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

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Abstract

This paper shows that the systematic risk (or "beta") of individual stocks increases by an economically and statistically significant amount on days of firm-specific news announcements, and reverts to its average level two to five days later. We employ intra-daily data and recent advances in econometric theory to obtain daily firm-level estimates of 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 greater information content and higher ex-ante uncertainty. We also find important differences in the behavior of beta across different industries. Our analysis reveals that changes in beta around news announcements are mostly driven by an increase in the covariance of announcing firms with other firms in the market. We provide a simple model of investors' expectations formation that helps explain our empirical findings: changes in beta can be generated by investors learning about the profitability of a given firm by using information on other 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 vary with firm-specific information flows? According to the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the systematic risk, or "beta", of a stock represents its sensitivity to underlying market risks. Early empirical studies of the CAPM assume that a stock's beta is constant through time, while later conditional versions of the CAPM allow for variation in beta and find evidence that beta changes at monthly or quarterly frequencies, typically with variables that are related to the business cycle.[1] While it is reasonable to expect that the sensitivity of a stock's return to market risks is affected by time-varying *aggregate* market conditions, whether one should expect a measure of systematic risk to be affected by variations in *firm-specific* conditions is less obvious. The answer to this question has implications for studies of market efficiency, for hedging strategies, and for asset pricing more generally.

In this paper we analyze the behavior of a stock's beta during times of firm-specific information flows. We employ intra-daily data and recent advances in the econometrics of risk measurement to obtain firm-level estimates of daily betas.[2] We focus on firms' quarterly earnings announcements, which represent regular and well-documented information disclosures, and are thus well-suited for a study of many stocks over a long time period. We estimate daily variations in betas around 22,575 earnings announcements for all stocks that are constituents of the S&P 500 index over the period 1995-2006.

We find that betas increase during firm-specific news announcements by a statistically and economically significant amount, regardless of whether the news is "good" or "bad". On average, betas increase by 0.08 (with a t-statistic of 8.03) on earnings announcement days, representing an increase of 8%, given that the cross-sectional average beta is unity by construction. Betas decline sharply after earnings announcements, and then slowly revert to their average level, about five days after the announcement. We also find considerable heterogeneity in the behavior of betas across different stocks in our sample.

What determines the increase in beta around firm-specific information flows? Given that the firms in our sample are constituents of the index that we use as the market portfolio (the S&P 500

[1] See Robichek and Cohn (1974), Ferson, *et al.* (1987), Shanken (1990), Ferson and Harvey (1991), Ferson and Schadt (1996), amongst others. Lewellen and Nagel (2006) estimate monthly and quarterly betas without specifying a set of state variables.

[2] See Andersen *et al.* (2003b) and Barndorff-Nielsen and Shephard (2004) for econometric theory underlying the estimation of volatility and covariance using high frequency data.

index), a change in the variance of a given stock's return will mechanically change its beta with the market. If the volatility of a stock's return increases on announcement dates then we would then observe a mechanical increase in the stock's beta. To better understand the underlying sources of the behavior of beta around news announcements, we decompose the beta of a stock into two estimable 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. Our analysis reveals that, on average, around 80% of the increase in beta around news events is attributable to an increase in the average covariance of the announcing firm's stock return with the returns on other stocks. This finding suggests that news from the announcing firm often represents valuable information for other firms in the market.

Since our estimation method allows us to detect daily movements in beta for individual stocks, we provide an extensive empirical analysis of cross-sectional differences in the behavior of beta around news announcements. We find that a stock's beta increases significantly during both positive and negative news surprises (0.13 and 0.08, respectively), but shows no significant movement during announcements with little information content (i.e. when earnings surprises are close to zero). Most of the observed change in beta is due to an increase in the covariance component of beta. We also find that changes in beta on announcement days increase with a stock's turnover (from 0.03 for the lowest quintile of turnover to 0.11 for the highest quintile), with a stock's analyst coverage (0.05 to 0.12), and with the dispersion in analyst forecasts of earnings (0.05 to 0.11). In contrast, there is little variation in betas across firms with different market capitalization or different book-to-market ratios. Our results show large differences in the behavior of betas across different sectors of the economy: the increase in beta is largest for stocks in the high tech sector (0.13, with a t-statistic of 3.70) and lowest for those in the health sector (-0.06 and not 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 (0.19 compared with 0.08), which includes the period of the "tech bubble". These cross-sectional differences in the behavior of beta are largely driven by differences in the covariance component of beta.

Our analysis of the changes in the variance and covariance components of beta reveals that news from a given firm can generate changes in the covariance of the announcing firm's return with the returns of other firms in the market. We formalize this insight by presenting a stylized theoretical model that helps explain the changes in betas and covariances that we observe around earnings announcements. The intuition behind the model is simple, and is based on three realistic assumptions of the news environment and firms' stock prices: Firstly, some portion of the earnings of a given firm reflects wider macroeconomic conditions. Secondly, investors use many sources of information to update their expectations about future earnings, not merely news from a single firm. Thirdly, firms only announce their earnings infrequently (e.g., quarterly). In such an environment, investors are able to update their expectations about a firm's profitability quite accurately when the firm announces its earnings, while in between earnings announcement dates they update their expectations using other pieces of information available to them, such as the announcements of other firms. As an individual firm's earnings figures contain some information on the wider macroeconomy, good (bad) news for one firm represents partial good (bad) news for other firms, and investors update their expectations accordingly. Thus on an announcement date the covariance of the announcing firm's return with other firms' returns goes up (regardless of whether the earnings news is good or bad), which also increases its beta with the market portfolio.

The extent to which the change in beta is attributable to a change in its covariance with other stocks reflects the degree of learning across stocks that takes place: if the common component in earnings is larger, *ceteris paribus*, then more cross-firm learning is possible, and the covariance component of the change in beta is larger. If the common component is small, then very little cross-firm learning is possible, and any change in beta is due to the mechanical effect stemming from a change in the volatility of the announcing firm. Using a specific example of a model capturing these effects, we provide comparative statics that support this intuition.

The idea that investors may learn about the profitability of a given company by observing the earnings announcements of other companies is supported by a rich anecdotal evidence. The financial press often refers to "bellwether" stocks when reporting earnings figures. These companies are closely watched by traders and analysts, since their earnings are taken as a signal about the earnings of other firms in the same industry or about the market as a whole.[3] For such firms we would expect to see larger reactions in beta around information flows, as investors update their beliefs about other companies; we indeed observe larger changes in beta for stocks with

[3] Consider, for example, this exerpt from a Financial Times article titled "Sentiment sullied by lacklustre guidances from bellwethers" (20 January 2005): *Wall Street stocks closed 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.*

higher trading volume and higher analyst following, characteristics that might be associated with bellwether firms.

The behavior of betas around earnings announcements is also analyzed in Ball and Kothari (1991), who estimate a cross-sectional beta for a sample of about 1,500 stocks during the period 1980-1988. They document an average increase in beta of 0.067 over a three-day window around earnings announcements. Our methodology allows us to estimate betas for *individual* stocks, rather than a cross-sectional average beta, which in turn enables us to link the behavior of betas to firm-specific characteristics and to better understand the dynamics of the behavior of beta around firm-specific information flows. Also related to our research question is work by Vijh (1994) and Barberis *et al.* (2005), who study changes in a stock's beta following additions to the S&P 500 index. These papers, however, examine changes in beta that are estimated over long horizons and are driven by a single event in the life of a stock.

Our analysis also relates to previous studies on the impact of macroeconomic news announcements on asset prices and volatility, see, for example, Andersen *et al.* (2003a, 2007), Boyd *et al.* (2005), Piazzesi (2005) and Faust *et al.* (2007). Our analysis differs from these papers in our focus on the reaction of beta rather than prices or volatility, and in our focus on firm-specific news and individual stock returns rather than macroeconomic announcements and aggregate indices or exchange rates. In common with those papers, though, is the important role that price discovery plays: the changes in beta that we document may be explained by price discovery and learning by investors across different individual companies.

The remainder of the paper is structured as follows. In Section 2 we review the econometric theory underlying our estimation of daily firm-level beta using high frequency data. Section 3 describes the data used in our analysis and its sources, Section 4 presents our main empirical results, and Section 5 presents robustness tests. Section 6 presents a simple theoretical model of investors' expectations formation using earnings announcements. We conclude in Section 7.

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) and Barndorff-Nielsen and Shephard (2004).[4] This

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

theory enables us to obtain an estimate of beta for an individual stock on each day, which means we can analyze the dynamic behavior of beta with greater accuracy and at a higher frequency than was possible in earlier work on the dynamics of systematic risk[5].

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, $\mathbf{W}(t)$ is a standard vector Brownian motion, 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 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 $I\beta_{it}$

[5] Work on time-varying systematic risk using lower frequency data or alternative methods includes Robichek and Cohn (1974), Ferson, *et al.* (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.* (2006) and Todorov and Bollerslev (2007), though the focus and coverage of those papers differ from ours. Christoffersen, *et al.* (2008) present a novel method for obtaining betas from option prices at a daily frequency.

is the "integrated beta" of asset i.[6] The integrated covariance matrix can be consistently estimated (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[7].

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

$$
R\beta_{it}^{(S)} \equiv \frac{RCov_{imt}^{(S)}}{RV_{mt}^{(S)}} \tag{8}
$$

$$
\sqrt{S}\left(R\beta_{it}^{(S)} - I\beta_{it}\right) \xrightarrow{D} N\left(0, W_{it}\right), \quad \text{as } S \to \infty \tag{9}
$$

When the sampling frequency is high (S is large), but not so high as to lead to problems coming

[6] An alternative definition of "integrated beta" is the integral of the ratio of the spot covariance to the spot market variance. In the presence of intra-daily heteroskedasticity this quantity will differ from that defined in equation (3), see Dovonon, *et al.* (2008) for example. We elect to use the definition given in equation (3) as it fits directly into the theoretical framework of Barndorff-Nielsen and Shephard (2004).

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

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:

$$R\beta_{it}^{(S)} = I\beta_{it} + \epsilon_{it}, \qquad (10)$$
$$\text{where} \ \ \epsilon_{it} \overset{a}{\sim} N\left(0, W_{it}/S\right).$$

With the above result, inference on integrated betas can be conducted using standard OLS regressions (though with autocorrelation and heteroskedasticity-robust standard errors), and more familiar "long span" asymptotics ($T \to \infty$), rather than the "continuous record" asymptotics ($S \to \infty$) of BNS.

One advantage of a regression-based approach is that it allows for the inclusion of control variables in the model specification, making it possible 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. Such effects are of critical importance in a study utilizing high frequency data, such as ours, and we treat this issue very seriously. One example of such an issue arises when estimating the beta of a stock which trades only infrequently relative to the market portfolio, which 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 way 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 main empirical analyses. 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.[8] This estimator is more difficult to implement, but may be 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.

To further address potential microstructure effects on our estimates of realized betas we include a number of control variables in our panel regression specification. Details on these control variables are presented in Section 4.2 below.

2.3 "Variance" and "covariance" components of beta

The goal of our study is to understand the dynamics of beta around firm-specific information flows. Given that the firms in our sample are constituents of the index that 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. We could therefore observe an increase in beta around announcement dates coming solely from an increase in the volatility of the stock's return, since it is well-known that the volatility of stock returns is higher than average on announcement dates, see Ball and Kothari (1991) for example.

We thus 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 identify changes in "total" beta that are due to a movement in the variance of a stock's returns, and changes that are driven instead by a movement in the covariance of a stock's returns with the returns of other stocks. To make things concrete, consider a market index constructed as a weighted-average of N individual stocks, with return described by:

$$r_{mt} = \sum_{j=1}^{N} \omega_{jt} r_{jt}. \tag{11}$$

[8] 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.

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

$$\begin{aligned}
\beta_{it} &\equiv \frac{Cov\left[r_{it}, r_{mt}\right]}{V\left[r_{mt}\right]} \\
&= \omega_{it}\frac{V\left[r_{it}\right]}{V\left[r_{mt}\right]} + \sum_{j=1, j\neq i}^{N} \omega_{jt}\frac{Cov\left[r_{it}, r_{jt}\right]}{V\left[r_{mt}\right]}. \qquad (12)
\end{aligned}$$

Note that if firm i is not a constituent of the market index then $\omega_{it} = 0$, and the firm's 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.[9]

A corresponding result also holds for realized beta:

$$\begin{aligned}
R\beta_{it} &\equiv \frac{RCov_{imt}}{RV_{mt}} \qquad (13) \\
&= \omega_{it}\frac{RV_{it}}{RV_{mt}} + \sum_{j=1, j\neq i}^{N} \omega_{jt}\frac{RCov_{ijt}}{RV_{mt}} \\
&\equiv R\beta_{it}^{(var)} + R\beta_{it}^{(cov)}.
\end{aligned}$$

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 from 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 realized betas using high frequency prices from the TAQ database for each of the 3014 trading days in our sample period. 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.

[9] These definitions are justified to the extent that both $V\left[r_{it}\right]$ and $Cov\left[r_{it}, r_{jt}\right]$ have a negligible impact on $V\left[r_{mt}\right]$. This will be true if the weight of any individual stock in the index is small, as the impact of $V\left[r_{it}\right]$ and $Cov\left[r_{it}, r_{jt}\right]$ on the market variance is of the order of the weight squared, i.e., a lower order of magnitude.

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. We combine these returns with the overnight return, computed between 4:00pm on the previous day and 9:45am on the current day,[10] yielding a total of 16 intra-daily returns. We choose a 25-minute frequency to measure returns to balance the desire for reduced measurement error with the need to avoid the microstructure biases that arise 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 (yielding 76 intra-daily price observations), and betas that are obtained using the Hayashi-Yoshida (2005) estimator.

The prices we use are the national best bid and offer prices, computed by examining quote prices from all exchanges offering quotes on a given stock.[11] 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, and available on the TAQ database) to measure the market return, as in Bandi *et al.* (2006) and Todorov and Bollerslev (2007).[12] 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. We finally compute daily realized betas as the ratio of a stock's covariance with the index to the variance of the index over a given day, as in equation (8). To reduce the impact of outliers in our sample, we delete observations that lie outside the 0.1% and 99.9% quantiles of the sample distribution of realized betas.[13]

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 period, 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. Moreover, to identify announcement dates as accurately as possible and limit the possibility of

[10] 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 at 9.45am.

[11] 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 pair of quotes.

[12] See Elton, *et al.* (2002) and Hasbrouck (2003) for studies of the SPDR.

[13] We find that our results are largely unchanged when using 0.01%/99.99% or 0.5%/99.5% quantiles as cut-offs.

errors, we only consider quarterly announcements for which the distance between COMPUSTAT and IBES dates is no greater than two days.[14]

Our combination of IBES and COMPUSTAT databases provides only the date 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. Without further assumptions, currently available data do not allow us to distinguish between these two dates. For a shorter span of time (2000-2003), Bagnoli, et al. (2005) use the Reuters Forecast Pro database, which contains both the date and time of an earnings announcement, in their study of strategic announcement times. Using their Table 1, we compute that 76% of their sample of around 4000 firms announce between midnight and 4pm.

Our 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.[15]

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 for the entire sample, we illustrate here an example of the behavior of beta around news announcements using two stocks.

[14] 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.

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

In Figure 1 we plot estimates of the change in market beta for Microsoft and Merck during a 21-day window centered around quarterly earnings announcements. The change in beta is computed relative to days outside this 21-day window. The estimates and confidence intervals are based on the 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 beta 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 event date. We observe an increase in beta on the earnings announcement date (event day 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: We observe a change in beta of 1.12 on event day 1,[16] which is both 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 Panel estimation method and specification

To analyze changes in realized betas for the entire sample of stocks we use a panel regression approach. We regress realized betas on event day dummies and control variables, using the following

[16] For Microsoft and several other stocks in the High Tech sector announcements appear to take place after 4pm, and so the largest impact appears on the following trading day (event day +1). For other stocks, such as Merck, announcements appear to take place before 4pm, and so the largest impact occurs on the same trading day (event day 0).

specification:

$$R\beta_{it} = \delta_{-10}I_{i,t+10} + ... + \delta_0 I_{i,t} + ... + \delta_{10}I_{i,t-10} \quad (14)$$
$$+\gamma_{i1}D_{1t} + \gamma_{i2}D_{2t} + ... + \gamma_{i12}D_{12t} + \boldsymbol{\gamma}'\mathbf{X}_{it} + \varepsilon_{it},$$

where $R\beta_{it}$ is the realized beta of stock i on day t, and $I_{i,t}$ are dummy variables defined over a 21-day event window around earnings announcements: $I_{i,t} = 1$ if day t is an announcement date for firm i, $I_{i,t} = 0$ otherwise. We allow for firm-year fixed effects in realized betas, to capture differences in betas across stocks, as well as low-frequency changes in beta for a given stock. These effects are captured through the variables D_{1t} to D_{12t}, which are dummy variables for each of the 12 years in the sample (1995 to 2006).

We also add a vector of control variables in our specification, $\mathbf{X}_t = \left[R\beta_{it-1}, \widehat{RV_{it}}, \, Volume_{it}\right]'$, which includes the lagged realized beta $R\beta_{it-1}$, the volatility of stock i on day t, $\widehat{RV_{it}}$, instrumented using lagged volatility and the event-day dummies, the trading volume of stock i on day t. We include lagged realized betas in the regression to account for autocorrelation in realized betas, see Andersen, *et al.* (2006b) for example, and a control for volatility, given existing empirical evidence that volatility can affect covariance estimates (Forbes and Rigobon (2002)). Further, 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. In Section 5 we confirm that our results are robust to also including the square and cube of volume as control variables, which allows for a nonlinear relation between volume and any bias present in the realized beta estimates.

We estimate the panel regression by allowing the observations to be clustered on any given day, following Wooldridge (2002, 2003) and Petersen (2009).[17] The estimation of panel data with clusters yields standard errors that are robust to heteroskedasticity and to any form of intra-cluster

[17] The number of days in our sample with at least one earnings announcement is 2366. The average number of announcements per day is 9.5, and the median is 4 announcements.

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 3014 days.[18]

From our regression specification, we can detect changes in betas during times of news announcements by testing the following hypotheses:

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

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 variables.

First, we consider 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. Next, we sort stocks based on their 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. Third, we group stocks into five industries on the basis of their 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. Fourth, we sort stocks into quintiles according to their 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.

[18] 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 (2009) and Thompson (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.

Our fifth sorting variable is "residual analyst coverage", defined as a stock's analyst coverage orthogonalized 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.

Next, we consider "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 beta 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.

Finally, our seventh sort is based on 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.

4.3 Results for the entire sample

In Table 2 and Figure 2 we present estimated changes in beta during a 21-day 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. On average, beta experiences 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 above its non-announcement average level. Beta then continues to decrease on day 2, to -0.03 below its average level. Over the next few days beta reverts back to its non-event average and the estimated coefficients are not significantly different from zero.[19]

How much of this increase in beta is attributable to a change in the covariance among stock returns during earnings announcements rather than to an increase in the return volatility of announcing companies? Our results suggest that the change in realized beta is mostly driven by a change in covariances: the covariance component of beta increases by 0.07 (t-statistic of 6.53) 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 also learn about the earnings of non-announcing firms, thus causing their stock prices to move in the same direction as that of the announcing firm.

4.4 A more detailed look at the changes in beta

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

[19] Our estimate of the change in beta on day 0 is comparable to that of Ball and Kothari (1991), who estimate cross-sectional regressions of stock excess returns on market risk premia using a sample of 1,550 firms during the period 1980-1988, and find that, on average, betas increase by 0.067 over a 3-day window around earnings announcements (relative to the average beta computed over the previous 9 days).

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 one example of the great degree of heterogeneity across all the different stocks in our sample. To be able to summarize our disaggregated findings in a meaningful way, we examine changes in betas for separate groups of stocks that share similar characteristics.

We consider two types of variables to aggregate firms into different groups. The first type 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 characterizes 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 (captured by 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 13). 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 announcements (0.08 for growth stocks and 0.09 for value stocks), as shown in Table 4 and Figure 4. However, the covariance components of beta show substantial differences: 0.05 for growth stocks and 0.08 for value stocks, suggesting that changes in covariances are the main determinants of changes 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 the increase in beta is 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.[20]

Finally, Table 6 and Figure 6 present estimation results for changes in beta across stocks with different levels of turnover (in the two months prior to the earnings announcement), a common measure of the liquidity of a stock, see Korajczyk and Sadka (2008) for a recent study. We find that 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 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 announcements by more liquid stocks.

4.4.2 Results by characteristics of the information environment

In this section 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, see Brennan *et al.* (1993), for example. We test whether changes in betas upon news releases are associated with residual analyst coverage (analyst coverage orthogonalized with respect to market capitalization, to remove the effect that larger firms tend to have greater analyst coverage). The estimates in Table 7 and Figure 7 suggest that stocks with

[20] 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.

low analyst coverage experience the smallest changes in beta during earnings announcements. The change in beta increases with analyst coverage monotonically until the fourth quintile (0.05 to 0.12), and is lower for stocks with the highest analyst following (0.07), although it is compensated by a substantial increase observed the day after the announcement. The coefficient estimates show that the change in beta is mostly driven by a change in the covariance component of realized beta.

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 earnings surprise, standardized by the stock price. Table 8 and Figure 8 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 large surprises (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), thus our results show evidence of an asymmetric pattern in beta changes − good news has a stronger impact on beta than bad news. It is also 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).

Finally, we analyze cross-sectional differences in beta changes related to investors' ex-ante uncertainty or disagreement about future earnings, measured 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 9. 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 of changes in beta increases monotonically from 65% to 89% as uncertainty increases.[21]

Taken together, these findings suggest that the positive change in beta observed on earnings announcement days is larger when a stock is followed by more analysts, when the announcement

[21] These results are confirmed when we use an alternative measure of uncertainty about earnings. We estimate the standard deviation of a stocks' growth rate of earnings, and use it 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 both larger changes in beta, and larger fractions explained by the covariance component of beta.

has a larger information content (regardless of whether it represents good news or bad news), and when there is more ex-ante uncertainty or disagreement about the information to be released in the future. Furthermore, from the decomposition of our estimates of realized beta into variance and covariance components, we can conclude that strong increases in betas on announcement days are driven by an increase in the average covariance of the return of the announcing firm with the returns of other stocks in the market index.

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 flows and systematic risk.

Table 10 and Figure 10 report changes in beta and changes in the covariance component of beta for the full sample of stocks in the two sample periods. 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 difference across the sub-samples.

The sub-sample analysis of stocks sorted by industry yields more interesting results, see Table 11 and Figure 11. 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 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 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. These results are suggestive of the idea that, in the time around the tech bubble, high tech firms may have been viewed as "bellwethers", carrying information about the broader "new economy". Thus good (bad) news for these firms may, in that period, have been interpreted more strongly as good (bad) news for other firms, thus leading to an increase in the average covariance among stock returns. We develop this idea in Section 6 of the paper. 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 period, and only the manufacturing sector shows an increase in 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 exhibit 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 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. As a further robustness test, we modify our regression specification to allow for a non-linear relationship between realized betas and trading volume.

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 proportions 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 covariance developed by Hayashi and Yoshida (2005) to handle the problem of non-synchronous trading. Non-synchronous trading leads realized covariances, and thus betas, 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 prices sampled at very high frequencies. We implement the HY estimator on 16 different sampling frequencies, ranging from 1 second to 30 minutes, and choose the optimal sampling frequency for each firm as the one that generates the HY covariance that is closest in absolute value to the covariance computed from daily returns (i.e., the one that minimizes the bias in the HY estimator). This is almost always *not* the highest frequency, consistent with Griffin and Oomen (2006). We combine our "optimal" HY estimator of the covariance with the realized variance of the market using 5-minute prices, and use 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 changes in beta over the event window are remarkably similar to those obtained from the basic regression using 25-minute betas. Changes in betas are slightly larger relative to our main empirical results (0.086 versus 0.084 on day 0, for example), but not uniformly or substantially. We thus conclude that our initial results using 25-minute betas are not much changed by using a more sophisticated estimator of beta.

5.3 Realized beta and trading volume

The last two columns of Table 12 report coefficient estimates of changes in realized betas and changes in the covariance component of beta when we add the square and cube of volume as control variables, to capture a possible nonlinear relationship between any bias in realized beta and the trading volume on a given day. The results show that the estimates of changes in beta with these nonlinear terms included are almost unchanged from our base specification.

6 A model of earnings announcements and expectations formation

In our empirical analysis we show that, on average, a stock's beta increases by a statistically and economically significant amount on its earnings announcement dates. We also show that most of this change in beta is driven by an increase in the covariance of the return of the announcing firm with the return of other firms in the market index. In this section we develop a simple model to understand how these changes in beta and in average covariances may arise. The firms studied in Section 4 announce their earnings only quarterly, roughly every 66 trading days. If stock prices are linked to expectations about future earnings, then in 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 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.[22]

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.[23]

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 taken as a growth rate over the past M days, which simplifies 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, and so 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

[22] 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.

[23] 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).

extreme form of heteroskedasticity:

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

where $I_{it}=1$ if day t is an announcement date for firm i and $I_{it}=0$ else, and $\sigma_I^2\to\infty$. 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:

$$\begin{aligned}\Delta\log\mathbf{X}_t &= \mathbf{g}+\boldsymbol{\gamma}Z_t+\mathbf{u}_t &(21)\\ \mathbf{y}_t &= \sum_{j=0}^{M-1}\Delta\log\mathbf{X}_{t-j}+\boldsymbol{\eta}_t &(22)\end{aligned}$$

where $\Delta\log\mathbf{X}_t=\left[\ \Delta\log X_{1t},...,\ \Delta\log X_{Nt}\right]'$, $\mathbf{g}=\left[g_1,...,g_N\right]'$, $\boldsymbol{\gamma}=\left[\gamma_1,...,\gamma_N\right]'$, $\mathbf{u}_t=\left[u_{1t},...,u_{Nt}\right]'$, $\mathbf{y}_t=\left[y_{1t},...,y_{Nt}\right]'$ and $\boldsymbol{\eta}_t=\left[\eta_{1t},...,\eta_{Nt}\right]'$. 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 I_N is an $N\times N$ identity matrix, $R=diag\left\{\left[\sigma_{\eta1}^2,\sigma_{\eta2}^2,...,\sigma_{\eta N}^2\right]\right\}$ and $\Gamma_t=diag\left\{\mathbf{I}_t\right\}$, where $diag\left\{\mathbf{a}\right\}$ is a diagonal matrix with the vector $\mathbf{a}$ on the main diagonal.

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 firm 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 $\sigma_{\eta i}^2$), while in between announcement dates it will efficiently combine information on firm i's earlier announcements with information on announcements by other firms.

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:[24]

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

[24] 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.

Substituting the above into our pricing equation, we obtain:

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

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

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

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.[25] In one of our comparative statics exercises we show the reactions in beta to news when $M = 12$ and $M = 6$. In all cases we simulate $T = 1000$ days,[26] 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

[25] 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 the variance component of beta around earnings announcements.

[26] We simulate daily data rather than intra-daily data purely for simplicity. Simulating high-frequency data would, as in reality, allow us to obtain more accurate estimates of betas, but we would then need to specify a model for high-frequency returns. To avoid this, we simply simulate a longer time series ($T = 1000$) of daily returns.

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 variations in beta due to 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 returns is explained by changes in expectations about future earnings. We vary this parameter between 0.01 and 0.04 in comparative statics.[27] This is close to the figure presented by Imhoff and Lobo (1992), who found a value of around 0.03 in their study of the relation between unexpected returns and earnings surprises in the 1979-1984 period.

In Figure 12 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 12 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

[27] 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 does not change for $\sigma_\varepsilon^2 > 0$, but the magnitudes of such changes are brought closer to zero for larger values of σ_ε^2.

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 12 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.

We next present some comparative statics varying the four main parameters in our model. In Figure 13 we consider varying R_z^2, the proportion of earnings innovations w_{it} that comes from the common component, 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 13 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 to larger responses in betas to earnings announcements.

In Figure 14 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 14 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.

In Figure 15 we vary the number of days between earnings announcements. We are computationally constrained to keep M no larger than 25, and in Figure 15 we consider reducing it to 12 days or 6 days. Of course, with fewer days between announcements our "event window" must also decrease, to ± 5 days and ± 2 days around announcements respectively. This figure shows that more frequent announcements lead to less reactions in beta around announcements, which is consistent with the intuition that in such environments earnings announcements carry less information: earnings news is released in frequent small quantities, rather than in infrequent "lumps".

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 12 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 empirically study whether the systematic risk of an individual firm, measured by its CAPM beta, changes during times of firm-specific information flows. We focus on earnings announcements as an example of such information flows, as they are regular and well-documented, and we 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 lower frequencies, such as monthly or quarterly.

Using intra-daily data for all companies in the S&P 500 index over the period 1995-2006 (a total of 810 distinct firms and 22,575 earnings announcements), we find that betas increase on announcement days by a statistically and economically significant amount, and decline on post-announcement days before reverting to their long-run average levels. 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 more "surprising" announcements (positive or negative) than for announcements closer to consensus expectations. Furthermore, the increase in beta around news announcements is larger when investors' ex-ante uncertainty, measured by analyst forecast dispersion, is higher. We also find important differences in changes in beta around news announcements across different industries: stocks in the high tech sector experience large increases in beta, particularly during the "tech bubble", whereas stocks in the health sector show almost no change in beta during news releases.

By decomposing a stock's beta into a "variance" component and a "covariance" component, we isolate the mechanical increase in beta that results from an increase in the announcing stock's volatility on announcement days. 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, and explains most of the increase in betas.

To help understand the sources of the changes in beta, we present a simple model of investors' expectations formation in the presence of intermittent earnings announcements and cross-sectionally correlated earnings. In such an environment, good (bad) news for announcing firms is interpreted as partial good (bad) news for other firms, which raises the average covariance of the return on the announcing firm with the returns on the other firms, and leads to a higher market beta. Thus the documented changes in beta around information flows may be explained by learning and price discovery by investors, which creates short-lived increases in covariances and betas around announcement dates. This interpretation of our empirical results is supported by the cross-sectional variations in beta reactions that we observe: Changes in beta are generally strongest in cases where the most learning is possible, such as for stocks with greater liquidity and higher visibility, and for earnings announcements that represent large (positive or negative) surprises or that resolve a larger amount of uncertainty.

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Table 1 - Panel A: Descriptive statistics

This table presents descriptive statistics of the sample 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 90 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 90-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	-0.023	0.008	10.42
1996	9.99	5.05	0.52	0.36	0.076	0.004	0.006	10.02
1997	13.19	6.09	0.46	0.40	0.106	0.005	0.008	10.33
1998	16.83	7.26	0.43	0.43	0.057	-0.026	0.010	10.74
1999	21.22	7.88	0.44	0.46	0.051	0.033	0.018	11.35
2000	24.10	7.61	0.53	0.56	0.048	0.026	0.017	11.02
2001	21.21	7.94	0.49	0.65	0.016	0.021	0.017	12.91
2002	18.10	7.49	0.54	0.73	-0.056	0.015	0.027	12.77
2003	17.69	7.55	0.60	0.69	0.146	0.033	0.034	12.05
2004	20.85	9.32	0.52	0.65	0.067	0.052	0.039	12.85
2005	22.37	10.84	0.47	0.68	0.033	0.033	0.040	12.88
2006	24.47	12.35	0.46	0.75	0.064	0.082	0.053	13.10
Average	18.16	7.80	0.50	0.56	0.060	0.021	0.023	11.70

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, non-durables, wholesale, retail, and some services (laundries, repair shops)); 2. *Manufacturing* (manufacturing, energy, and utilities); 3. *High Tech* (business equipment, telephone and television transmission, computer programming and data processing, computer integrated systems design, computer processing, data preparation, computer facilities management service, computer rental and leasing, computer maintenance and repair, computer related services, research, development, testing labs); 4. *Health* (health care, medical equipment, and drugs); 5. *Other* (mines, construction, building maintenance, transportation, hotels, business services, entertainment, finance).

Industry classification	**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

Notes to Tables

Table 2 presents coefficient estimates for changes in realized beta and changes in the covariance component of beta around earnings announcements. The estimates are obtained from a panel regression of daily realized betas (or covariance components of realized betas) on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions include a stock's volume, lagged beta, and volatility as control variables, and account for firm and year fixed effects. t-statistics are computed from standard errors that are robust to heteroskedasticity and to arbitrary intra-day correlation.

Tables 3 to 9 present coefficient estimates for changes in realized beta 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 estimates are obtained from a panel regression of daily realized betas (or covariance components of realized betas) on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions include a stock's volume, lagged beta, and volatility as control variables, and account for 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 estimates are obtained from a panel regression of daily realized betas (or covariance components of realized betas) on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions include a stock's volume, lagged beta, and volatility as control variables, and account for 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 robustness tests for changes in realized beta and changes in the covariance component of beta 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 estimates are obtained from a panel regression of daily realized betas (or covariance components of realized betas) on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions include a stock's volume, lagged beta, and volatility as control variables, and account for firm and year fixed effects. The dependent variables in the last two columns are the 25-minute realized beta and covariance component of realized beta (as in all previous tables). The regression specification includes the square and cube of volume as control variables. In all specifications, 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, full 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

	Realized beta					Covariance component				
Day	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

Day	Realized beta					Covariance component				
	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: Robustness tests

	5-minute beta		HY beta		Volume controls	
Day	Realized beta	Covariance	Realized beta	Covariance	Realized beta	Covariance
−10	-0.001	-0.001	-0.016	-0.016	-0.001	-0.001
	(-0.26)	(-0.26)	(-1.90)	(-1.89)	(-0.20)	(-0.22)
−9	0.003	0.003	-0.008	-0.008	0.000	0.000
	(0.55)	(0.56)	(-0.90)	(-0.89)	(-0.04)	(-0.01)
−8	0.005	0.005	0.002	0.002	0.004	0.004
	(0.85)	(0.88)	(0.21)	(0.22)	(0.52)	(0.51)
−7	0.003	0.003	-0.010	-0.010	0.008	0.008
	(0.61)	(0.61)	(-1.23)	(-1.23)	(1.10)	(1.12)
−6	-0.002	-0.002	0.002	0.002	-0.005	-0.005
	(-0.29)	(-0.31)	(0.25)	(0.24)	(-0.71)	(-0.68)
−5	0.009	0.010	0.009	0.009	0.011	0.011
	(1.78)	(1.79)	(1.03)	(1.05)	(1.68)	(1.68)
−4	0.008	0.009	0.005	0.005	0.006	0.006
	(1.63)	(1.64)	(0.58)	(0.60)	(0.92)	(0.95)
−3	0.008	0.008	0.000	-0.001	0.012	0.012
	(1.54)	(1.51)	(-0.04)	(-0.06)	(1.67)	(1.61)
−2	0.016	0.015	0.023	0.022	0.019	0.018
	(2.90)	(2.77)	(2.40)	(2.33)	(2.63)	(2.50)
−1	0.010	0.009	0.025	0.024	0.010	0.009
	(1.91)	(1.69)	(2.60)	(2.47)	(1.45)	(1.27)
0	0.072	0.059	0.086	0.072	0.084	0.068
	(8.70)	(7.05)	(7.01)	(5.85)	(8.02)	(6.49)
1	0.012	0.000	0.018	0.005	0.020	0.006
	(1.48)	(-0.01)	(1.62)	(0.48)	(2.04)	(0.62)
2	-0.027	-0.026	-0.021	-0.021	-0.028	-0.027
	(-4.75)	(-4.63)	(-2.50)	(-2.44)	(-3.88)	(-3.79)
3	-0.026	-0.025	-0.008	-0.008	-0.027	-0.027
	(-4.65)	(-4.59)	(-0.93)	(-0.90)	(-3.86)	(-3.86)
4	-0.018	-0.017	-0.006	-0.005	-0.016	-0.016
	(-3.41)	(-3.30)	(-0.65)	(-0.59)	(-2.44)	(-2.34)
5	-0.013	-0.012	-0.011	-0.010	-0.009	-0.009
	(-2.53)	(-2.35)	(-1.19)	(-1.10)	(-1.37)	(-1.25)
6	-0.012	-0.011	-0.003	-0.002	-0.011	-0.009
	(-2.54)	(-2.33)	(-0.31)	(-0.19)	(-1.59)	(-1.43)
7	-0.009	-0.009	0.007	0.007	0.000	0.001
	(-1.80)	(-1.70)	(0.75)	(0.81)	(0.07)	(0.18)
8	-0.008	-0.007	0.009	0.009	0.001	0.001
	(-1.45)	(-1.39)	(0.98)	(1.02)	(0.09)	(0.11)
9	-0.006	-0.005	0.016	0.016	-0.004	-0.004
	(-1.14)	(-1.06)	(1.71)	(1.75)	(-0.62)	(-0.56)
10	-0.008	-0.008	0.000	0.001	-0.002	-0.002
	(-1.73)	(-1.60)	(-0.02)	(0.06)	(-0.36)	(-0.27)

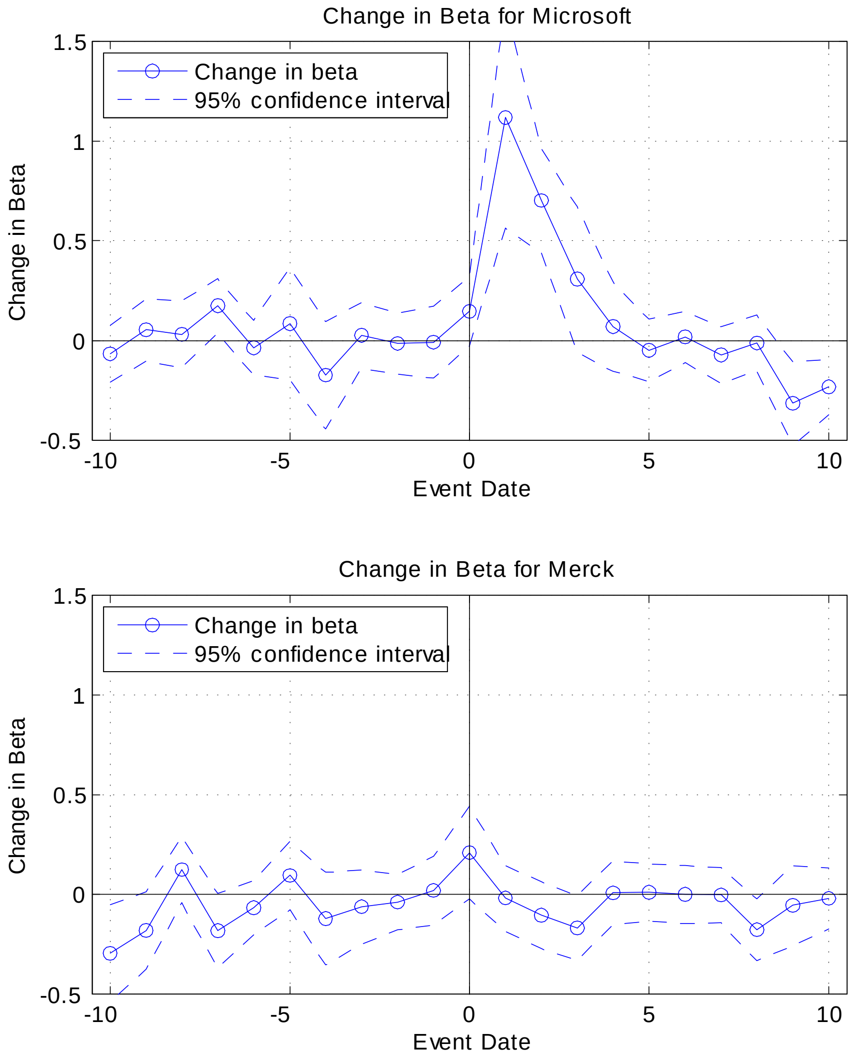

Figure 1: *Changes in estimated market beta of returns on Microsoft (top panel) and Merck (lower panel) on each of 21 days around quarterly earnings announcement dates, relative to days outside this 21-day window. Estimates are based on intra-daily prices sampled every 25 minutes, and the overnight return,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

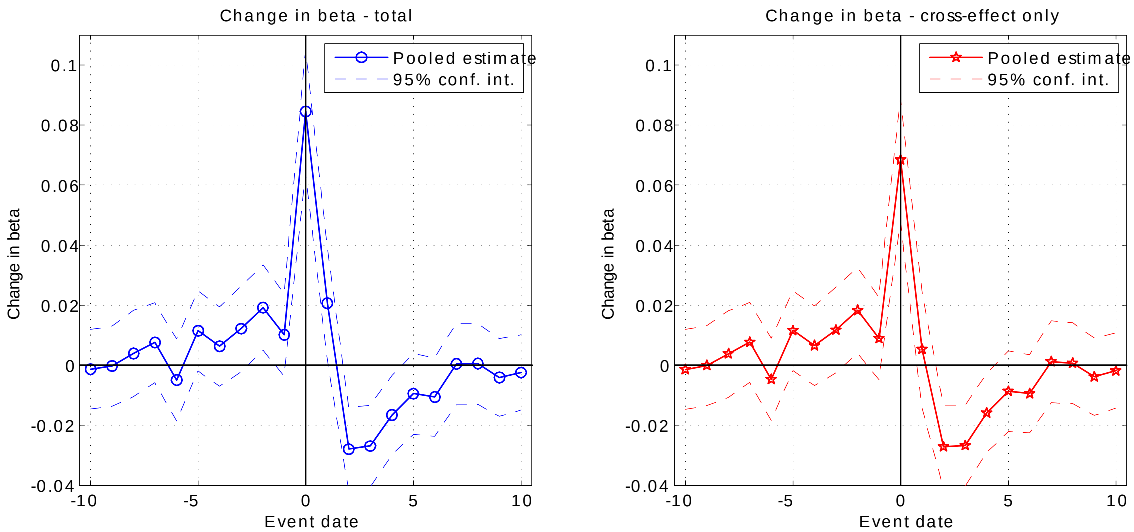

Figure 2: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) reported in Table 2. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed line.*

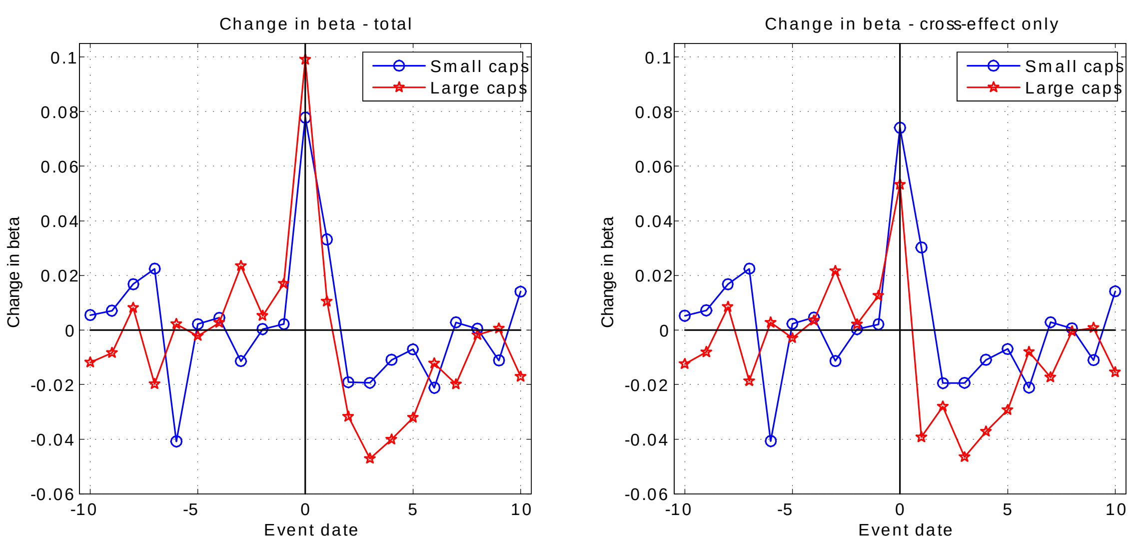

Figure 3: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the smallest and largest quintiles by market capitalization, as reported in Table 3.*

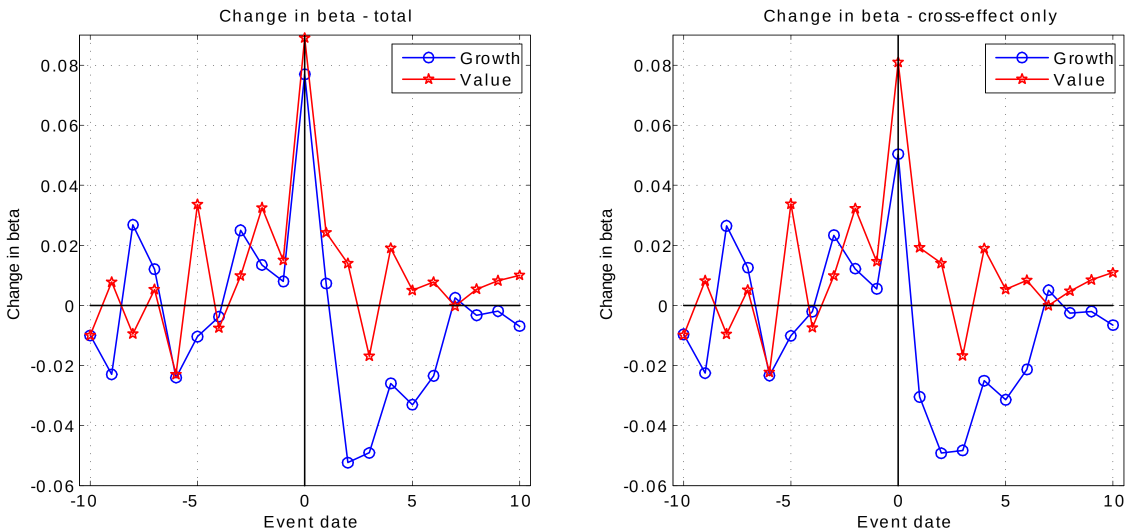

Figure 4: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by book-to-market ratio, as reported in Table 4.*

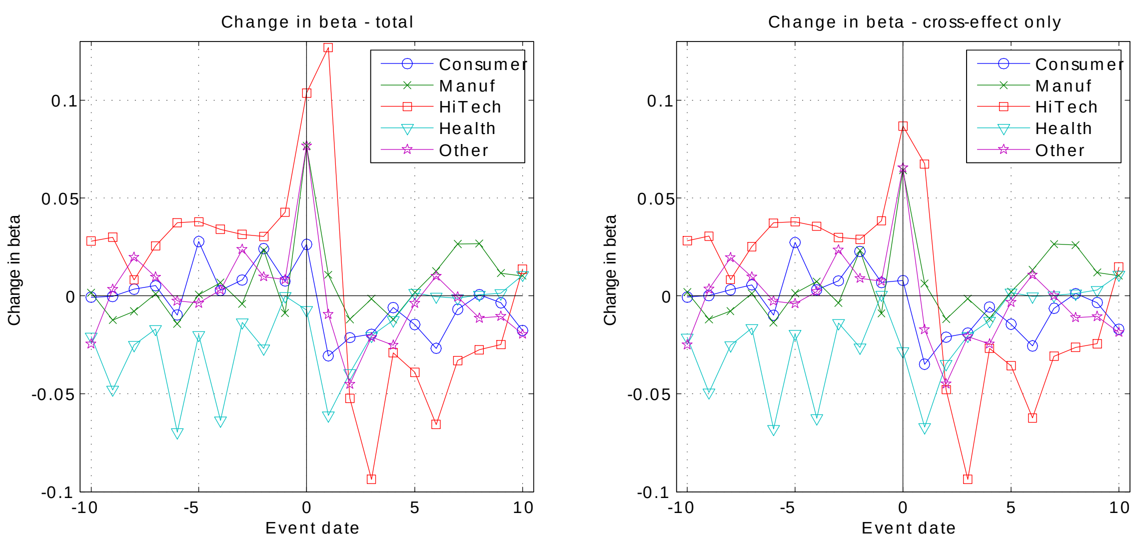

Figure 5: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the five industry groupings, as reported in Table 5.*

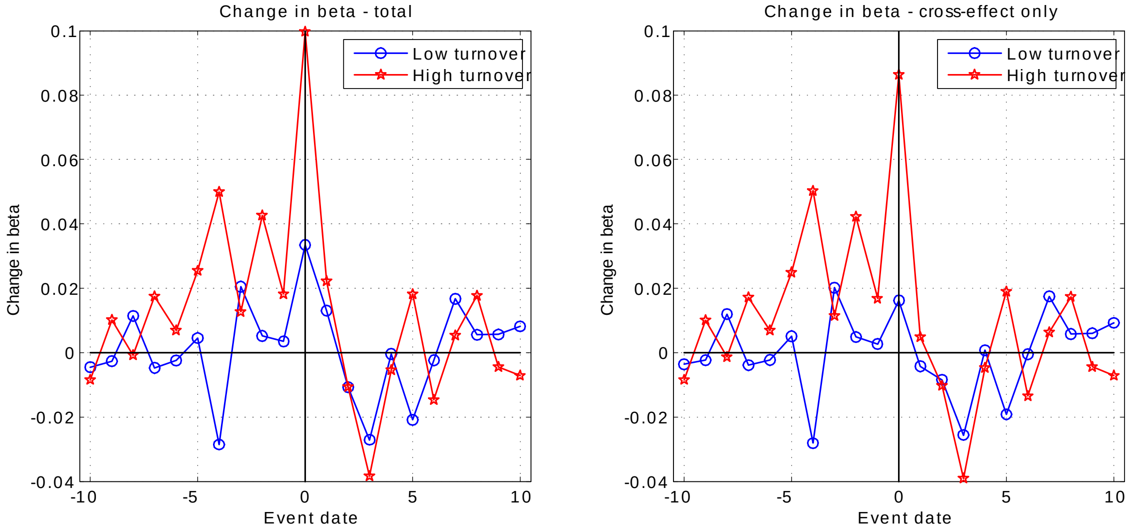

Figure 6: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by turnover, as reported in Table 6.*

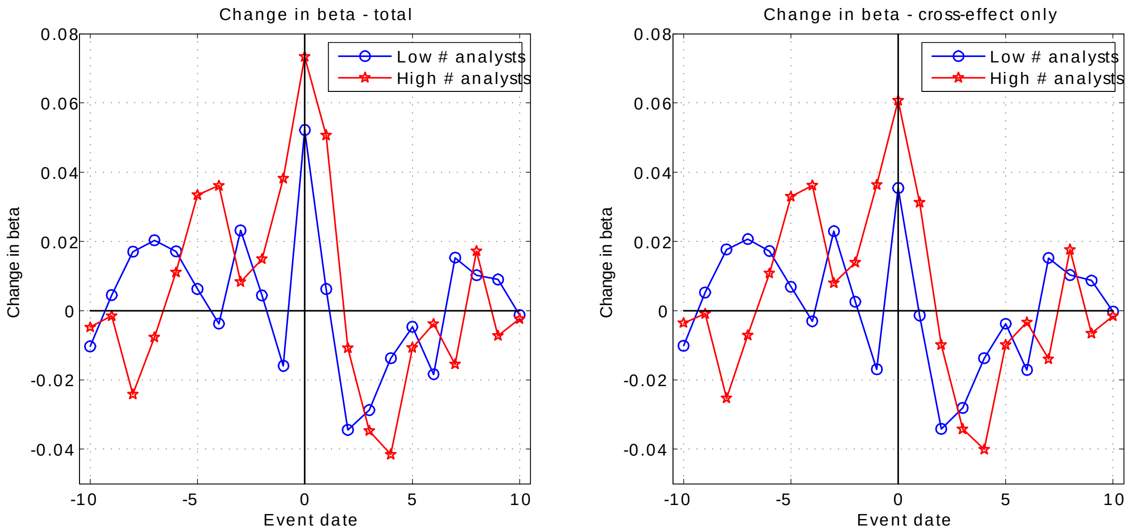

Figure 7: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by number of analysts, as reported in Table 7.*

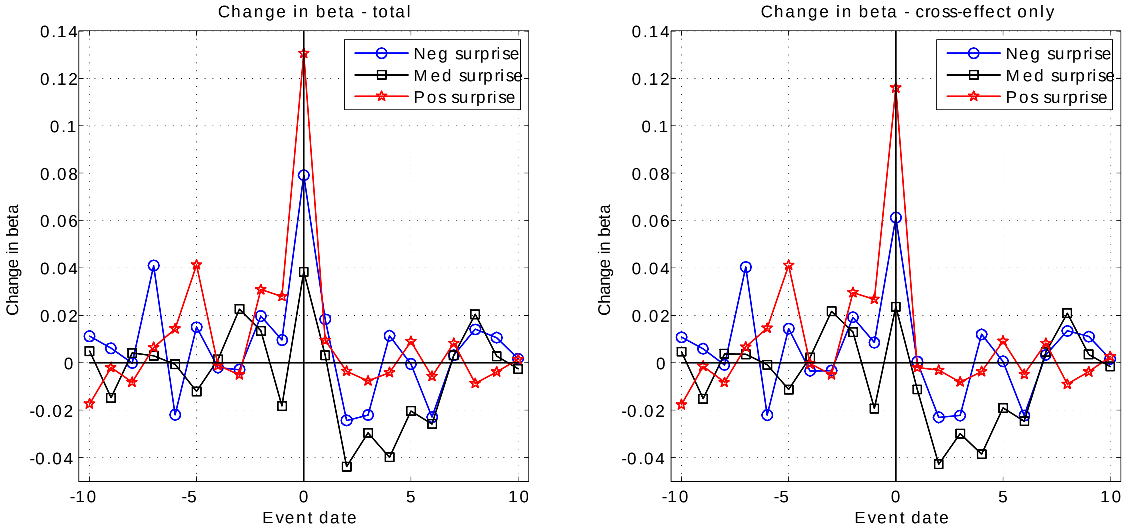

Figure 8: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by earnings surprise, as reported in Table 8.*

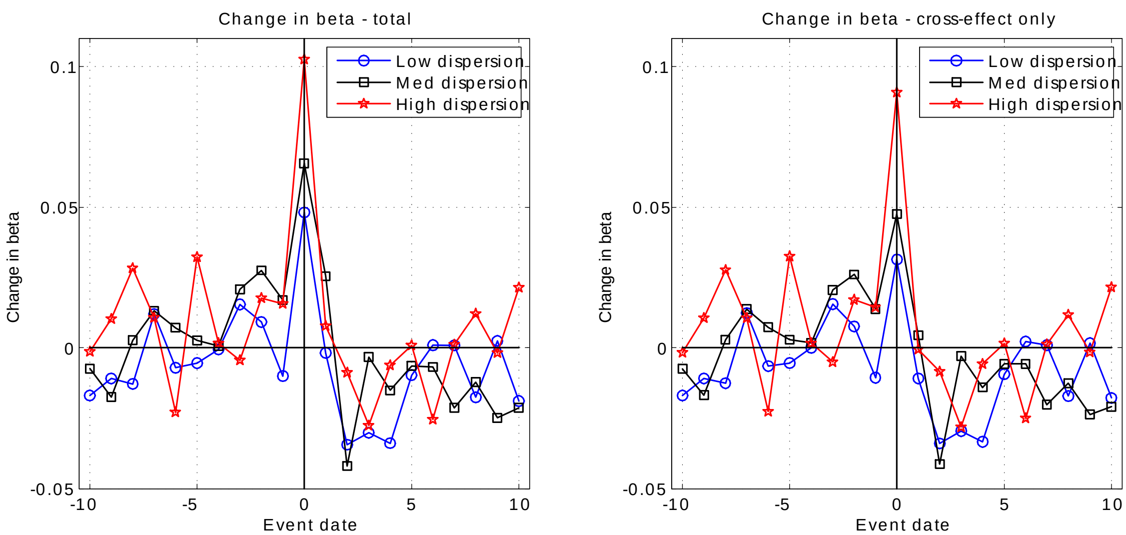

Figure 9: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by analyst forecast dispersion, as reported in Table 9.*

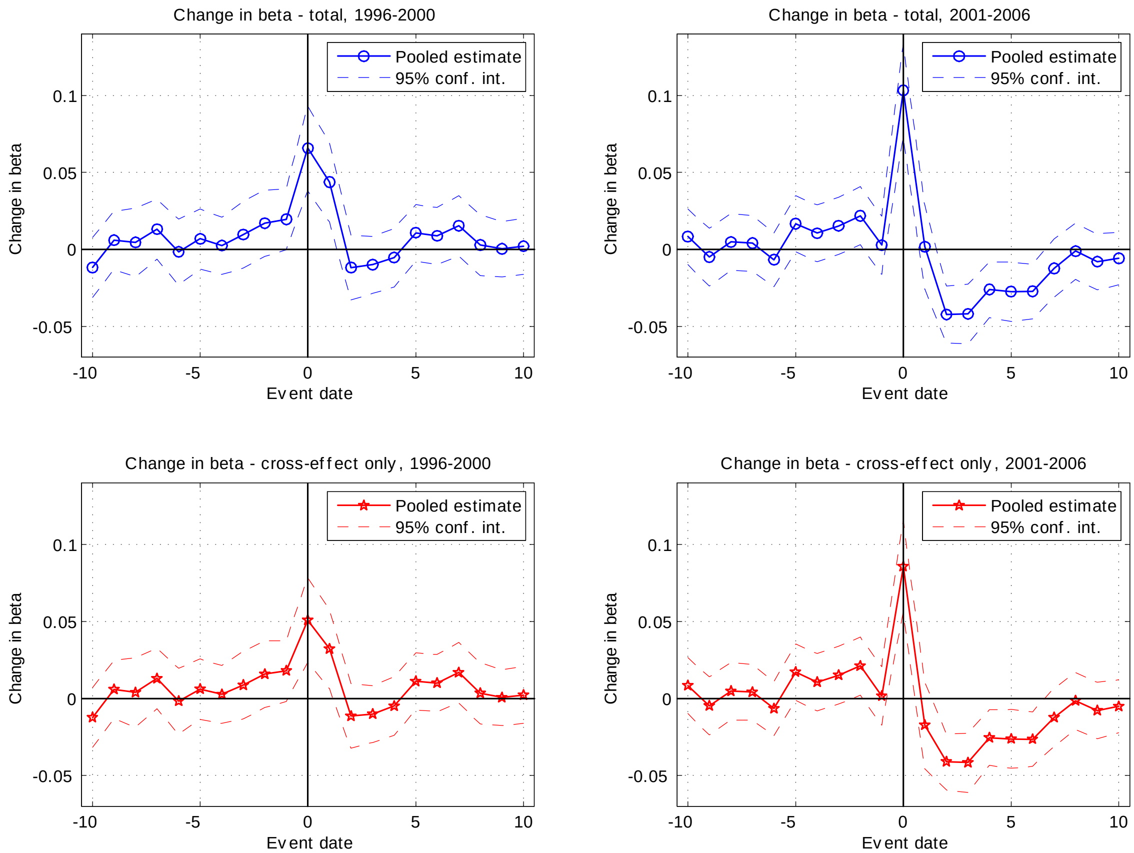

Figure 10: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) over two sub-samples, as reported in Table 10. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed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

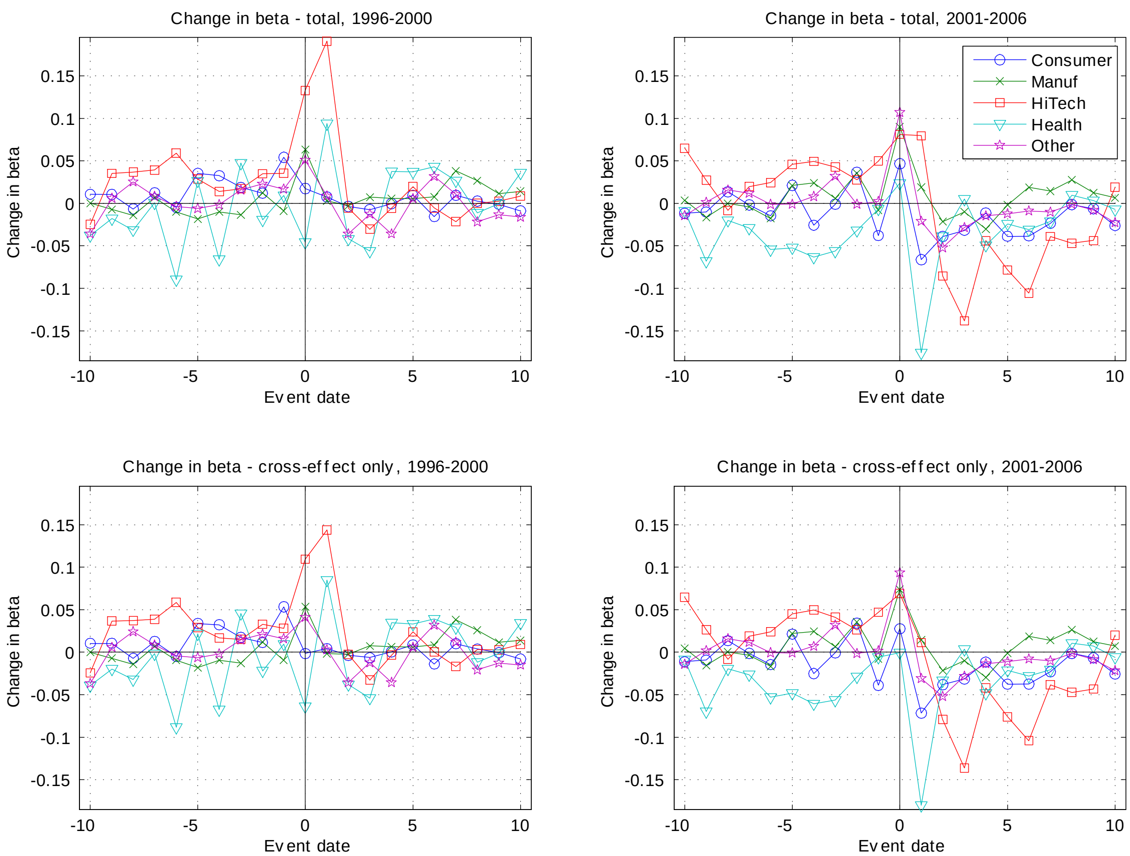

Figure 11: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) across two sub-samples, for the five industry groupings, as reported in Table 11.*

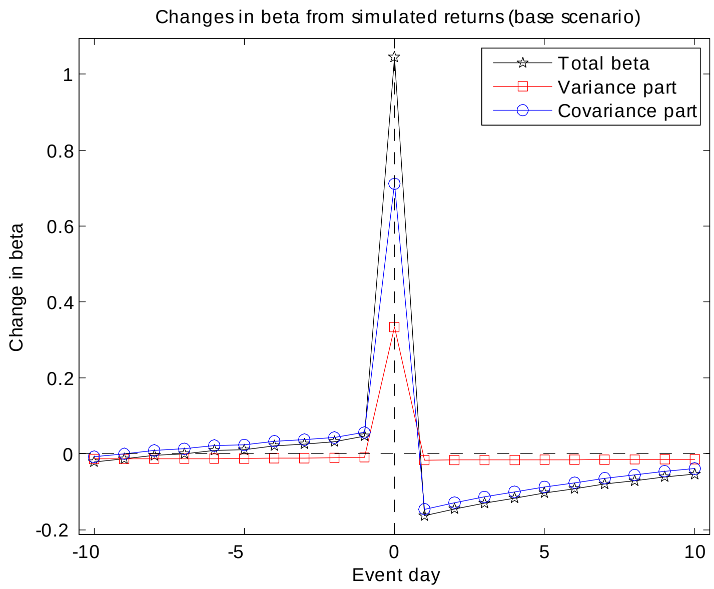

Figure 12: *Change in beta around event dates for benchmark scenario.*

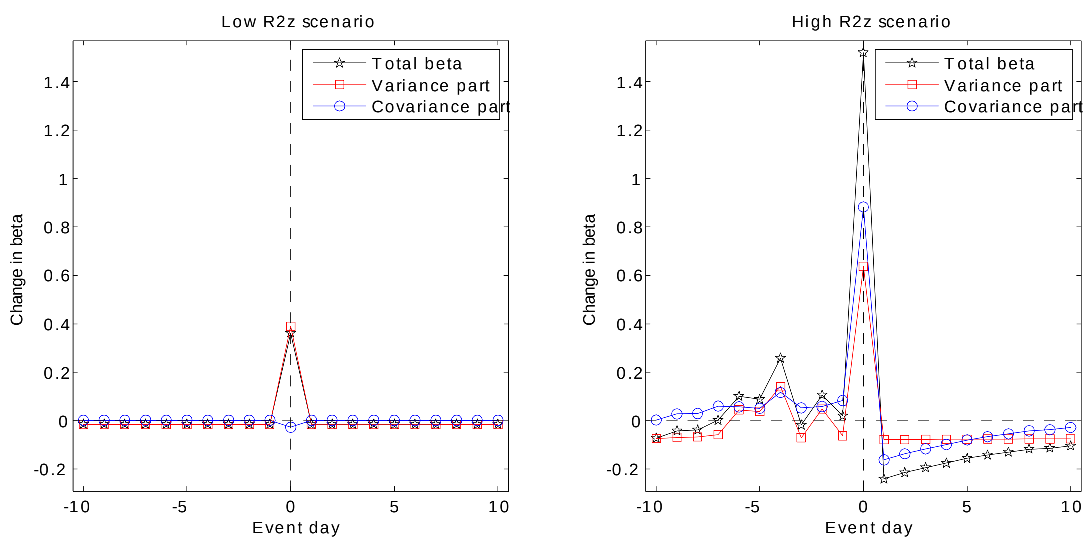

Figure 13: *Changes in beta around event dates for low and high values of the ratio of the variance of the common component in earnings innovations to total variance,* $R_z^2 = \sigma_z^2/\sigma_w^2$.

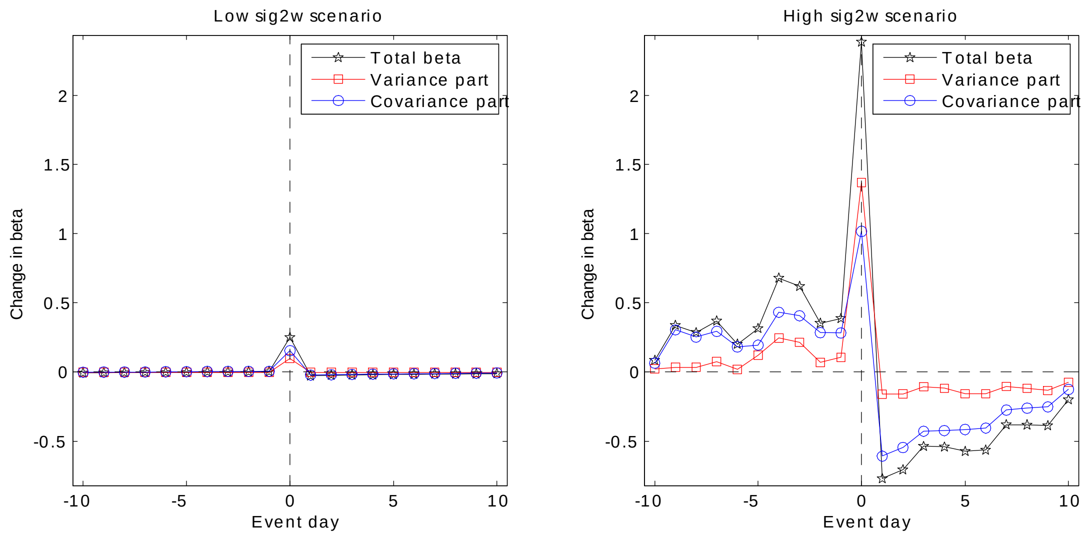

Figure 14: *Changes in beta around event dates for low and high values of the variance of earnings innovations,* σ_w^2.

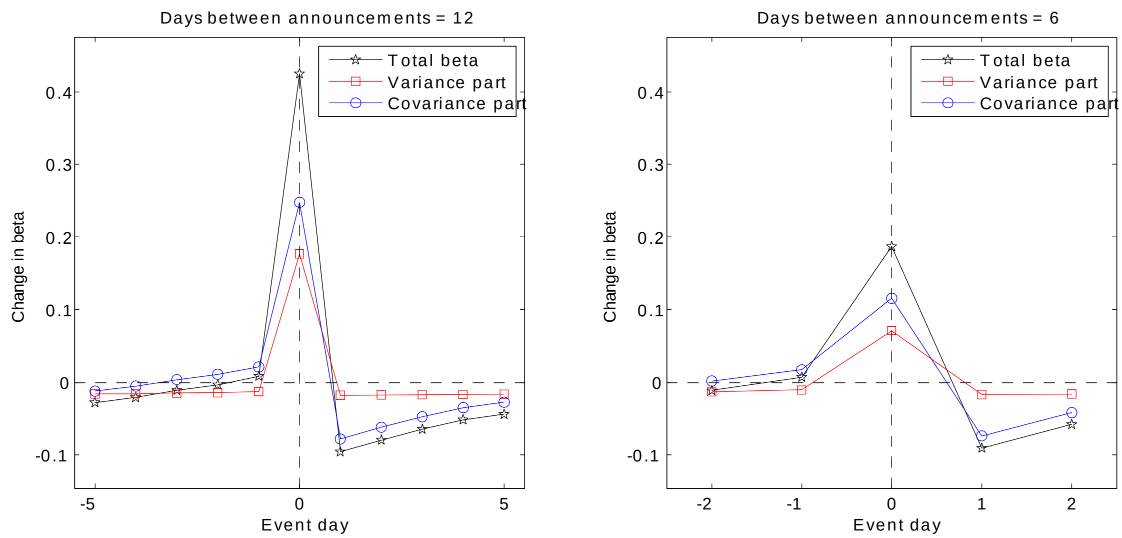

Figure 15: *Changes in beta around event dates when the number of days between announcements is lower.*

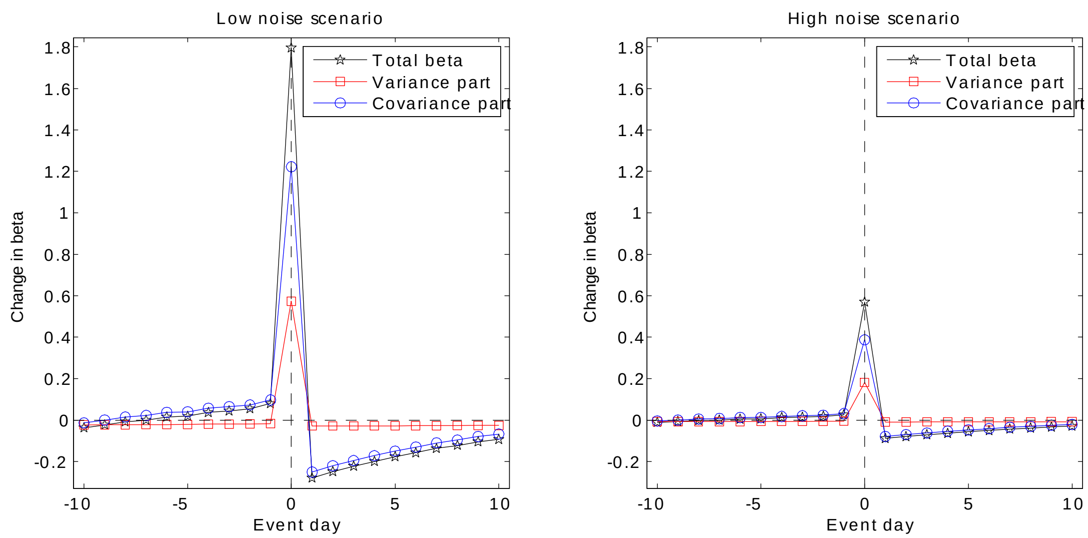

Figure 16: *Changes in beta around event dates for low and high values of the ratio of the variance of the part of daily returns* not *explained by changes in expectations about future earnings,* σ_e^2.