-0.63)	(-2.07)
4	-0.014	-0.003	-0.011	-0.017	-0.042	-0.014	-0.001	-0.011	-0.016	-0.040
	(-1.06)	(-0.24)	(-0.85)	(-1.25)	(-2.67)	(-1.07)	(-0.12)	(-0.86)	(-1.19)	(-2.59)
5	-0.005	-0.015	-0.015	0.003	-0.011	-0.004	-0.014	-0.014	0.004	-0.010
	(-0.38)	(-1.21)	(-1.19)	(0.24)	(-0.66)	(-0.30)	(-1.15)	(-1.11)	(0.31)	(-0.61)
6	-0.018	-0.010	-0.008	-0.014	-0.004	-0.017	-0.009	-0.006	-0.014	-0.003
	(-1.58)	(-0.84)	(-0.70)	(-1.10)	(-0.23)	(-1.47)	(-0.71)	(-0.56)	(-1.05)	(-0.21)
7	0.015	-0.007	0.000	0.007	-0.015	0.015	-0.006	0.000	0.007	-0.014
	(1.23)	(-0.55)	(-0.01)	(0.47)	(-1.02)	(1.23)	(-0.48)	(0.04)	(0.52)	(-0.92)
8	0.010	-0.018	-0.009	0.000	0.017	0.010	-0.017	-0.009	-0.001	0.018
	(0.80)	(-1.39)	(-0.68)	(-0.03)	(1.04)	(0.81)	(-1.36)	(-0.68)	(-0.04)	(1.07)
9	0.009	-0.011	-0.010	0.000	-0.007	0.009	-0.011	-0.011	0.000	-0.007
	(0.75)	(-0.94)	(-0.84)	(-0.01)	(-0.48)	(0.74)	(-0.88)	(-0.88)	(0.03)	(-0.44)
10	-0.001	-0.024	0.013	0.001	-0.002	0.000	-0.023	0.013	0.001	-0.002
	(-0.10)	(-2.05)	(1.08)	(0.08)	(-0.16)	(-0.02)	(-1.97)	(1.12)	(0.07)	(-0.10)

Table 8: Changes in beta by Earnings Surprise

Day	Realized beta					Covariance component				
	Earnings surprise quintile					Earnings surprise quintile				
	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	0.011	-0.008	0.005	0.002	-0.017	0.011	-0.008	0.005	0.002	-0.018
	(0.76)	(-0.69)	(0.39)	(0.12)	(-1.21)	(0.73)	(-0.68)	(0.38)	(0.14)	(-1.24)
-9	0.006	0.015	-0.015	-0.007	-0.002	0.006	0.015	-0.015	-0.007	-0.001
	(0.42)	(1.16)	(-1.15)	(-0.58)	(-0.14)	(0.41)	(1.18)	(-1.18)	(-0.56)	(-0.10)
-8	0.000	-0.003	0.004	0.028	-0.008	-0.001	-0.003	0.004	0.029	-0.008
	(-0.01)	(-0.21)	(0.31)	(2.10)	(-0.53)	(-0.06)	(-0.23)	(0.29)	(2.15)	(-0.54)
-7	0.041	-0.011	0.003	-0.002	0.006	0.040	-0.012	0.004	-0.002	0.007
	(2.70)	(-0.85)	(0.23)	(-0.19)	(0.45)	(2.67)	(-0.89)	(0.28)	(-0.12)	(0.47)
-6	-0.022	0.009	-0.001	-0.019	0.014	-0.022	0.010	-0.001	-0.019	0.015
	(-1.55)	(0.72)	(-0.05)	(-1.51)	(0.90)	(-1.56)	(0.82)	(-0.06)	(-1.51)	(0.92)
-5	0.015	-0.006	-0.012	0.021	0.041	0.014	-0.006	-0.011	0.021	0.041
	(1.07)	(-0.50)	(-1.00)	(1.62)	(2.82)	(1.03)	(-0.50)	(-0.94)	(1.62)	(2.82)
-4	-0.002	0.023	0.001	0.004	-0.001	-0.003	0.023	0.002	0.005	0.000
	(-0.14)	(1.84)	(0.10)	(0.31)	(-0.07)	(-0.24)	(1.84)	(0.17)	(0.42)	(-0.03)
-3	-0.003	0.035	0.023	0.018	-0.005	-0.003	0.033	0.022	0.018	-0.005
	(-0.20)	(2.56)	(1.79)	(1.27)	(-0.37)	(-0.23)	(2.47)	(1.72)	(1.33)	(-0.36)
-2	0.020	-0.001	0.013	0.028	0.031	0.019	-0.002	0.013	0.026	0.030
	(1.32)	(-0.10)	(1.07)	(2.04)	(1.95)	(1.29)	(-0.16)	(1.03)	(1.96)	(1.88)
-1	0.010	0.015	-0.018	0.014	0.028	0.009	0.012	-0.019	0.013	0.027
	(0.66)	(1.11)	(-1.43)	(0.99)	(1.99)	(0.59)	(0.94)	(-1.51)	(0.94)	(1.91)
0	0.079	0.090	0.038	0.080	0.131	0.061	0.071	0.024	0.066	0.116
	(3.04)	(4.40)	(1.96)	(3.50)	(4.92)	(2.37)	(3.50)	(1.21)	(2.89)	(4.39)
1	0.018	0.016	0.003	0.048	0.009	0.000	0.001	-0.011	0.030	-0.002
	(0.83)	(0.85)	(0.16)	(2.41)	(0.42)	(0.02)	(0.05)	(-0.57)	(1.54)	(-0.09)
2	-0.024	-0.041	-0.044	-0.026	-0.004	-0.023	-0.040	-0.043	-0.026	-0.003
	(-1.52)	(-3.19)	(-3.35)	(-1.86)	(-0.24)	(-1.44)	(-3.17)	(-3.28)	(-1.82)	(-0.22)
3	-0.022	-0.044	-0.030	-0.023	-0.008	-0.022	-0.043	-0.030	-0.023	-0.008
	(-1.50)	(-3.30)	(-2.33)	(-1.83)	(-0.53)	(-1.53)	(-3.22)	(-2.36)	(-1.81)	(-0.57)
4	0.011	-0.038	-0.040	-0.013	-0.004	0.012	-0.038	-0.039	-0.012	-0.004
	(0.79)	(-2.97)	(-3.39)	(-1.00)	(-0.30)	(0.84)	(-3.00)	(-3.31)	(-0.91)	(-0.27)
5	-0.001	-0.026	-0.020	-0.003	0.009	0.001	-0.025	-0.019	-0.002	0.009
	(-0.04)	(-2.18)	(-1.73)	(-0.27)	(0.62)	(0.04)	(-2.11)	(-1.63)	(-0.19)	(0.63)
6	-0.023	0.000	-0.026	0.000	-0.006	-0.022	0.001	-0.025	0.002	-0.005
	(-1.64)	(-0.02)	(-2.14)	(-0.02)	(-0.42)	(-1.59)	(0.07)	(-2.04)	(0.12)	(-0.36)
7	0.003	-0.010	0.003	-0.004	0.008	0.003	-0.009	0.005	-0.004	0.008
	(0.22)	(-0.83)	(0.26)	(-0.35)	(0.58)	(0.23)	(-0.73)	(0.37)	(-0.30)	(0.58)
8	0.014	-0.008	0.021	-0.018	-0.009	0.013	-0.008	0.021	-0.017	-0.009
	(0.99)	(-0.66)	(1.60)	(-1.42)	(-0.62)	(0.94)	(-0.62)	(1.65)	(-1.37)	(-0.64)
9	0.011	-0.017	0.003	-0.012	-0.004	0.011	-0.018	0.003	-0.012	-0.004
	(0.75)	(-1.39)	(0.22)	(-1.01)	(-0.26)	(0.78)	(-1.43)	(0.29)	(-0.97)	(-0.26)
10	0.002	-0.016	-0.003	0.002	0.001	0.002	-0.016	-0.002	0.003	0.003
	(0.13)	(-1.35)	(-0.21)	(0.19)	(0.10)	(0.12)	(-1.36)	(-0.13)	(0.26)	(0.17)

Table 9: Changes in beta by Forecast Dispersion

Day	Realized beta					Covariance component				
	Dispersion quintile					Dispersion quintile				
	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	-0.017	0.002	-0.007	0.008	-0.001	-0.017	0.002	-0.007	0.009	-0.002
	(-1.40)	(0.19)	(-0.55)	(0.60)	(-0.09)	(-1.41)	(0.15)	(-0.55)	(0.62)	(-0.11)
-9	-0.011	0.011	-0.018	-0.007	0.010	-0.011	0.011	-0.017	-0.007	0.011
	(-0.91)	(0.88)	(-1.35)	(-0.49)	(0.67)	(-0.91)	(0.85)	(-1.30)	(-0.50)	(0.69)
-8	-0.013	0.014	0.003	-0.014	0.028	-0.013	0.013	0.003	-0.014	0.028
	(-1.01)	(1.09)	(0.19)	(-0.96)	(1.69)	(-0.99)	(1.05)	(0.21)	(-1.00)	(1.66)
-7	0.012	0.001	0.013	-0.004	0.011	0.012	0.001	0.014	-0.004	0.011
	(1.00)	(0.11)	(1.04)	(-0.24)	(0.62)	(1.03)	(0.11)	(1.10)	(-0.27)	(0.62)
-6	-0.007	0.013	0.007	-0.015	-0.023	-0.006	0.012	0.007	-0.015	-0.023
	(-0.60)	(0.98)	(0.51)	(-1.08)	(-1.40)	(-0.55)	(0.94)	(0.53)	(-1.04)	(-1.39)
-5	-0.005	-0.001	0.003	0.030	0.032	-0.005	-0.001	0.003	0.029	0.033
	(-0.47)	(-0.10)	(0.20)	(2.06)	(1.96)	(-0.46)	(-0.06)	(0.22)	(1.98)	(1.98)
-4	-0.001	-0.007	0.001	0.030	0.002	0.000	-0.006	0.002	0.029	0.002
	(-0.05)	(-0.56)	(0.05)	(1.98)	(0.10)	(0.00)	(-0.50)	(0.14)	(1.88)	(0.10)
-3	0.015	0.025	0.021	0.006	-0.004	0.016	0.023	0.021	0.006	-0.005
	(1.23)	(1.92)	(1.53)	(0.43)	(-0.27)	(1.24)	(1.80)	(1.52)	(0.42)	(-0.31)
-2	0.009	0.023	0.028	0.012	0.018	0.008	0.022	0.026	0.012	0.017
	(0.74)	(1.71)	(2.11)	(0.81)	(1.02)	(0.62)	(1.65)	(2.02)	(0.80)	(0.99)
-1	-0.010	-0.015	0.017	0.037	0.016	-0.011	-0.015	0.014	0.036	0.014
	(-0.80)	(-1.12)	(1.24)	(2.58)	(0.94)	(-0.86)	(-1.17)	(1.01)	(2.52)	(0.87)
0	0.048	0.064	0.066	0.109	0.102	0.031	0.045	0.048	0.095	0.091
	(2.38)	(2.88)	(3.04)	(5.12)	(4.21)	(1.56)	(2.05)	(2.22)	(4.50)	(3.75)
1	-0.002	0.003	0.025	0.048	0.008	-0.011	-0.019	0.005	0.033	-0.001
	(-0.09)	(0.17)	(1.29)	(2.17)	(0.34)	(-0.57)	(-0.93)	(0.23)	(1.49)	(-0.03)
2	-0.034	-0.036	-0.042	-0.024	-0.009	-0.034	-0.034	-0.041	-0.023	-0.008
	(-2.82)	(-2.78)	(-3.12)	(-1.51)	(-0.51)	(-2.79)	(-2.61)	(-3.08)	(-1.49)	(-0.50)
3	-0.030	-0.025	-0.003	-0.041	-0.028	-0.030	-0.025	-0.003	-0.041	-0.028
	(-2.50)	(-1.94)	(-0.23)	(-2.84)	(-1.68)	(-2.45)	(-1.93)	(-0.21)	(-2.83)	(-1.72)
4	-0.034	-0.014	-0.015	-0.021	-0.006	-0.033	-0.013	-0.014	-0.020	-0.006
	(-2.81)	(-1.16)	(-1.20)	(-1.47)	(-0.38)	(-2.78)	(-1.09)	(-1.12)	(-1.43)	(-0.35)
5	-0.010	-0.024	-0.006	-0.004	0.001	-0.009	-0.023	-0.006	-0.003	0.002
	(-0.81)	(-1.95)	(-0.48)	(-0.29)	(0.05)	(-0.78)	(-1.86)	(-0.43)	(-0.21)	(0.10)
6	0.001	-0.020	-0.007	-0.003	-0.025	0.002	-0.019	-0.006	-0.002	-0.025
	(0.08)	(-1.75)	(-0.51)	(-0.25)	(-1.62)	(0.19)	(-1.64)	(-0.43)	(-0.14)	(-1.60)
7	0.001	0.010	-0.021	0.000	0.001	0.001	0.012	-0.020	0.000	0.001
	(0.07)	(0.89)	(-1.61)	(-0.03)	(0.07)	(0.08)	(1.02)	(-1.52)	(0.03)	(0.07)
8	-0.018	0.010	-0.012	0.003	0.012	-0.017	0.011	-0.013	0.004	0.012
	(-1.49)	(0.87)	(-0.90)	(0.22)	(0.74)	(-1.46)	(0.91)	(-0.93)	(0.26)	(0.71)
9	0.002	-0.005	-0.025	0.011	-0.002	0.002	-0.005	-0.024	0.011	-0.002
	(0.21)	(-0.44)	(-2.01)	(0.80)	(-0.11)	(0.14)	(-0.39)	(-1.93)	(0.81)	(-0.10)
10	-0.019	0.006	-0.021	-0.008	0.021	-0.018	0.007	-0.021	-0.007	0.022
	(-1.62)	(0.49)	(-1.76)	(-0.57)	(1.38)	(-1.53)	(0.56)	(-1.75)	(-0.55)	(1.40)

Table 10: Sub-period analysis

Day	1995-2000		2001-2006	
	Realized beta	**Covariance**	**Realized beta**	**Covariance**
-10	-0.012	-0.012	0.008	0.008
	(-1.19)	(-1.24)	(0.89)	(0.91)
-9	0.006	0.006	-0.005	-0.005
	(0.62)	(0.62)	(-0.52)	(-0.50)
-8	0.004	0.004	0.005	0.005
	(0.39)	(0.35)	(0.51)	(0.51)
-7	0.013	0.013	0.004	0.004
	(1.31)	(1.30)	(0.43)	(0.45)
-6	-0.002	-0.002	-0.007	-0.006
	(-0.15)	(-0.16)	(-0.76)	(-0.72)
-5	0.007	0.006	0.017	0.017
	(0.68)	(0.62)	(1.79)	(1.84)
-4	0.002	0.003	0.010	0.011
	(0.26)	(0.29)	(1.11)	(1.12)
-3	0.010	0.009	0.015	0.015
	(0.87)	(0.79)	(1.61)	(1.59)
-2	0.017	0.016	0.022	0.021
	(1.54)	(1.44)	(2.26)	(2.18)
-1	0.020	0.018	0.003	0.002
	(1.93)	(1.77)	(0.28)	(0.16)
0	0.066	0.051	0.103	0.086
	(4.68)	(3.64)	(6.70)	(5.59)
1	0.044	0.032	0.002	-0.017
	(3.32)	(2.45)	(0.12)	(-1.19)
2	-0.012	-0.011	-0.042	-0.041
	(-1.10)	(-1.05)	(-4.49)	(-4.38)
3	-0.010	-0.010	-0.042	-0.042
	(-1.07)	(-1.06)	(-4.24)	(-4.24)
4	-0.005	-0.005	-0.026	-0.025
	(-0.55)	(-0.50)	(-2.82)	(-2.74)
5	0.011	0.011	-0.027	-0.026
	(1.15)	(1.19)	(-2.81)	(-2.68)
6	0.009	0.010	-0.027	-0.026
	(0.92)	(1.06)	(-3.02)	(-2.92)
7	0.015	0.017	-0.012	-0.012
	(1.54)	(1.69)	(-1.28)	(-1.27)
8	0.003	0.003	-0.001	-0.001
	(0.27)	(0.34)	(-0.12)	(-0.15)
9	0.000	0.001	-0.008	-0.008
	(0.03)	(0.07)	(-0.86)	(-0.83)
10	0.002	0.002	-0.006	-0.005
	(0.21)	(0.25)	(-0.66)	(-0.57)

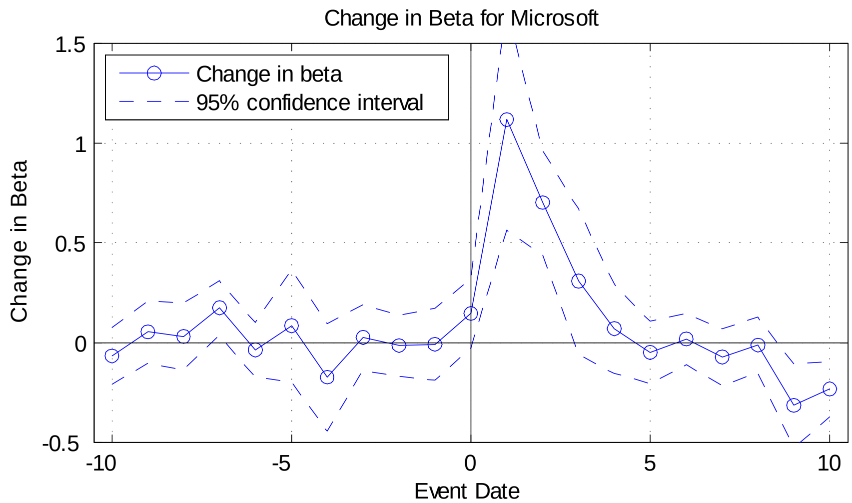
Table 11, Panel A: Sub-period analysis, by industry: Realized beta

	1995-2000					2001-2006				
Day	Cnsmr	Manuf	HiTec	Hlth	Other	Cnsmr	Manuf	HiTec	Hlth	Other
-10	0.011	0.000	-0.025	-0.038	-0.036	-0.012	0.004	0.065	-0.009	-0.014
	(0.62)	(0.02)	(-0.80)	(-1.07)	(-1.80)	(-0.66)	(0.21)	(2.65)	(-0.32)	(-0.88)
-9	0.010	-0.007	0.035	-0.018	0.006	-0.010	-0.016	0.027	-0.068	0.001
	(0.57)	(-0.46)	(1.32)	(-0.44)	(0.33)	(-0.62)	(-0.89)	(1.07)	(-2.18)	(0.08)
-8	-0.006	-0.014	0.037	-0.031	0.025	0.014	0.000	-0.008	-0.020	0.016
	(-0.30)	(-0.85)	(1.30)	(-0.87)	(1.23)	(0.76)	(-0.01)	(-0.30)	(-0.76)	(1.02)
-7	0.012	0.007	0.039	0.001	0.008	-0.002	-0.004	0.020	-0.029	0.012
	(0.69)	(0.43)	(1.31)	(0.02)	(0.44)	(-0.11)	(-0.22)	(0.72)	(-1.05)	(0.69)
-6	-0.005	-0.010	0.059	-0.090	-0.004	-0.014	-0.018	0.024	-0.054	-0.001
	(-0.27)	(-0.58)	(1.84)	(-2.64)	(-0.18)	(-0.87)	(-0.94)	(0.88)	(-1.92)	(-0.07)
-5	0.035	-0.018	0.029	0.026	-0.006	0.021	0.021	0.046	-0.052	-0.001
	(1.99)	(-1.20)	(0.96)	(0.70)	(-0.34)	(1.17)	(1.13)	(1.66)	(-1.89)	(-0.05)
-4	0.032	-0.010	0.014	-0.066	-0.001	-0.026	0.024	0.049	-0.063	0.008
	(1.84)	(-0.68)	(0.48)	(-1.62)	(-0.08)	(-1.44)	(1.20)	(1.80)	(-2.54)	(0.52)
-3	0.019	-0.013	0.017	0.047	0.016	-0.001	0.006	0.043	-0.056	0.032
	(1.06)	(-0.81)	(0.61)	(1.25)	(0.73)	(-0.06)	(0.29)	(1.56)	(-1.79)	(1.86)
-2	0.012	0.012	0.035	-0.019	0.023	0.037	0.035	0.028	-0.032	-0.001
	(0.62)	(0.77)	(1.21)	(-0.49)	(1.07)	(2.08)	(1.66)	(1.03)	(-1.21)	(-0.06)
-1	0.054	-0.009	0.035	0.009	0.017	-0.038	-0.008	0.050	-0.007	0.002
	(2.90)	(-0.63)	(1.20)	(0.26)	(0.78)	(-2.10)	(-0.40)	(1.73)	(-0.23)	(0.13)
0	0.017	0.063	0.133	-0.046	0.051	0.047	0.090	0.081	0.024	0.107
	(0.64)	(2.93)	(3.59)	(-0.94)	(1.83)	(1.33)	(2.99)	(2.39)	(0.43)	(3.79)
1	0.008	0.003	0.191	0.094	0.009	-0.066	0.019	0.079	-0.176	-0.021
	(0.33)	(0.15)	(4.27)	(1.82)	(0.38)	(-2.49)	(0.78)	(1.61)	(-3.60)	(-0.88)
2	-0.004	-0.003	-0.005	-0.042	-0.036	-0.039	-0.021	-0.085	-0.038	-0.052
	(-0.21)	(-0.18)	(-0.20)	(-1.36)	(-1.74)	(-2.17)	(-1.12)	(-2.95)	(-1.32)	(-3.26)
3	-0.007	0.007	-0.030	-0.056	-0.013	-0.032	-0.010	-0.138	0.005	-0.028
	(-0.43)	(0.49)	(-1.12)	(-1.68)	(-0.71)	(-1.76)	(-0.52)	(-5.32)	(0.16)	(-1.58)
4	0.000	0.006	-0.006	0.037	-0.036	-0.011	-0.030	-0.044	-0.050	-0.014
	(-0.01)	(0.39)	(-0.19)	(1.14)	(-2.15)	(-0.69)	(-1.54)	(-1.68)	(-1.83)	(-0.88)
5	0.009	0.006	0.020	0.037	0.006	-0.039	-0.002	-0.078	-0.024	-0.012
	(0.56)	(0.33)	(0.72)	(1.04)	(0.34)	(-2.13)	(-0.09)	(-3.25)	(-0.88)	(-0.74)
6	-0.015	0.008	-0.005	0.043	0.032	-0.038	0.019	-0.106	-0.031	-0.009
	(-0.93)	(0.56)	(-0.21)	(1.26)	(1.68)	(-2.33)	(1.02)	(-4.05)	(-0.95)	(-0.57)
7	0.009	0.038	-0.021	0.027	0.011	-0.023	0.014	-0.039	-0.021	-0.010
	(0.56)	(2.34)	(-0.86)	(0.88)	(0.56)	(-1.40)	(0.80)	(-1.53)	(-0.67)	(-0.56)
8	0.003	0.027	0.000	-0.011	-0.022	-0.001	0.027	-0.047	0.010	-0.001
	(0.13)	(1.65)	(0.00)	(-0.34)	(-1.31)	(-0.09)	(1.46)	(-1.93)	(0.33)	(-0.05)
9	-0.001	0.011	0.003	-0.001	-0.013	-0.006	0.012	-0.044	0.003	-0.008
	(-0.05)	(0.84)	(0.09)	(-0.01)	(-0.82)	(-0.37)	(0.68)	(-1.68)	(0.13)	(-0.45)
10	-0.009	0.014	0.009	0.036	-0.016	-0.026	0.007	0.019	-0.007	-0.023
	(-0.52)	(0.94)	(0.31)	(0.98)	(-0.94)	(-1.54)	(0.40)	(0.75)	(-0.24)	(-1.46)

Table 11, Panel B: Sub-period analysis, by industry: Covariance component

	1995-2000					2001-2006				
Day	Cnsmr	Manuf	HiTec	Hlth	Other	Cnsmr	Manuf	HiTec	Hlth	Other
-10	0.010	0.000	-0.024	-0.039	-0.037	-0.011	0.004	0.064	-0.009	-0.014
	(0.61)	(-0.01)	(-0.80)	(-1.12)	(-1.88)	(-0.65)	(0.25)	(2.67)	(-0.33)	(-0.87)
-9	0.010	-0.007	0.037	-0.020	0.006	-0.009	-0.016	0.027	-0.069	0.002
	(0.58)	(-0.47)	(1.39)	(-0.49)	(0.30)	(-0.57)	(-0.85)	(1.06)	(-2.28)	(0.11)
-8	-0.007	-0.014	0.037	-0.032	0.024	0.014	0.000	-0.008	-0.020	0.016
	(-0.34)	(-0.87)	(1.32)	(-0.89)	(1.20)	(0.77)	(0.01)	(-0.32)	(-0.76)	(1.04)
-7	0.013	0.007	0.039	-0.002	0.008	-0.001	-0.004	0.019	-0.026	0.012
	(0.71)	(0.43)	(1.31)	(-0.05)	(0.44)	(-0.08)	(-0.20)	(0.70)	(-0.97)	(0.69)
-6	-0.005	-0.009	0.059	-0.088	-0.004	-0.015	-0.017	0.024	-0.053	-0.001
	(-0.29)	(-0.55)	(1.86)	(-2.61)	(-0.22)	(-0.87)	(-0.89)	(0.88)	(-1.89)	(-0.05)
-5	0.034	-0.018	0.029	0.022	-0.007	0.021	0.022	0.045	-0.048	-0.001
	(1.94)	(-1.19)	(0.98)	(0.58)	(-0.36)	(1.18)	(1.19)	(1.66)	(-1.74)	(-0.05)
-4	0.032	-0.010	0.017	-0.067	-0.002	-0.025	0.025	0.050	-0.061	0.007
	(1.84)	(-0.66)	(0.58)	(-1.64)	(-0.11)	(-1.42)	(1.23)	(1.83)	(-2.44)	(0.44)
-3	0.017	-0.013	0.015	0.046	0.015	-0.001	0.006	0.041	-0.056	0.032
	(0.98)	(-0.79)	(0.55)	(1.21)	(0.68)	(-0.05)	(0.31)	(1.52)	(-1.80)	(1.88)
-2	0.011	0.012	0.033	-0.022	0.021	0.034	0.036	0.026	-0.029	-0.002
	(0.59)	(0.74)	(1.15)	(-0.57)	(1.00)	(1.98)	(1.67)	(0.99)	(-1.11)	(-0.09)
-1	0.053	-0.009	0.028	0.010	0.016	-0.039	-0.008	0.047	-0.006	0.002
	(2.87)	(-0.67)	(0.97)	(0.27)	(0.74)	(-2.16)	(-0.40)	(1.66)	(-0.21)	(0.09)
0	-0.002	0.054	0.109	-0.064	0.041	0.028	0.074	0.069	-0.001	0.093
	(-0.06)	(2.51)	(3.00)	(-1.30)	(1.49)	(0.79)	(2.48)	(2.05)	(-0.01)	(3.32)
1	0.004	-0.002	0.144	0.085	0.003	-0.072	0.015	0.011	-0.180	-0.031
	(0.18)	(-0.09)	(3.23)	(1.67)	(0.13)	(-2.70)	(0.60)	(0.22)	(-3.68)	(-1.28)
2	-0.004	-0.002	-0.003	-0.038	-0.035	-0.038	-0.022	-0.079	-0.033	-0.052
	(-0.20)	(-0.16)	(-0.10)	(-1.24)	(-1.73)	(-2.14)	(-1.13)	(-2.76)	(-1.14)	(-3.26)
3	-0.006	0.007	-0.033	-0.054	-0.012	-0.031	-0.010	-0.136	0.003	-0.028
	(-0.38)	(0.50)	(-1.23)	(-1.61)	(-0.69)	(-1.76)	(-0.52)	(-5.29)	(0.11)	(-1.58)
4	0.000	0.006	-0.003	0.035	-0.036	-0.012	-0.030	-0.042	-0.048	-0.014
	(0.02)	(0.43)	(-0.12)	(1.07)	(-2.13)	(-0.70)	(-1.51)	(-1.62)	(-1.76)	(-0.83)
5	0.009	0.006	0.024	0.033	0.006	-0.038	-0.001	-0.076	-0.021	-0.011
	(0.52)	(0.35)	(0.89)	(0.96)	(0.35)	(-2.07)	(-0.06)	(-3.15)	(-0.78)	(-0.68)
6	-0.014	0.008	0.000	0.039	0.032	-0.037	0.019	-0.104	-0.028	-0.008
	(-0.84)	(0.62)	(0.00)	(1.16)	(1.72)	(-2.28)	(1.03)	(-4.00)	(-0.87)	(-0.51)
7	0.010	0.038	-0.017	0.029	0.012	-0.023	0.014	-0.038	-0.021	-0.010
	(0.59)	(2.36)	(-0.69)	(0.97)	(0.64)	(-1.38)	(0.78)	(-1.52)	(-0.66)	(-0.56)
8	0.004	0.026	0.003	-0.012	-0.021	-0.002	0.027	-0.047	0.011	-0.001
	(0.19)	(1.61)	(0.10)	(-0.35)	(-1.27)	(-0.09)	(1.42)	(-1.95)	(0.37)	(-0.07)
9	-0.001	0.012	0.003	-0.002	-0.013	-0.007	0.013	-0.043	0.007	-0.009
	(-0.03)	(0.87)	(0.10)	(-0.05)	(-0.78)	(-0.39)	(0.69)	(-1.67)	(0.27)	(-0.49)
10	-0.008	0.014	0.009	0.034	-0.015	-0.026	0.007	0.020	-0.006	-0.022
	(-0.47)	(0.93)	(0.32)	(0.95)	(-0.89)	(-1.51)	(0.44)	(0.81)	(-0.21)	(-1.40)

Table 12: Alternative measures of beta				
	5-minute beta		HY beta	
Day	**Realized beta**	**Covariance**	**Realized beta**	**Covariance**
-10	-0.001	-0.001	-0.016	-0.016
	(-0.26)	(-0.26)	(-1.90)	(-1.89)
-9	0.003	0.003	-0.008	-0.008
	(0.55)	(0.56)	(-0.90)	(-0.89)
-8	0.005	0.005	0.002	0.002
	(0.85)	(0.88)	(0.21)	(0.22)
-7	0.003	0.003	-0.010	-0.010
	(0.61)	(0.61)	(-1.23)	(-1.23)
-6	-0.002	-0.002	0.002	0.002
	(-0.29)	(-0.31)	(0.25)	(0.24)
-5	0.009	0.010	0.009	0.009
	(1.78)	(1.79)	(1.03)	(1.05)
-4	0.008	0.009	0.005	0.005
	(1.63)	(1.64)	(0.58)	(0.60)
-3	0.008	0.008	0.000	-0.001
	(1.54)	(1.51)	(-0.04)	(-0.06)
-2	0.016	0.015	0.023	0.022
	(2.90)	(2.77)	(2.40)	(2.33)
-1	0.010	0.009	0.025	0.024
	(1.91)	(1.69)	(2.60)	(2.47)
0	0.072	0.059	0.086	0.072
	(8.70)	(7.05)	(7.01)	(5.85)
1	0.012	0.000	0.018	0.005
	(1.48)	(-0.01)	(1.62)	(0.48)
2	-0.027	-0.026	-0.021	-0.021
	(-4.75)	(-4.63)	(-2.50)	(-2.44)
3	-0.026	-0.025	-0.008	-0.008
	(-4.65)	(-4.59)	(-0.93)	(-0.90)
4	-0.018	-0.017	-0.006	-0.005
	(-3.41)	(-3.30)	(-0.65)	(-0.59)
5	-0.013	-0.012	-0.011	-0.010
	(-2.53)	(-2.35)	(-1.19)	(-1.10)
6	-0.012	-0.011	-0.003	-0.002
	(-2.54)	(-2.33)	(-0.31)	(-0.19)
7	-0.009	-0.009	0.007	0.007
	(-1.80)	(-1.70)	(0.75)	(0.81)
8	-0.008	-0.007	0.009	0.009
	(-1.45)	(-1.39)	(0.98)	(1.02)
9	-0.006	-0.005	0.016	0.016
	(-1.14)	(-1.06)	(1.71)	(1.75)
10	-0.008	-0.008	0.000	0.001
	(-1.73)	(-1.60)	(-0.02)	(0.06)



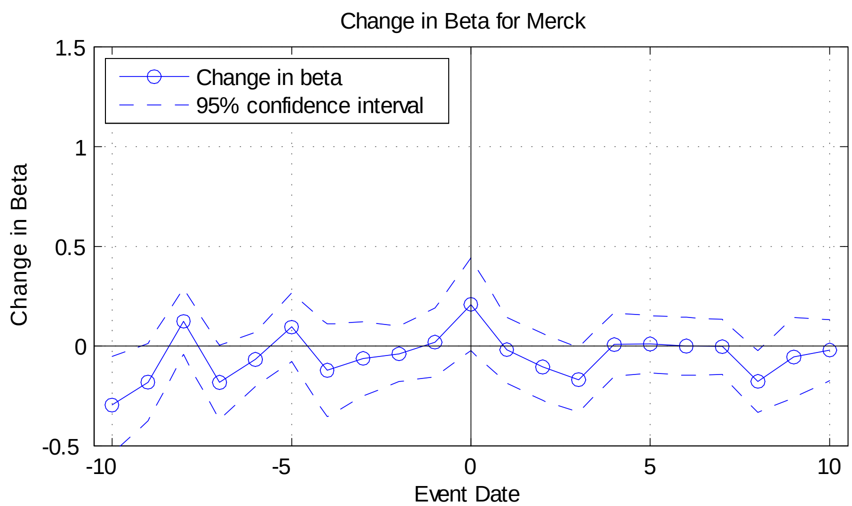


Figure 1: *Changes in estimated market beta of returns on Microsoft (top panel) and Merck (lower panel) on each of 21 days around quarterly earnings announcement dates, relative to days outside this 21-day window. Estimates are based on intra-daily prices sampled every 25 minutes, and the overnight return, over the period January 1995 to December 2006. 95% confidence intervals are computed using Barndorff-Nielsen and Shephard (2004).*

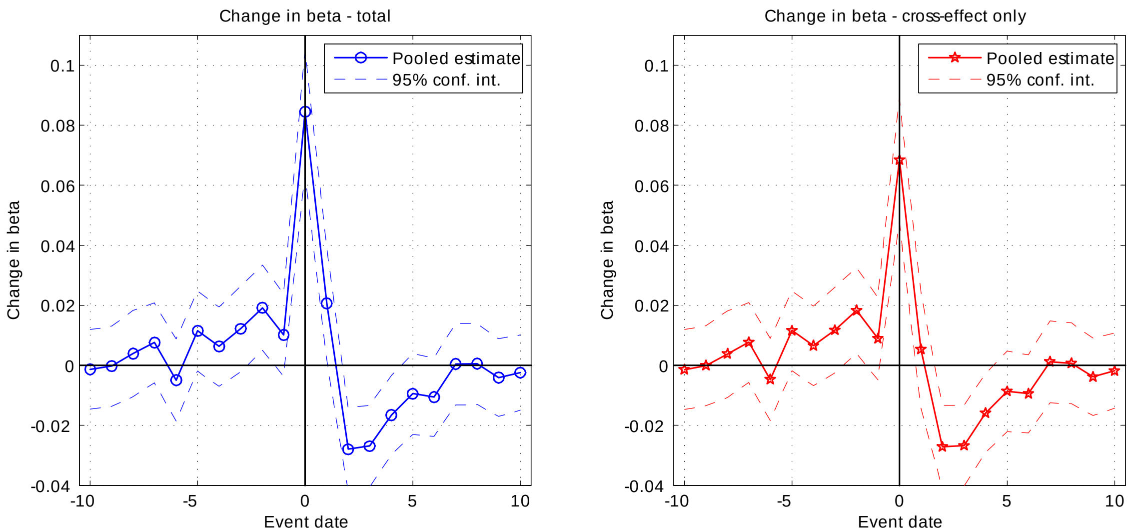


Figure 2: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) reported in Table 2. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed line.*

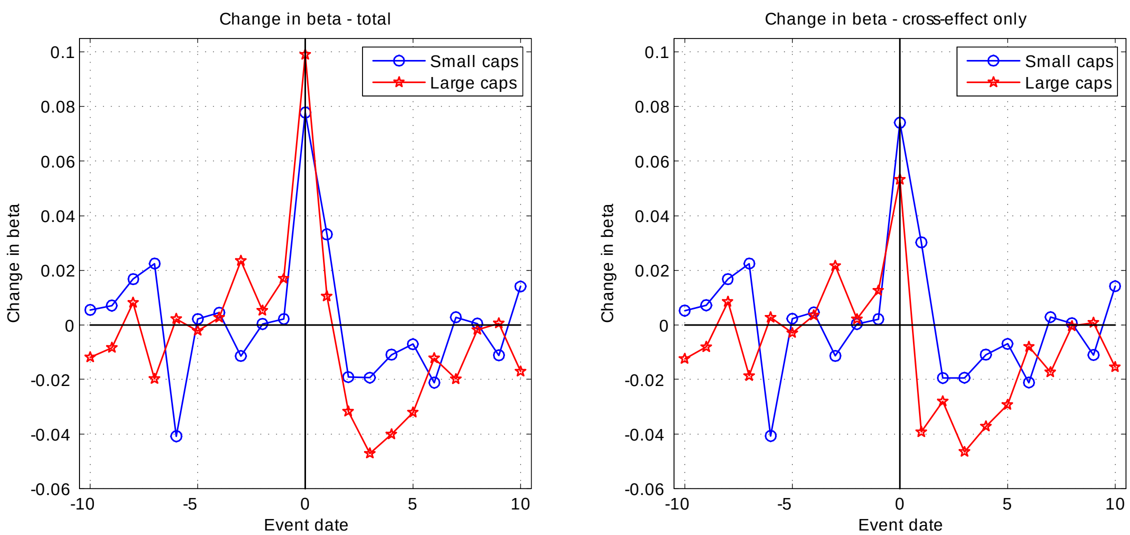


Figure 3: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the smallest and largest quintiles by market capitalization, as reported in Table 3.*

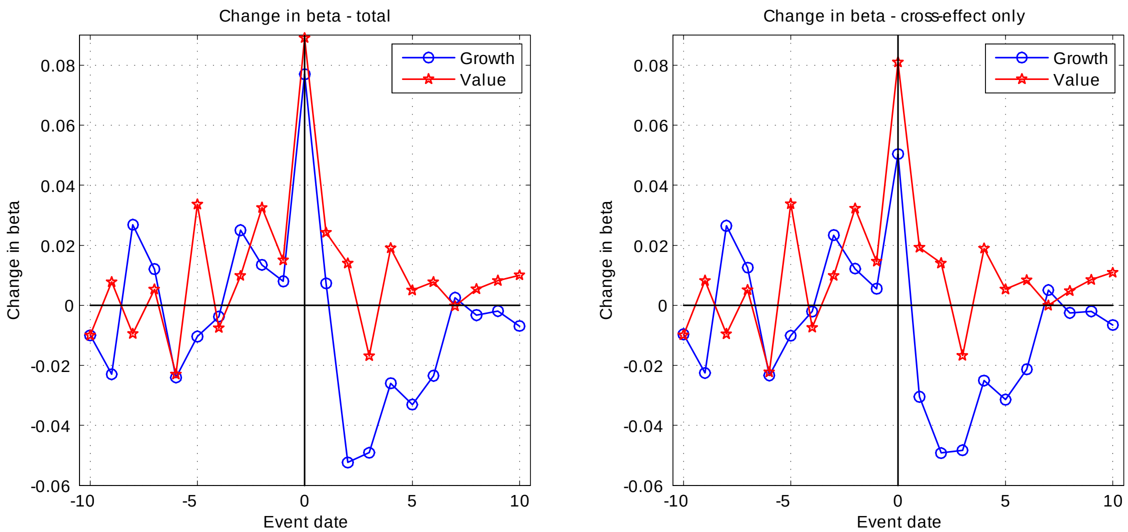


Figure 4: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by book-to-market ratio, as reported in Table 4.*

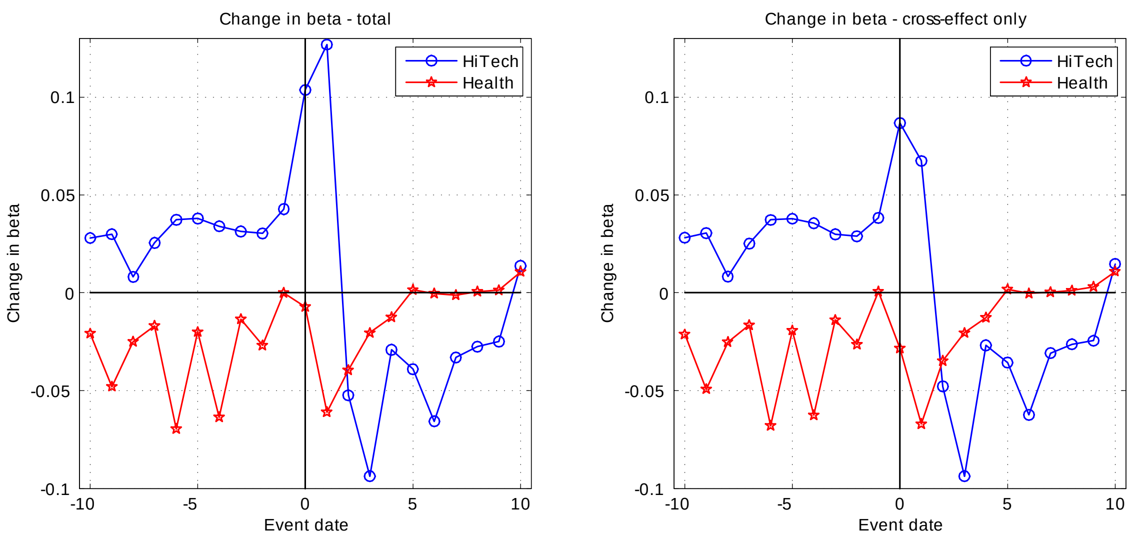


Figure 5: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the High Tech and Health industries, as reported in Table 5.*

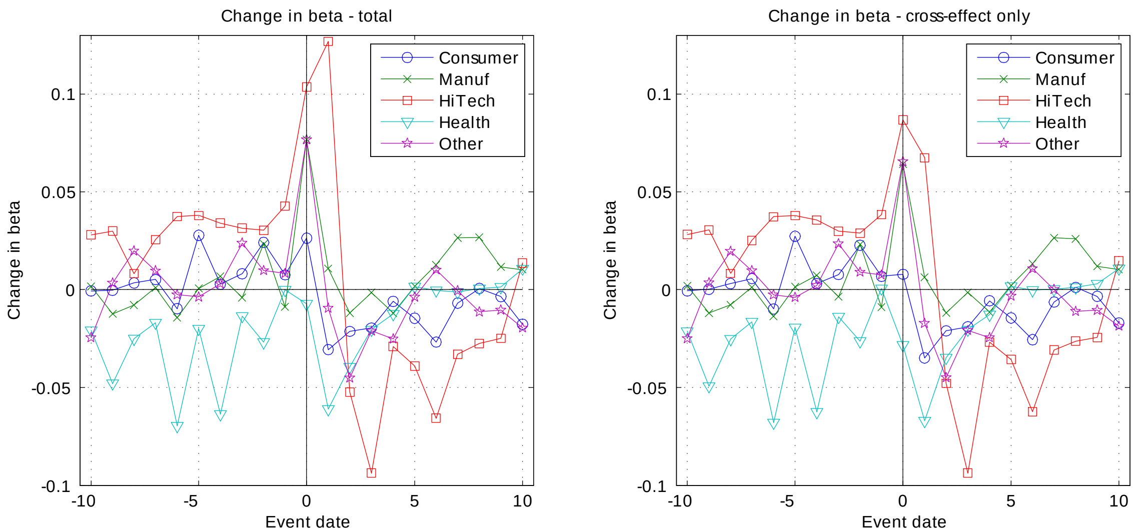


Figure 6: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the five industry groupings, as reported in Table 5.*

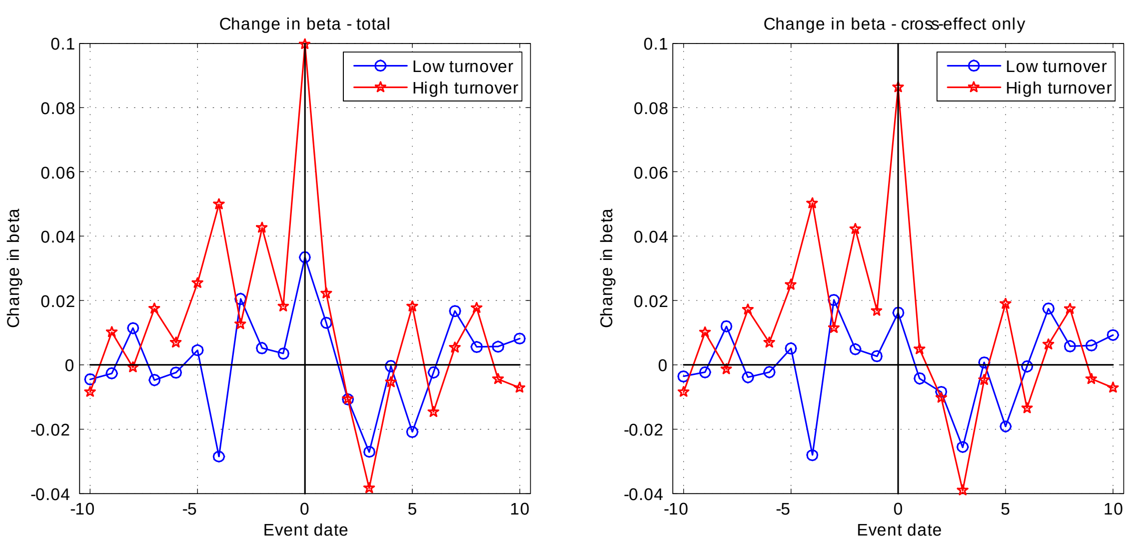


Figure 7: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by turnover, as reported in Table 6.*

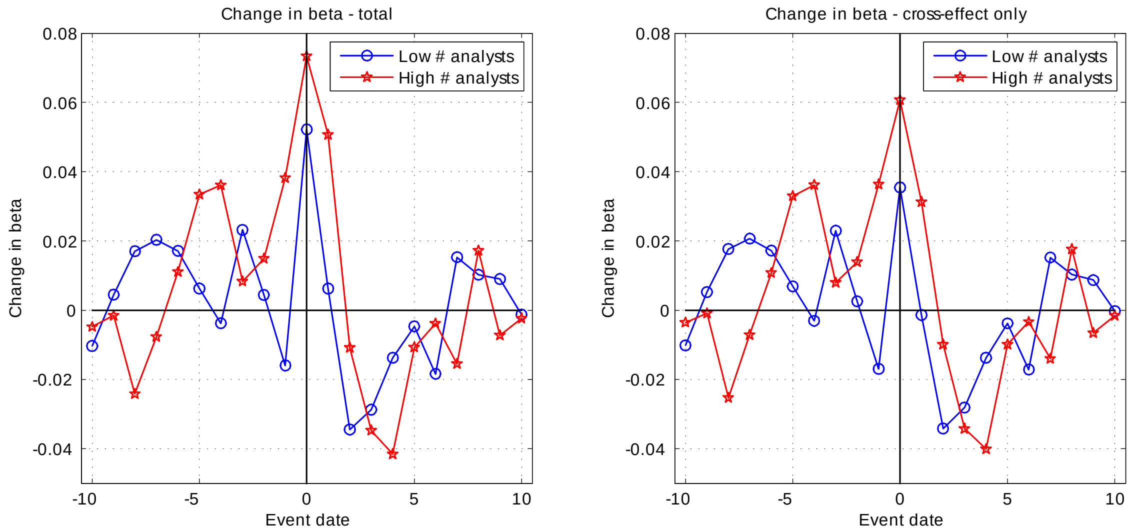


Figure 8: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by number of analysts, as reported in Table 7.*

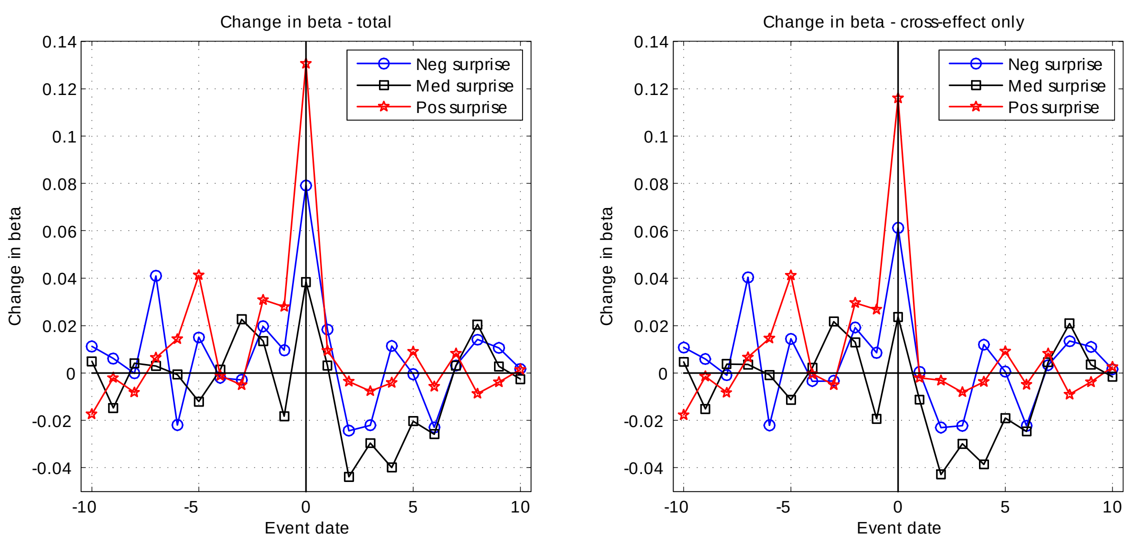


Figure 9: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by earnings surprise, as reported in Table 8.*

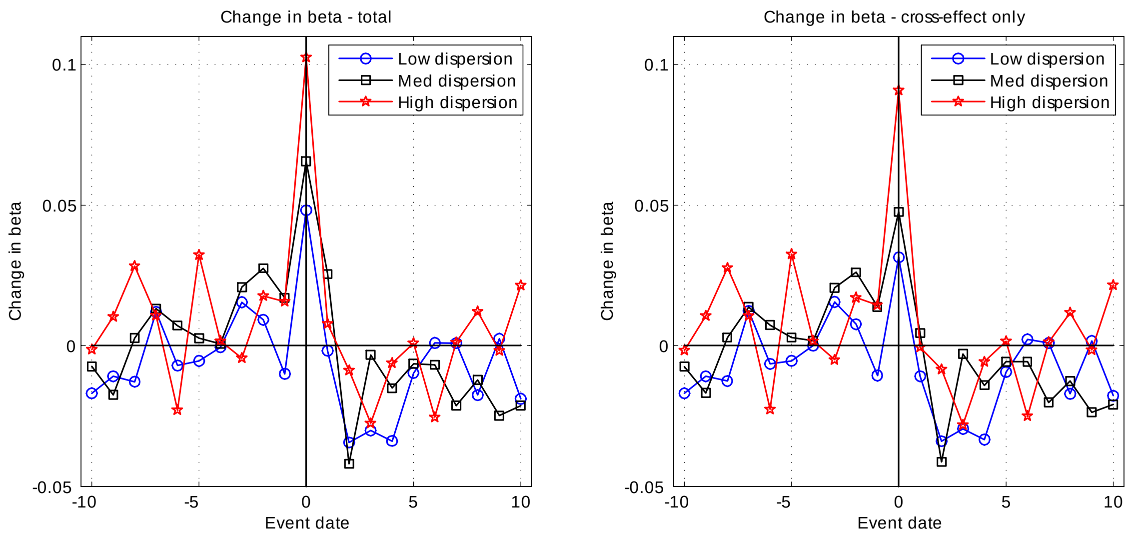


Figure 10: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by analyst forecast dispersion, as reported in Table 9.*

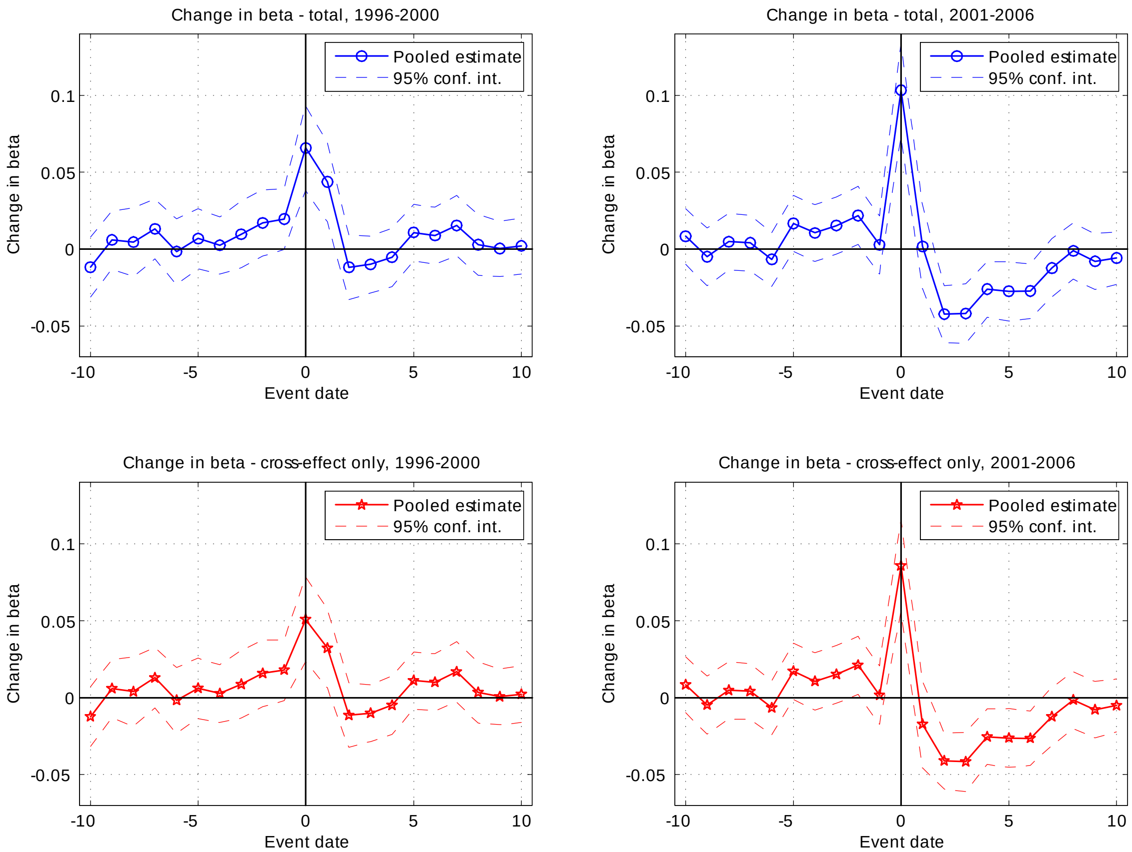


Figure 11: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) over two sub-samples, as reported in Table 10. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed line.*

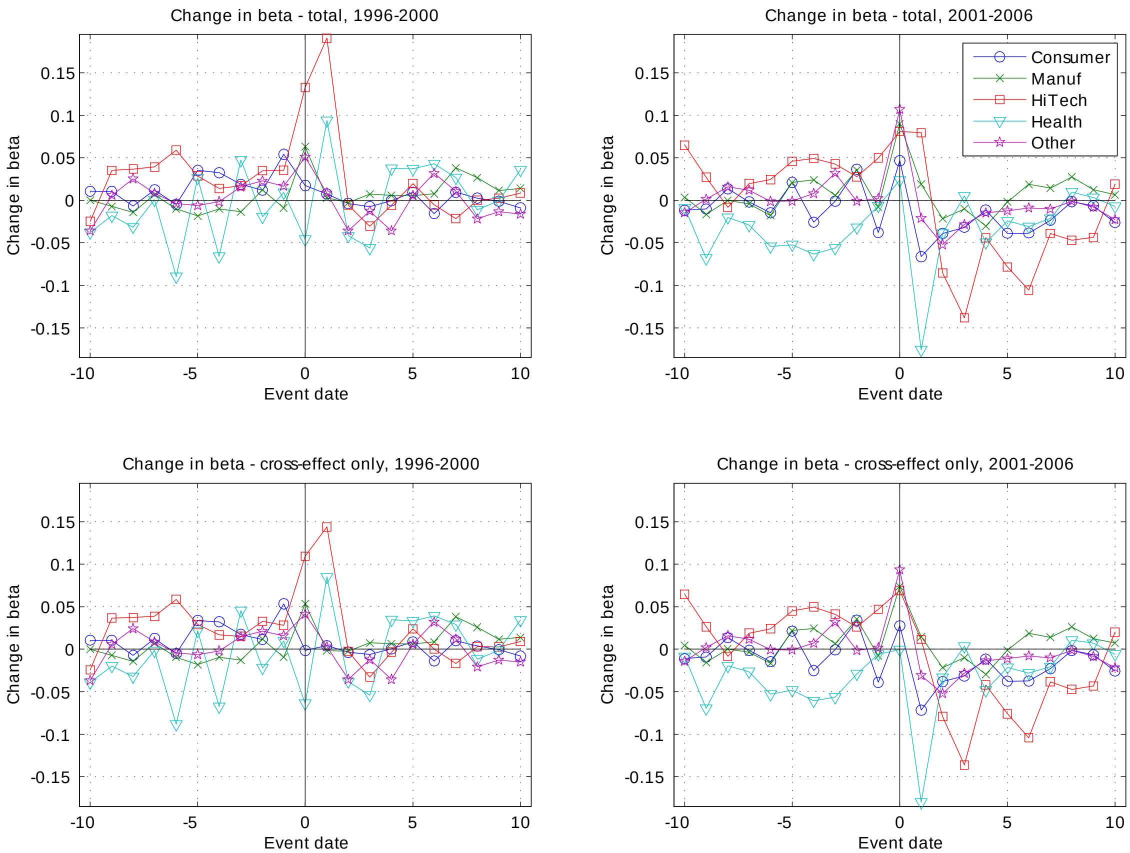


Figure 12: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) across two sub-samples, for the five industry groupings, as reported in Table 11.*

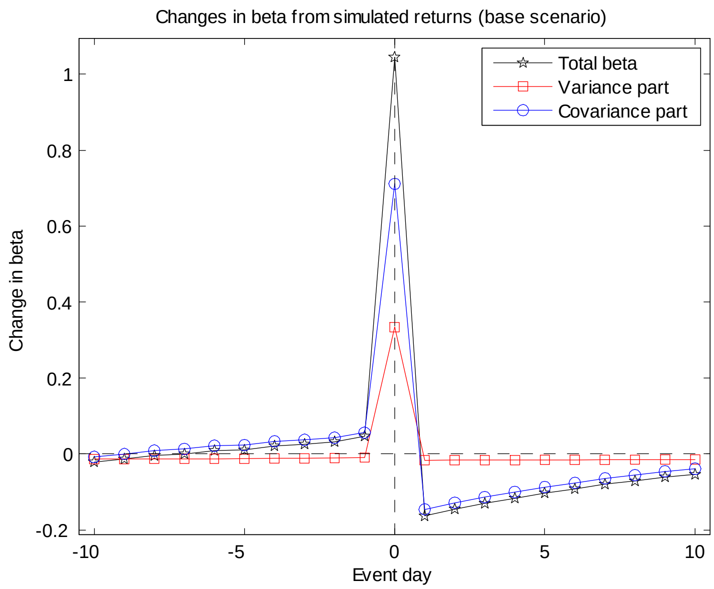


Figure 13: *Change in beta around event dates for base scenario simulation.*

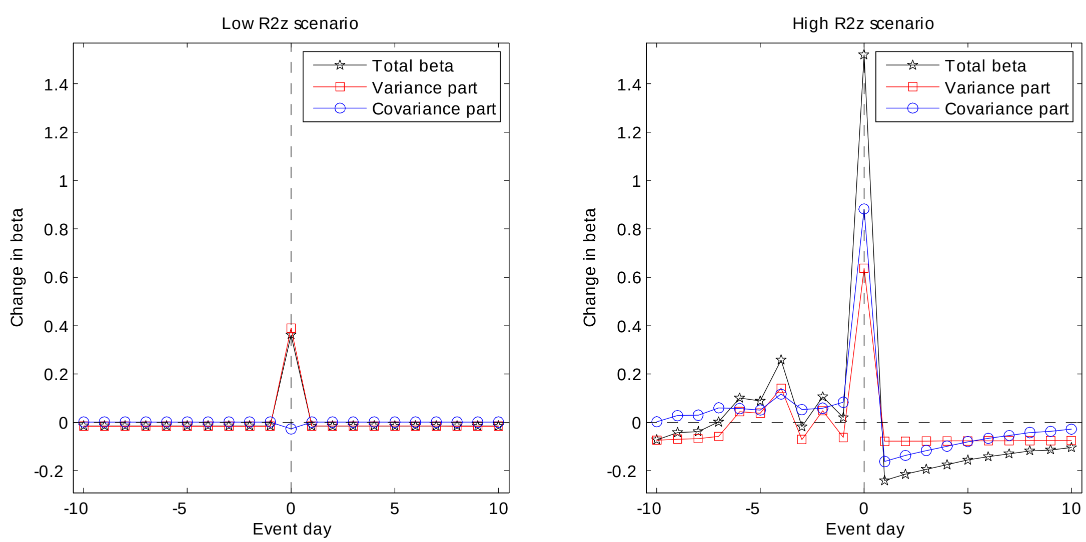


Figure 14: *Changes in beta around event dates for low and high values of the ratio of the variance of the common component in earnings innovations to total variance,* $R_z^2 = \sigma_z^2/\sigma_w^2$.

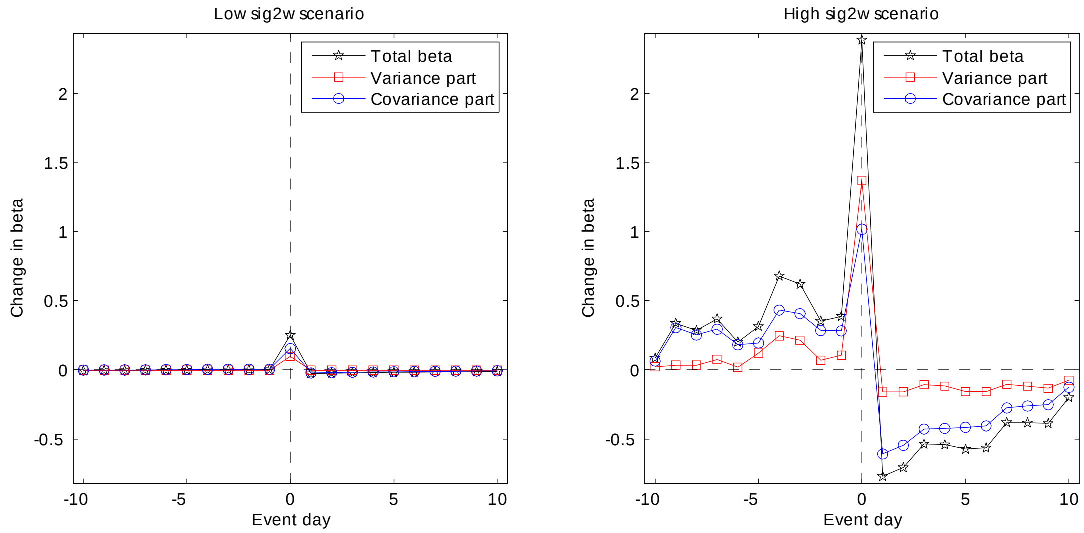


Figure 15: *Changes in beta around event dates for low and high values of the variance of earnings innovations,* σ_w^2.

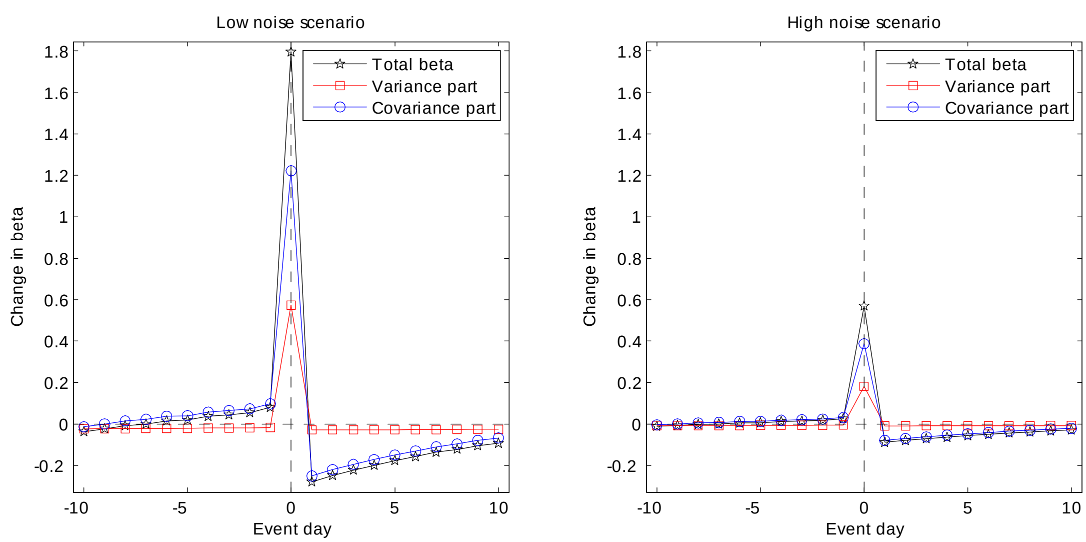


Figure 16: *Changes in beta around event dates for low and high values of the ratio of the variance of the part of daily returns* not *explained by changes in expectations about future earnings,* σ_e^2.