Does Beta Move with News?

Firm-Specific Information Flows and Learning about Profitability*

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Abstract

This paper finds that the betas of individual stocks increase by an economically and statistically significant amount on days of quarterly earnings announcements, and revert to their average levels two to five days later. This finding is based on estimates of daily, firm-level betas for all constituents of the S&P 500 index over the period 1996-2006, and nearly 18,000 earnings announcements. The increase in beta is greater for more liquid and more visible stocks, for larger earnings surprises, and for announcements that resolve greater uncertainty. We provide a simple model of investors' expectations formation that helps explain these 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: Earnings announcements, high-frequency data, realized volatility, comovement, realized covariance.

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

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1 Introduction

The covariation of a stock's return with the market portfolio, usually measured by its beta, is critically important for portfolio management and hedging decisions, and is of interest more widely as a measure of the systematic risk of the stock. Early empirical studies typically assume constant betas through time, while later analyses find significant evidence of variation in beta at monthly or quarterly frequencies, typically associated with variables related to the business cycle.[1] Empirical work on variations in beta at higher frequencies, associated with variables such as daily market conditions or news announcements, has been hampered by a lack of reliable data and by the econometric difficulties of studying such betas. In this paper we draw on recent advances in econometric theory and on a large database of high frequency prices to investigate whether *daily* betas of *individual* stocks vary with the release of firm-specific news. We uncover statistically significant and economically important variations in betas around news announcements. The variations we detect are short-lived (lasting around two to five days) and are thus difficult to detect using lower frequency methods.

Understanding the behavior of daily betas around news releases is important for several reasons. First, the estimation of daily variations in betas is relevant for the implementation of trading strategies that involve tracking portfolios or hedging market risks at high frequencies: the growth of index tracking funds and of "portable alpha" strategies have generated an increase in the demand for methods that accurately track the covariance of individual stocks with market indices. Second, daily variations in betas around news announcements are relevant for event study applications that use daily data and short event windows. Such event studies typically employ betas that are estimated from historical data over relatively long horizons, and are assumed to remain constant over the event window. Third, our analysis contributes to our understanding of the price discovery process associated with the release of news. In particular, we shed light on how the process of incorporation of new information into prices affects the covariance among stock returns, an issue that is still unexplored.

We use intra-daily data and recent advances in the econometrics of risk measurement to obtain firm-level estimates of daily betas, and study the variations in beta that occur around times of

[1] See Robichek and Cohn (1974), Ferson, *et al.* (1987), Shanken (1990), Ferson and Harvey (1991), Ferson and Schadt (1996) and Lewellen and Nagel (2006), amongst others.

firm-specific information flows.[2] We focus on firms' quarterly earnings announcements, which represent regular and well-documented information disclosures, and are thus ideal for a study of many stocks over a long time period. We estimate daily variations in betas around 17,936 earnings announcements for all stocks that are constituents of the S&P 500 index over the period 1996-2006, a total of 733 distinct firms. We find that betas increase on days of 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 0.12 (with a t-statistic of 5.61) on announcement days. Betas drop by 0.05 on the day after the earnings announcement (with a t-statistic of -4.80), before reverting to their average level about five days after the announcement.

What might underlie the increase and subsequent decrease in beta following firm-specific information flows? To answer this, we provide a simple model of learning that helps explain our empirical results. The intuition behind this model is simple, and is based on considering just a few, important, features of the environment. We consider a model where investors know the parameters of the processes governing a firm's earnings and the mapping of earnings into stock prices; the only uncertainty investors face relates to the level of profitability of each firm on each day. Since firms only announce their earnings once per quarter, on the intervening days investors must infer the level of earnings for their firm (and thus the value of the stock) from the information available to them. If the earnings processes of different firms are at least partially correlated, and if different firms announce on different days, then investors can update their expectations about the profitability of a given firm using the earnings announcements of other firms. Anecdotal evidence suggests that investors do indeed learn about the profitability of a given company from information on other companies: the financial press, for example, often refers to "bellwether" stocks, which are closely followed by traders and analysts as their earnings are taken to represent information on the prospects of other firms in the market.[3] This process of learning "across firms" drives *up* the covariance of the returns on the announcing stock with other stocks regardless of whether the announcing firm reveals good or bad news: investors interpret good (bad) news from the announcing firm as partial good (bad) news for other firms, which drives covariances up on announcement days

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

[3] Consider, for example, this excerpt from a Financial Times article on 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".

and in turn drives up the beta of the announcing stock. The magnitude of the change in beta is a function of the correlation amongst earnings processes, the size of the surprise component in earnings announcements, the ex-ante uncertainty about a firm's profitability, and the importance of earnings information in determining the stock price. In Section 6 we present a concrete example of such a model, along with some comparative statics to provide further intuition.

Given that the firms in our sample are constituents of the index that we use as the market portfolio (the S&P 500 index), a change in the variance of a given stock's return implies a mechanical change in its beta with the market portfolio. We thus decompose beta into two estimable components: the first component captures variations in beta that are driven by the fact that the stock has non-zero weight in the market portfolio, and the second component captures variations in beta attributable to other sources, which can be shown to be related to the average covariance of the announcing stock with the remaining stocks in the market index. Our analysis reveals that on average only around 30% of the increase in beta is attributable to the mechanical increase associated with the volatility of the announcing stock, while the remaining 70% is due 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 represents valuable information on other firms in the market: investors update their expectations of the value of these firms in the same direction as the announcing firm, thereby driving covariances upwards. This interpretation is supported by our theoretical model of learning: when the degree of learning across stocks in our model is greater, the covariance component of the change in beta is larger. Conversely, when the parameters of the model are chosen so that there is no potential for learning across stocks, changes in beta are driven purely by the change in the volatility of the announcing stock.

Our estimation methodology allows us to detect daily movements in beta for individual stocks and for groups of stocks sorted on various characteristics. We exploit this attribute to shed light on cross-sectional variations in changes in beta around news flows. We find that a stock's beta increases significantly for both positive and negative news surprises, defined as the difference between the actual earnings figure and the consensus forecast of earnings by equity analysts. Beta increases by 0.20 and 0.17 for good and bad news, respectively, but shows no significant movement during announcements with little information content (i.e. when earnings surprises are close to zero). This finding suggests that, consistent with our learning model, news about a stock represents partial news for other stocks in the market, leading prices to move together and covariances to increase, regardless of whether the news is positive or negative. The increase in beta on announcement days is larger for stocks characterized by higher dispersion in analyst forecasts of earnings (0.22 vs. 0.05). Dispersion can be viewed as ex-ante uncertainty about the prospects of a stock, and the larger increase in beta suggests that more learning takes place for announcements that resolve more uncertainty. Furthermore, the increase in beta is larger for firms announcing their earnings sooner after the end of the fiscal quarter (0.16 for early announcers vs. 0.09 for late announcers), suggesting that investors learn more from companies that provide earlier information disclosures.

We also find that changes in beta on announcement days are larger for stocks with higher turnover (0.19 vs. 0.07) and broader analyst coverage (0.24 vs. 0.07). Such characteristics of liquidity and visibility are likely to be associated with bellwether stocks, thus information releases about these companies might imply a larger degree of learning across firms. We then examine whether firms whose returns are more related with the returns of other firms in the market, namely those with higher ex-ante betas, exhibit higher changes in beta during earnings announcements. We find that high ex-ante beta firms do indeed experience larger changes in beta on announcement days (0.26 for high beta firms vs. 0.07 for low beta firms).

Our paper is related to previous work investigating the behavior of beta around firm-specific events. Ball and Kothari (1991) estimate a cross-sectional beta around earnings announcements from a market model regression during the period 1980-1988, and document an average increase in beta of 0.067 over a three-day window around announcements. Similarly, Brennan and Copeland (1988) study beta changes around stock splits using a market model regression. Our methodology allows us to estimate daily 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. Vijh (1994) and Barberis *et al.* (2005) find that betas tend to increase after a stock is added to the S&P 500 index. In these papers betas are estimated over long horizons before and after the addition to the index. A long horizon is also used to estimate betas in Greenwood (2008), who focuses on cross-sectional rather than event-driven differences in betas, and finds that Nikkei 225 stocks that are overweighted relative to a value-weighted index have higher betas compared to other stocks in the index.

Our analysis also relates to previous studies on price discovery following macroeconomic news announcements, 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 betas 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 briefly 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 econometrics of realized betas

In this section we briefly review the econometric theory underlying high frequency beta estimation, and we present a more detailed description of this approach in Appendix A. This 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 beta.[4] The framework of Barndorff-Nielsen and Shephard (2004) (BNS henceforth) allows us to estimate the beta of stock i on day t by computing daily "realized betas" as follows:

$$R\beta_{it}^{(S)} \equiv \frac{RCov_{imt}^{(S)}}{RV_{mt}^{(S)}} = \frac{\sum_{k=1}^{S} r_{i,t,k} r_{m,t,k}}{\sum_{k=1}^{S} r_{m,t,k}^2}, \tag{1}$$

where $r_{i,t,k} = \log P_{i,t,k} - \log P_{i,t,k-1}$ is the return on asset i during the k^{th} intra-day period on day t, and S is the number of intra-daily periods. The theory developed by BNS yields the asymptotic distribution of realized beta for a given stock i. When the sampling frequency is high (S is large), but not so high as to lead to problems coming from market microstructure effects (discussed in

[4] Work on time-varying betas using lower frequency data or alternative methods includes Robichek and Cohn (1974), Ferson, *et al.* (1987), Shanken (1990), 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) and Buss and Vilkov (2009) study betas estimated from option prices at a daily frequency.

detail below), then we may treat our estimated realized betas as noisy but unbiased estimates of the true betas, known as "integrated betas":

$$R\beta_{it}^{(S)} = I\beta_{it} + \epsilon_{it}, \text{ where } \epsilon_{it} \overset{a}{\sim} N\left(0, W_{it}/S\right). \tag{2}$$

With the above result from BNS, inference on true daily betas can be conducted using standard OLS regressions (though with autocorrelation and heteroskedasticity-robust standard errors). Such an approach is based on more familiar "long span" asymptotics ($T \to \infty$) rather than the "continuous record" asymptotics ($S \to \infty$) of BNS. An important 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 market microstructure effects related to various firm characteristics (such as return volatility or trading volume).

2.1 Dealing with market microstructure effects

At very high frequencies, market microstructure effects can lead the behavior of realized variance and realized beta to differ from that predicted by econometric 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 beta 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.[5] This estimator is more difficult to implement, but may be expected to perform better for less frequently-traded stocks. Griffin and Oomen (2009) 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 (2009) 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 4.1 below.

2.2 Decomposing 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 which captures "mechanical" variations in beta related to our use of a market portfolio that places non-zero weight on the announcing stock, and the other which captures variations in beta attributable to other sources. To make things concrete, consider a market index constructed as a weighted-average of N individual stocks, with return described by:

$$r_{mt} = \sum_{j=1}^{N} \omega_{jt} r_{jt}. \tag{3}$$

[5] 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 an individual firm's market beta can be decomposed into two terms:

$$\begin{aligned}\beta_{it} &\equiv \frac{Cov\left[r_{it}, r_{mt}\right]}{V\left[r_{mt}\right]} \\ &= \omega_{it}\frac{V\left[r_{it}\right]}{V\left[r_{mt}\right]} + \sum_{j=1,j\neq i}^{N} \omega_{jt}\frac{Cov\left[r_{it}, r_{jt}\right]}{V\left[r_{mt}\right]}. \end{aligned} \tag{4}$$

If the announcing firm was not a constituent of the market portfolio, then $\omega_{it} = 0$ and the first term above would drop out. A corresponding result also holds for realized beta:

$$\begin{aligned}R\beta_{it} &\equiv \frac{RCov_{imt}}{RV_{mt}} \\ &= \omega_{it}\frac{RV_{it}}{RV_{mt}} + \sum_{j=1,j\neq i}^{N} \omega_{jt}\frac{RCov_{ijt}}{RV_{mt}} \\ &\equiv R\beta_{it}^{(var)} + R\beta_{it}^{(cov)}. \end{aligned} \tag{5}$$

We label these two components of realized beta as the "volatility" and the "covariance" components, given the terms that appear in each of them.[6] In our empirical analysis we study changes in total realized beta, $R\beta_{it}$, and changes in the component of beta *not* related to the fact that the announcing stock is a constituent of the market portfolio, $R\beta_{it}^{(cov)}$.[7]

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 1996 and December 2006. We compute realized betas using high frequency prices from the TAQ database for each of the 2770 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.

[6] Of course, since the covariance between two asset returns can be written as the product of the standard deviations of the two returns and their correlation, the term labeled the "covariance component" can also be thought of as having a volatility component. The key for our interpretation is that the second component appears whether or not the announcing stock is a constituent of the market portfolio, while the first component only appears when ω_{it} is strictly greater than zero. All empirical and model-based results in this paper go through without difficulty if we use correlations and volatility rather than covariances and volatility to decompose betas. We elect to conduct the analysis using covariances as these are more easily handled in linear factor models.

[7] Up to an error term of the order $1/N$, this second component can be interpreted as the beta of the stock with a re-weighted market index that puts zero weight on the announcing stock and only uses the remaining $N-1$ stocks.

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, yielding a total of 16 intra-daily returns.[8] We choose a 25-minute frequency for 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 (2009)). 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.[9] The market return for our analysis is the Standard & Poor's Composite Index return (S&P 500 index). We use the exchange traded fund tracking the S&P 500 index (SPDR, traded on Amex with ticker SPY, and available on the TAQ database) to measure the market return, as in Bandi *et al.* (2006) and Todorov and Bollerslev (2007).[10] 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 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 (1).

We identify quarterly earnings announcements using the announcement dates and the announcement times recorded in the Thomson Reuters IBES database. We only use announcement dates for which we have a valid time stamp (we delete observations with a time of announcement equal to 00:00, which limits our sample period to start in the year 1996). Announcements recorded as occurring after 4:00pm on a given date are re-labeled, for the purposes of our empirical analysis, to have the following trading day's date, to reflect the fact that reactions to such announcements cannot take place until the following trading day. This means that "day 0" in our event window is

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

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

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

the day in which investors can react to the earnings announcement.[11,12]

Our final sample includes 733 different firms and a total of 17,936 earnings announcements. The number of firm-day observations used in the empirical analysis is 1,362,256. Table 1 shows descriptive statistics of our sample, computed as daily cross-sectional means or medians and then averaged within a given year. It also shows the number of earnings announcements per year across the firms in our sample. As can be seen from the table, the number of announcements is low in 1996 and 1997, increases to 1,642 in 1998 and to almost 2,000 in the subsequent years of the sample.

4 Empirical evidence on changes in beta

4.1 Panel estimation of variations in betas

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

$$\begin{aligned} R\beta_{it} &= \delta_{-10} I_{i,t+10} + ... + \delta_0 I_{i,t} + ... + \delta_{10} I_{i,t-10} \\ &\quad + \bar{\beta}_{i1} D_{1t} + \bar{\beta}_{i2} D_{2t} + ... + \bar{\beta}_{i,11} D_{11,t} + \boldsymbol{\gamma}' \mathbf{X}_{it} + \varepsilon_{it}, \end{aligned} \tag{6}$$

where $R\beta_{it}$ is the estimated 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 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_{11t}, which are dummy variables for each of the 11 years in the sample (1996 to 2006).

We also add a vector of control variables in our specification, $\mathbf{X}_{it} = \left[R\beta_{it-1}, \widehat{RV}_{it}, Volume_{it} \right]'$,

[11] About 72% of the announcements in our sample occur before 4:00pm. This proportion is similar to that in Bagnoli et al. (2005), who use the Reuters Forecast Pro database for a larger sample of firms over a shorter time period (4000 firms over the period 2000-2003). Using their Table 1, we compute that 76% of the firms in their sample announce before 4:00pm.

[12] In an earlier version of this paper we used earnings announcement information that did not include a time stamp. To deal with inaccurate recording of the date of announcements, we followed DellaVigna and Pollet (2008) and used all announcements present in both IBES and COMPUSTAT, and took the earlier date as the true date in case of disagreement. With this set of dates (a total of 22,575) we obtained similar results, though the inability to distinguish between announcements made before 4pm and those made after 4pm (and thus whether a given announcement occurred on "day 0" or "day +1") made the resulting estimates noisier.

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 biases present in the 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).[13] The estimation of panel data with clusters yields standard errors that are robust to heteroskedasticity and to any form of intra-cluster correlation. This procedure is flexible and allows for different cluster sizes, as is the case in our unbalanced sample. Moreover, the estimation procedure yields consistent standard errors when the number of clusters (days) is large relative to the number of intra-cluster observations (firm/days). This is a feature of our sample, which consists of about 500 firms per day over a sample period of 2,770 days.[14]

From our regression specification in equation (6), we can detect changes in betas during times of news announcements by simply examining the coefficients on the event day indicator variables, δ_j, $j = -10, -9, ..., 10$. The average beta *outside* of the event window is captured by the firm-year fixed effects (which also allows this beta to change through time), and the δ_j parameters capture

[13] The number of days in our sample with at least one earnings announcement is 2045, with an average number of announcements per day of 8.8 and a median of 4 announcements per day.

[14] 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.

the deviation of beta from this average level on each event day. The significance of the change in beta can be determined simply by looking at the t-statistic on each of these δ_j coefficients.

4.2 Determinants of changes in beta around information flows

In addition to estimating average changes in betas around information flows, 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 "earnings surprise", defined as the standardized difference between actual and expected earnings:

$$sur_{i,t} = \frac{e_{i,t} - E_{t-1}\left[e_{i,t}\right]}{P_{i,t-15}},$$

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 standardize the surprise using the firm's stock price 15 trading days before the announcement (i.e. outside of the event window). 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. 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.

Our second 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.

Next, we sort stocks based on the number of days between the end of a company's fiscal quarter and the date of its earnings announcement. This analysis allows us to test whether investors learn more from early announcers than from late announcers. To perform this test we keep only firms with fiscal quarters ending in March, June, September and December. The number of announcements in this reduced sample is 15,324, representing about 85% of the total number of announcements. We sort stocks into terciles to obtain a clearer and more stable identification of the "delay" of announcement for different stocks. The average distance between the fiscal-quarter-end and the announcement date for each group of stocks, averaged over time, is 17, 24, and 34 calendar days, respectively.

For our fourth and fifth sorts, we consider market capitalization and the book-to-market ratio, both measured 15 trading days before the earnings announcement day. We use these measures to test whether changes in betas around earnings announcements exhibit different patterns for large and small stocks or for value and growth stocks.

We then sort stocks into quintiles according to their average daily turnover, and according to their average daily beta, each computed during the two months that precede the earnings announcement month. Turnover 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. Past beta measures the degree of relatedness across companies, or the extent to which a given firm's returns covary with the returns of all the other firms in the market.

Our eighth and final sort is based on "residual analyst coverage", defined as a stock's analyst coverage orthogonalized with respect to its market capitalization. Analyst coverage has been used to proxy for the degree of "visibility" of a stock in several previous studies, see Brennan *et al.* (1993) for example, and has been found to relate to the speed with which information is incorporated into prices, see Hong, *et al.* (2000) and Hou and Moskowitz (2005) Since the number of analysts covering a stock is well-known to be positively correlated with a stock's market capitalization, we control for market cap by estimating the following cross-sectional regression at the end of each month:

$$\ln(1 + na_{i,t}) = \alpha_t + \beta_t \ln(cap_{i,t-15}) + \varepsilon_{i,t},$$

where $na_{i,t}$ is the number of distinct analysts who have issued a forecast for stock i in the 90 days leading up to the announcement on day t, and $cap_{i,t-15}$ is the market capitalization of stock i 15 trading days before the announcement. Given estimates of the parameters α_t and β_t, we obtain estimates of $\varepsilon_{i,t}$, the "residual analyst coverage".

4.3 Changes in beta across the entire sample of news events

In Table 2 and Figure 1 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 Section 4.1. 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 2.2.

The coefficient estimates on the event window dummy variables show no evidence of changes in beta during the first seven days of the event window (day -10 to day -4): the coefficient estimates are generally not significantly different from zero. On average, beta experiences a slight increase on days -3 to -1, albeit small in magnitude and only weakly significant. On day 0, the earnings announcement day, beta experiences a sharp increase of 0.12 (with a t-statistic of 5.61), followed by an immediate drop on day 1, to 0.05 below its non-announcement average level. Beta remains lower on days 2 and 3, at 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 after event day 5.[15]

How much of this increase in beta is attributable to a change in the covariance among stock returns during earnings announcements? Our results suggest that the change in realized beta is mostly driven by a change in covariances: the covariance component of beta increases by 0.081 (t-statistic of 3.94) on announcement days, accounting for about 70% of the total change in beta. Thus the observed change in beta is not purely mechanical; the bulk of the change is the result of an increase in the average covariance of the announcing stock with other stocks in the market portfolio. This evidence supports our model of learning "across firms": 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.

[15] Our estimate of the change in beta on day 0 can be compared to 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).

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 0.12 on earnings announcement days, with around 70% of that change coming from an increase in the average covariance with other stocks, and the remaining 30% being attributable to a mechanical effect related to the stock's volatility. Our estimation method allows us to analyze changes in betas around news announcements for each individual stock in our sample, or for groups of stocks sorted by firm or market characteristics.

We consider two types of variables to sort firms into different groups. The first type of variables characterize the "information environment" of the earnings announcement, such as the size and sign of the earnings surprise (measured with respect to the consensus of analyst forecasts of earnings), the degree of ex-ante uncertainty or disagreement about the earnings figure (captured by the dispersion of analyst forecasts), and the delay with which a company announces its earnings after the end of the fiscal quarter. The second type of variables include stock characteristics, such as market capitalization, the book-to-market ratio, share turnover, average past beta and the degree of analyst coverage of the stock.

4.4.1 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. We firstly examine 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 3 and Figure 2 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, 0.17 for bad news, 0.05 for no news, and 0.20 for good news (with t-statistics of 2.48, 1.41, and 3.70 respectively). The contribution of the covariance component of beta is lowest for the quintile of stocks reporting no news (41%), and increases for announcements with larger earnings surprises (74% for large negative surprises and 85% for large positive surprises). These results lend support to our story of learning "across firms":

irrespective of the sign of the earnings news, announcements with larger information content are associated with an increase in beta, consistent with investors learning from the newly released information and updating their expectations about non-announcing stocks as well. In contrast, earnings announcements with no information content do not cause any significant change in the degree of covariation of returns across stocks in the market index.

Next, 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 4 and Figure 3. Stocks with low dispersion of forecasts experience an increase in beta of 0.05 (not significant), while stocks with large forecast dispersion show a change in beta of 0.22. Moreover, the contribution of the covariance component of changes in beta increases from 40% to 89% (although not monotonically) as uncertainty increases.[16] Consistent with the predictions of our model, learning is stronger for announcements that resolve more ex-ante uncertainty, and is reflected in a significant increase in the covariance component of realized beta.

Third, we investigate whether firms that announce their quarterly earnings soon after the end of the fiscal quarter exhibit different changes in betas than firms that announce later. To the extent that variations in beta are related to the amount of cross-stock learning that is possible from a given earnings announcement, early announcers should generate larger increases in beta, with a larger proportion due to the covariance component of beta. To avoid confusing late announcers and early announcers with different fiscal year-ends (e.g., a late announcing December-year-end firm and an early announcing January-year-end firm), we use the sub-sample of firms with March, June, September or December fiscal quarter-ends for this analysis.[17] Table 5 presents the results from this analysis, and Figure 4 illustrates the patterns in betas and covariances. The findings reveal that first announcers indeed experience larger increases in beta: the average change in beta is 0.18 for early announcers and 0.09 for late announcers. Most of the change is explained by an increase

[16] These results are confirmed when we use an alternative measure of ex-ante uncertainty about a firm's earnings, namely the standard deviation of the growth rate of earnings. We find that, as the standard deviation of earnings growth increases, changes in beta around earnings announcements become larger and are increasingly explained by the covariance component of beta.

[17] These firms represent the bulk of the earnings announcements in our sample (86%). Estimating our baseline specification on this sub-sample of firms yields very similar results to those in Table 2, and so the two samples of firms do not present any systematic difference in the behavior of betas around earnings announcements.

in the covariance component of realized beta, which accounts for 81% of the increase in beta for early announcers and for 65% of the increase in beta for late announcers.

4.4.2 Results by characteristics of the firm

We next turn to sorting variables that relate to characteristics of the firm. Table 6 and Figure 5 present the results for stocks classified according to market capitalization. The regression estimates show that the effect of new information on betas is similar for small and big firms, with an increase in beta on the announcement date of 0.15 for small stocks and 0.14 for large stocks (the change in beta is somewhat lower for medium cap stocks). However, there is a substantial difference in the behavior of the variance and covariance components: for large stocks, the mechanical increase in beta accounts for over two-thirds of the total increase in beta, and the increase attributable to changes in covariances is not significant. For small stocks, on the other hand, the change in beta is almost entirely due to the covariance component (an increase of 0.14 and statistically significant). This difference is not so surprising, as the S&P 500 index is value-weighted, and thus the mechanical component of betas for small cap stocks is lower than for large cap stocks (see equation 5). It is noteworthy, however, that small cap firm announcements still lead to substantial changes in covariances, suggesting that their announcements generate a significant amount of learning.

Growth stocks exhibit a larger increase in beta, on average, than value stocks: the increase in beta is 0.13 for growth stocks and 0.07 for value stocks, as shown in Table 7 and Figure 6. The change in the covariance component is not significant for these extreme book-to-market stocks, but is large and significant for the intermediate stocks and represents most of the change in their total realized beta.

We also examine changes in betas for companies with different share turnover (measured in the two months prior to the earnings announcement). Turnover can be viewed as a measure of the liquidity of a stock, see Korajczyk and Sadka (2008) for a recent study. Table 8 and Figure 7 shows that turnover is strongly associated with changes in beta: Low turnover stocks show a smaller increase in beta (0.07, with a t-statistic of 2.34) than stocks characterized by high turnover (0.19, with a t-statistic of 3.35). The same pattern is reflected in the covariance component of beta, which is not significant for low turnover stocks and amounts to over 80% of the total change in beta for high turnover stocks. These findings are consistent with the intuition that illiquid stocks incorporate information slowly and thus react less to news *on day 0*. They also suggest that high turnover stocks, being more visible and liquid, are more likely to be followed by investors and to present the characteristics of "bellwether" stocks, from which investors learn about other stocks in the market.

We next examine the behavior of betas around earnings announcements for stocks sorted on different average levels of beta, estimated during two months before the earnings announcement window. A stock's average beta can be viewed as a proxy for the average level of relatedness of a stock's returns with the returns of all other stocks in the market index. To the extent that earnings are positively related to stock prices, this measure represents also a proxy for the degree of relatedness in the fundamentals of different companies. Table 9 and Figure 8 confirm the intuition that stocks with higher ex-ante betas allow for greater learning by investors in other stocks. We find that stocks with the lowest ex-ante average betas experience a change in realized beta of 0.07 on announcement days (t-statistic of 2.05); stocks in the second and third quintiles have smaller and not significant changes in beta, while for stocks with the highest ex-ante betas the increase in beta on announcement days is 0.26 (the t-statistic is 4.16). This large increase in beta is driven mostly by the covariance component, which accounts for 76% of the total change. Unreported tests reveal a very similar pattern in betas if we sort stocks by the ex-ante average covariance component of realized beta, instead of using total realized beta in the sorting procedure.

Finally, we consider the visibility of a stock, measured by its level of analyst coverage. 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 10 and Figure 9 reveal that the change in beta on news announcement days is 0.07 (t-statistic of 1.83) for stocks with low analyst coverage, and 0.24 (t-statistic of 4.69) for stocks in the top quintile of residual coverage, and is mostly driven by a change in the covariance component of realized beta. This finding is consistent with the intuition that stocks that are more visible and more followed by analysts are more like to exhibit the characteristics of "bellwether" stocks. Thus information releases about these companies may imply a larger degree of learning from investors across the market.

Overall, these findings suggest that the positive change in beta observed on earnings announcement days is larger when the announcement contains a larger "surprise" component (regardless of whether it represents a good or bad surprise), when it occurs earlier in the earnings announcement season, and when there is more ex-ante disagreement about the earnings figure. The variations in beta are also larger for more liquid firms, for firms with high past betas, and for firms that are followed by more analysts. Furthermore, from the decomposition of our estimates of realized beta into "mechanical" and covariance components, we can conclude that strong increases in betas on announcement days are primarily 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.

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. The results are presented in Table 11.

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 11 we present results based on realized betas computed from 5-minute intra-daily prices 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 (0.118 vs. 0.115). 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 beta rather than on the *level* of beta, which provides some built-in protection against level biases arising from market microstructure effects. The similarity also provides some support for our method of controlling for biases in estimated betas as these biases are known to be larger at higher frequencies (e.g., 5 minutes rather than 25 minutes).

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 (2009) 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 (2009). 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 11. 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 (0.125 versus 0.115 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 11 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 (with a day 0 change of 0.118 versus 0.115 in the base specification), providing further confidence in our empirical results.

6 A model of earnings announcements and learning

In this section we formalize the intuition given in the Introduction and develop a simple theoretical model in which investors update their expectations about future earnings for one company using news announcements by related companies. We show that this updating process can lead to short-lived changes in beta of the form observed in our empirical results.

Before describing the model that links expected future 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:

$$\log D_{it} = g_i + \log D_{i,t-1} + w_{it}, \tag{7}$$

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:

$$\begin{aligned} D_{it} &= \lambda_i X_{it} && (8) \\ \text{so} \quad \log X_{it} &= \log D_{it} - \log \lambda_i \\ &= g_i + (\log \lambda_i + \log X_{i,t-1}) + w_{it} - \log \lambda_i \\ \text{and so} \quad \Delta \log X_{it} &= g_i + w_{it} && (9) \end{aligned}$$

and thus log-earnings also follow a random walk with drift, which is linked to work in financial accounting, see Ball and Watts (1972) and Kothari (2001) for example[18]. We write the process in log-differences so that the left-hand side variable is stationary.

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}:

$$w_{it} = \gamma_i Z_t + u_{it} \tag{10}$$

[18]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.

where γ_i captures the importance of the common component for stock i.[19]

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

$$y_{it} = \sum_{j=0}^{M-1} \Delta \log X_{i,t-j} + \eta_{it} \tag{11}$$

The earnings announcement is taken as a growth over the past M days (rather than as the level of earnings over the past M days) as this simplifies 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 extreme form of heteroskedasticity:

$$V\left[\eta_{it}|I_{it}\right] = \sigma^2_{\eta i} \cdot I_{it} + \sigma^2_I \left(1 - I_{it}\right) \tag{12}$$

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

Stacking the above equations for all N firms we obtain the equations for a state-space model

[19] 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).

for all stocks, with the vector of daily earnings forming our state equation, and the (noisy) earnings announcements our measurement equation:

$$\begin{aligned} \Delta \log \mathbf{X}_t &= \mathbf{g} + \boldsymbol{\gamma} Z_t + \mathbf{u}_t \qquad (13) \\ \mathbf{y}_t &= \sum_{j=0}^{M-1} \Delta \log \mathbf{X}_{t-j} + \boldsymbol{\eta}_t \qquad (14) \end{aligned}$$

where $\Delta \log \mathbf{X}_t = [\ \Delta \log X_{1t}, ...,\ \Delta \log X_{Nt}]'$, $\mathbf{g} = [g_1, ..., g_N]'$, $\boldsymbol{\gamma} = [\gamma_1, ..., \gamma_N]'$, $\mathbf{u}_t = [u_{1t}, ..., u_{Nt}]'$, $\mathbf{y}_t = [y_{1t}, ..., y_{Nt}]'$ and $\boldsymbol{\eta}_t = [\eta_{1t}, ..., \eta_{Nt}]'$. Extending the approach of Sinopoli *et al.* (2004) to the multivariate case is straightforward, and the heteroskedasticity in $\boldsymbol{\eta}_t$ becomes:

$$V[\boldsymbol{\eta}_t | \mathbf{I}_t] = R \cdot \Gamma_t + \sigma_I^2 (I_N - \Gamma_t) \qquad (15)$$

where I_N is an $N \times N$ identity matrix, $R = diag\left\{\left[\sigma_{\eta 1}^2, \sigma_{\eta 2}^2, ..., \sigma_{\eta N}^2\right]\right\}$ and $\Gamma_t = diag\{\mathbf{I}_t\}$, where $diag\{\mathbf{a}\}$ 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 $\mathcal{F}_t = \sigma(\mathbf{y}_{t-j}, \mathbf{I}_{t-j}; j \geq 0)$. The Kalman filter enables us to easily compute expectations of earnings of firm i for each day in the sample: $\hat{E}[X_{it} | \mathcal{F}_t]$. 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:

$$\begin{aligned} P_{it} &= \sum_{j=1}^{\infty} \frac{E_t[D_{i,t+j}]}{(1+r_i)^j} \qquad (16) \\ &= \sum_{j=1}^{\infty} \frac{\lambda_i E_t[X_{i,t+j}]}{(1+r_i)^j}, \text{ assuming } D_{it} = \lambda_i X_{it}\ \forall t \end{aligned}$$

where $D_{i,t+j}$ is the dividend paid at time $t+j$ by firm i, and r_i is the discount rate, which is assumed for analytical tractability to be constant. 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:[20]

$$\begin{aligned}\hat{E}_t\left[X_{i,t+j}\right] &\approx \exp\left\{\hat{E}_t\left[\log X_{i,t+j}\right] + \frac{1}{2}\hat{V}_t\left[\log X_{i,t+j}\right]\right\} \\ &\approx \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\}\exp\left\{jg_i + \frac{1}{2}j\sigma_{wi}^2\right\}\end{aligned} \tag{17}$$

Substituting the above into our pricing equation, we obtain:

$$\begin{aligned}P_{it} &= \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\}\sum_{j=1}^{\infty}\frac{\lambda_i\exp\left\{jg_i + \frac{1}{2}j\sigma_{wi}^2\right\}}{(1+r_i)^j} \\ &= \exp\left\{\hat{E}_t\left[\log X_{it}\right]\right\}\frac{\lambda_i\exp\left\{g_i + \frac{1}{2}\sigma_{wi}^2\right\}}{1+r_i-\exp\left\{g_i + \frac{1}{2}\sigma_{wi}^2\right\}}\end{aligned} \tag{18}$$

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

$$\begin{aligned}R_{i,t+1} &\equiv \log P_{i,t+1} - \log P_{it} \\ &= \hat{E}_{t+1}\left[\log X_{it+1}\right] - \hat{E}_t\left[\log X_{it}\right].\end{aligned} \tag{19}$$

[20] 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 (19), which has precisely no effect on our numerical results and so we do not report it here.

6.3 Numerical results and analysis

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

We set the number of firms (N) to 100 and the number of days between earnings announcements (M) to 25.[21] 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,[22] 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 733 firms over the period 1996-2006 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 0.16 and 0.59. We use $\sigma_w^2 = 0.3^2/66$ as our value for the *daily* variance of earnings innovations in our base scenario, and vary it between $0.15^2/66$ and $0.6^2/66$ across simulations. We set the proportion of σ_w^2 attributable to the common component, $R_z^2 \equiv \sigma_z^2/\sigma_w^2$, to 0.05, and vary it between 0 and 0.10 to study the impact of learning – a higher value for R_z^2 means more of the variability of the earnings innovation can be learned from other firms' earnings announcements. In unreported simulation results we find only limited evidence of 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

$$\tilde{R}_{it} = R_{it} + \varepsilon_{it} \tag{20}$$

where $\varepsilon_{it} \sim iid \; N\left(0, \sigma_\varepsilon^2\right)$ and R_{it} is as given in equation (19) above. We set σ_ε^2 so that the ratio

[21] 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 "mechanical" component of beta around earnings announcements.

[22] 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.

$V[R_{it}]/V\left[\tilde{R}_{it}\right]$ 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.[23] 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 10 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 10 reveals that part of the spike on the event date is driven by the "mechanical" or "variance" component, but the majority (around 70%) is driven by an increase in the average covariance between the announcing firm and other firms. This increase in average covariances is a result of learning: when firm i has an announcement that represents good (bad) news, its price moves up (down). In the absence of an announcement for firm j, for example, expectations about earnings for firm j are updated using the information contained in the announcement of firm i, and so its price will move in the same direction as firm i. This leads to an increase in the covariance between the returns on stock i and stock j on firm i's announcement date.

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 certain 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 revise their nowcasts for firm i by less than average, which lowers their beta on that day. 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 10 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.

[23] 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.

We next present some comparative statics varying the four main parameters in our model. In Figure 11 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 11 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 "mechanical" component); 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 and the weight of the stock in the market index. 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 12 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 12 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 13 we vary the number of days between earnings announcements. We are computationally constrained to keep M no larger than 25, and in Figure 13 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 14 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 14 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 10 to 14 reveal that with just a few parameters our simple model of learning by investors 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 investigate whether daily stock betas vary with the release of firm-specific news. Using high frequency price data for all companies in the S&P 500 index and their quarterly earnings announcements over the period 1996-2006 (a total of 17,936 events), 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. The variations we detect are short-lived (lasting around two to five days) and thus difficult to detect using the lower frequency methods employed in most previous studies. We estimate and remove the mechanical increase in beta that results from an increase in the announcing stock's volatility on announcement days, which accounts for around 30% of the increase on average, and find that around 70% of the change in beta is due to an increase in the average covariance of the announcing stock returns with the returns of other stocks in the market index.

To help understand the determinants 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, leading to an increase in its beta. Thus the documented changes in beta around information flows may be explained by learning and price discovery by investors.

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 earnings announcements that represent large (positive or negative) surprises, or that resolve a larger amount of uncertainty, or that come early rather than late in the announcement season. We also find that changes in beta are greatest for stocks with higher liquidity and greater analyst following.

The patterns of time-variation in betas that we uncover in this study are relevant for portfolio management applications that involve hedging risks at daily frequencies, and for event study applications. More generally, the analysis in this paper contributes to our understanding of the process of price discovery and incorporation of new information into prices, estimating its effects on the covariance among stock returns.

Appendix A: The theory of realized betas

The use of high frequency data for estimating daily betas in this paper is based on recent econometric work on the estimation of volatility and covariance using high frequency data, see Andersen *et al.* (2003b) and Barndorff-Nielsen and Shephard (2004) for example. These analyses are based on an underlying multivariate stochastic volatility diffusion process for the $N \times 1$ vector of returns on a collection of assets, denoted $d \log \mathbf{P}(t)$:

$$\begin{aligned} d \log \mathbf{P}(t) &= d\mathbf{M}(t) + \Theta(t)\, d\mathbf{W}(t) \\ \Sigma(t) &= \Theta(t)\, \Theta(t)' \end{aligned} \tag{21}$$

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":

$$ICov_t = \int_{t-1}^{t} \Sigma(\tau)\, d\tau. \tag{22}$$

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:

$$I\beta_{it} \equiv \frac{ICov_{imt}}{IV_{mt}}, \tag{23}$$

where $ICov_{ijt}$ is the (i, j) element of the matrix $ICov_t$, $IV_{mt} = ICov_{mmt}$ is the integrated variance of the market portfolio, $ICov_{imt}$ is the integrated covariance between asset i and the market, and $I\beta_{it}$ is the "integrated beta" of asset i.[24] The integrated covariance matrix can be consistently estimated (as the number of intra-daily returns diverges to infinity) by the $N \times N$ "realized covariance" matrix:

$$RCov_t^{(S)} = \sum_{k=1}^{S} \mathbf{r}_{t,k}\mathbf{r}'_{t,k} \xrightarrow{p} ICov_t \quad \text{as } S \to \infty, \tag{24}$$

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 in equation (1).

An important contribution of Barndorff-Nielsen and Shephard (2004) is a central limit theorem for the realized covariance estimator:

$$\sqrt{S}\left(vec\left(RCov_t^{(S)}\right) - vec\left(ICov_t\right)\right) \xrightarrow{D} N\left(0, \Omega_t\right) \quad \text{as } S \to \infty, \tag{25}$$

where the "vec" operator converts a $N \times N$ matrix into a $N^2 \times 1$ vector, and Ω_t can be consistently estimated using intra-daily returns.[25] Combining the above asymptotic distribution result with

[24] 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 (23), see Dovonon, *et al.* (2008) for example. We elect to use the definition given in equation (23) as it fits directly into the theoretical framework of Barndorff-Nielsen and Shephard (2004).

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

the "delta method" yields the asymptotic distribution of realized beta, defined in equation (1), for stock i on day t :

$$\sqrt{S}\left(R\beta_{it}^{(S)} - I\beta_{it}\right) \xrightarrow{D} N\left(0, W_{it}\right), \text{ as } S \to \infty \tag{26}$$

This can then be re-expressed as

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

as in equation (2).

(2008) and Dovonon, *et al.* (2008).

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Table 1: 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 1996-2006, a total of 733 different firms and 17,936 earnings announcements. The reported statistics are annual cross-sectional medians of variables measured before earnings announcements, as specified in the description that follows. *Cap* is a firm's market capitalization, measured 15 trading days before the earnings announcement date. *B/M* is a firm's book-to-market, measured 15 trading days before the earnings announcement date. *Turn* is a stock's average daily turnover (volume of trade/shares outstanding) measured over the two months that precede the earnings announcement month. *Anlst* is the number of analysts following a firm during the 90-day interval before the earnings announcement date. *Sur* is the 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. *Disp* is the dispersion in analyst forecasts, computed as the ratio of the standard deviation of earnings forecasts to the absolute value of the mean forecast, where both variables are estimated during the 90-day interval before the earnings announcement day. *Announcm* is the total number of quarterly earnings announcements across all firms in a given year.

Year	**Cap** ($ Bn)	**B/M**	**Turn** (%)	**Anlst**	**Sur** (%)	**Disp** (%)	**Announcm** (Sum)
1996	6,899	0.42	0.21	9	0.01	2.94	120
1997	9,911	0.33	0.28	10	0.01	2.73	418
1998	7,603	0.34	0.33	9	0.01	3.76	1642
1999	7,805	0.36	0.35	9	0.01	3.62	1978
2000	7,746	0.40	0.43	8	0.02	3.35	1959
2001	7,836	0.38	0.50	10	0.01	4.50	1985
2002	7,559	0.41	0.52	10	0.02	4.23	1983
2003	7,279	0.50	0.53	10	0.03	4.03	1984
2004	9,252	0.43	0.48	10	0.04	3.85	1980
2005	10,674	0.41	0.50	10	0.04	3.63	1961
2006	12,365	0.40	0.55	11	0.05	4.04	1926

Tables 2-11: 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 10 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: Earnings surprise; Table 4: Analyst forecast dispersion; Table 5: Distance from fiscal quarter end; Table 6: Market capitalization; Table 7: Book-to-market; Table 8: Turnover; Table 9: Average ex-ante beta; Table 10: Residual analyst coverage. The 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.

Table 11 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	0.003	0.003
	(0.28)	(0.27)
-9	0.010	0.010
	(1.03)	(1.05)
-8	0.014	0.013
	(1.57)	(1.53)
-7	-0.015	-0.015
	(-1.71)	(-1.74)
-6	0.005	0.005
	(0.61)	(0.61)
-5	0.015	0.015
	(1.97)	(1.96)
-4	0.004	0.003
	(0.42)	(0.38)
-3	0.018	0.018
	(2.21)	(2.13)
-2	0.014	0.012
	(1.76)	(1.54)
-1	0.018	0.015
	(1.91)	(1.61)
0	0.115	0.081
	(5.61)	(3.94)
1	-0.047	-0.048
	(-4.80)	(-4.91)
2	-0.035	-0.034
	(-4.54)	(-4.42)
3	-0.031	-0.031
	(-3.95)	(-3.90)
4	-0.024	-0.022
	(-2.63)	(-2.51)
5	-0.019	-0.017
	(-2.39)	(-2.21)
6	-0.012	-0.011
	(-1.50)	(-1.36)
7	-0.003	-0.003
	(-0.37)	(-0.32)
8	-0.005	-0.005
	(-0.56)	(-0.54)
9	0.002	0.002
	(0.20)	(0.26)
10	-0.006	-0.005
	(-0.78)	(-0.64)

Table 3: Changes in Beta by Earnings Surprise

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	0.052	-0.016	-0.012	-0.001	0.004	0.052	-0.016	-0.013	0.000	0.004
	(1.54)	(-1.17)	(-0.79)	(-0.10)	(0.26)	(1.54)	(-1.19)	(-0.91)	(-0.02)	(0.26)
-9	0.016	-0.005	-0.027	0.032	0.037	0.016	-0.005	-0.026	0.032	0.037
	(0.84)	(-0.35)	(-1.71)	(1.94)	(1.09)	(0.82)	(-0.36)	(-1.67)	(1.97)	(1.10)
-8	0.043	-0.011	0.025	-0.005	0.027	0.041	-0.011	0.024	-0.004	0.026
	(1.93)	(-0.72)	(1.71)	(-0.36)	(1.52)	(1.85)	(-0.73)	(1.68)	(-0.29)	(1.51)
-7	-0.001	0.005	-0.026	-0.022	-0.026	-0.001	0.002	-0.027	-0.022	-0.025
	(-0.03)	(0.31)	(-1.92)	(-1.29)	(-1.47)	(-0.03)	(0.12)	(-1.95)	(-1.26)	(-1.44)
-6	0.005	-0.010	-0.001	0.000	0.051	0.005	-0.009	-0.001	0.000	0.051
	(0.28)	(-0.68)	(-0.05)	(0.01)	(2.73)	(0.25)	(-0.64)	(-0.04)	(-0.01)	(2.73)
-5	0.044	0.008	-0.014	0.006	0.026	0.043	0.008	-0.013	0.006	0.027
	(2.36)	(0.59)	(-0.92)	(0.37)	(1.61)	(2.32)	(0.57)	(-0.91)	(0.40)	(1.67)
-4	-0.001	0.016	0.003	0.009	-0.007	-0.003	0.015	0.003	0.011	-0.007
	(-0.04)	(1.11)	(0.25)	(0.63)	(-0.42)	(-0.15)	(1.06)	(0.23)	(0.71)	(-0.40)
-3	-0.018	0.018	0.032	0.059	0.008	-0.019	0.017	0.030	0.059	0.008
	(-1.01)	(1.20)	(2.02)	(3.67)	(0.44)	(-1.05)	(1.14)	(1.98)	(3.64)	(0.43)
-2	0.041	0.007	0.002	-0.001	0.024	0.039	0.004	0.001	-0.002	0.023
	(2.11)	(0.47)	(0.15)	(-0.06)	(1.44)	(2.03)	(0.28)	(0.07)	(-0.16)	(1.34)
-1	0.036	0.013	-0.014	0.010	0.058	0.034	0.010	-0.017	0.008	0.054
	(1.53)	(0.82)	(-0.85)	(0.54)	(2.77)	(1.43)	(0.64)	(-1.07)	(0.46)	(2.61)
0	0.167	0.111	0.051	0.111	0.199	0.123	0.078	0.021	0.075	0.169
	(2.48)	(3.08)	(1.41)	(2.72)	(3.70)	(1.83)	(2.17)	(0.58)	(1.85)	(3.13)
1	-0.055	-0.051	-0.057	-0.046	-0.028	-0.055	-0.052	-0.058	-0.047	-0.029
	(-2.44)	(-2.86)	(-3.59)	(-2.36)	(-1.29)	(-2.44)	(-2.94)	(-3.65)	(-2.43)	(-1.35)
2	-0.019	-0.062	-0.041	-0.031	-0.018	-0.017	-0.061	-0.040	-0.030	-0.018
	(-1.06)	(-4.41)	(-2.89)	(-2.07)	(-0.96)	(-0.98)	(-4.37)	(-2.82)	(-1.98)	(-0.95)
3	-0.017	-0.024	-0.042	-0.019	-0.030	-0.017	-0.024	-0.041	-0.019	-0.029
	(-0.94)	(-1.70)	(-2.87)	(-1.28)	(-1.87)	(-0.93)	(-1.69)	(-2.84)	(-1.25)	(-1.84)
4	-0.019	-0.046	-0.037	-0.029	0.012	-0.017	-0.046	-0.035	-0.028	0.013
	(-0.63)	(-3.23)	(-2.91)	(-1.88)	(0.72)	(-0.57)	(-3.22)	(-2.76)	(-1.80)	(0.75)
5	-0.014	-0.022	-0.012	-0.030	-0.006	-0.012	-0.021	-0.010	-0.028	-0.006
	(-0.70)	(-1.64)	(-0.87)	(-2.12)	(-0.38)	(-0.60)	(-1.55)	(-0.77)	(-1.96)	(-0.34)
6	-0.013	-0.012	-0.031	0.011	-0.007	-0.012	-0.011	-0.030	0.012	-0.006
	(-0.78)	(-0.81)	(-2.38)	(0.72)	(-0.48)	(-0.74)	(-0.74)	(-2.27)	(0.82)	(-0.41)
7	0.013	-0.018	0.001	-0.010	-0.002	0.013	-0.017	0.001	-0.009	-0.003
	(0.72)	(-1.31)	(0.04)	(-0.65)	(-0.14)	(0.71)	(-1.23)	(0.09)	(-0.60)	(-0.16)
8	-0.003	0.005	0.011	-0.011	-0.026	-0.003	0.004	0.012	-0.010	-0.025
	(-0.15)	(0.27)	(0.84)	(-0.63)	(-1.45)	(-0.16)	(0.24)	(0.91)	(-0.59)	(-1.44)
9	0.025	0.005	-0.021	-0.001	0.004	0.025	0.005	-0.020	0.000	0.004
	(1.41)	(0.37)	(-1.25)	(-0.06)	(0.26)	(1.45)	(0.39)	(-1.21)	(-0.02)	(0.25)
10	0.021	-0.022	-0.010	0.003	-0.009	0.021	-0.021	-0.008	0.004	-0.007
	(1.27)	(-1.71)	(-0.72)	(0.19)	(-0.53)	(1.27)	(-1.66)	(-0.63)	(0.30)	(-0.45)

Table 4: Changes in Beta by Forecast Dispersion

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	-0.010	0.007	-0.032	0.020	0.036	-0.010	0.006	-0.033	0.019	0.036
	(-0.66)	(0.50)	(-1.98)	(1.20)	(1.04)	(-0.67)	(0.44)	(-1.98)	(1.19)	(1.05)
-9	-0.022	0.014	-0.006	0.037	0.026	-0.021	0.014	-0.007	0.037	0.026
	(-1.52)	(0.95)	(-0.38)	(1.10)	(1.14)	(-1.47)	(0.97)	(-0.39)	(1.09)	(1.15)
-8	0.003	0.022	0.002	0.015	0.035	0.003	0.023	0.002	0.012	0.034
	(0.20)	(1.61)	(0.13)	(0.78)	(1.43)	(0.19)	(1.63)	(0.14)	(0.68)	(1.40)
-7	-0.008	-0.001	0.008	-0.040	-0.030	-0.008	-0.005	0.008	-0.040	-0.030
	(-0.58)	(-0.09)	(0.48)	(-2.24)	(-1.30)	(-0.57)	(-0.34)	(0.52)	(-2.23)	(-1.28)
-6	-0.007	0.011	0.030	0.000	0.009	-0.007	0.011	0.029	-0.001	0.009
	(-0.52)	(0.72)	(1.85)	(-0.01)	(0.40)	(-0.54)	(0.76)	(1.82)	(-0.03)	(0.43)
-5	-0.009	-0.008	0.014	0.027	0.044	-0.009	-0.008	0.014	0.027	0.044
	(-0.69)	(-0.59)	(0.93)	(1.67)	(1.96)	(-0.72)	(-0.57)	(0.95)	(1.68)	(1.96)
-4	-0.003	0.000	-0.003	0.022	0.000	-0.003	-0.001	-0.002	0.019	-0.001
	(-0.27)	(-0.01)	(-0.18)	(1.28)	(-0.02)	(-0.20)	(-0.07)	(-0.16)	(1.14)	(-0.02)
-3	0.021	0.034	0.034	0.017	-0.001	0.021	0.033	0.033	0.016	-0.001
	(1.50)	(2.03)	(2.08)	(0.95)	(-0.06)	(1.51)	(1.92)	(2.04)	(0.93)	(-0.07)
-2	-0.005	0.002	-0.006	0.043	0.041	-0.007	0.001	-0.009	0.041	0.040
	(-0.39)	(0.15)	(-0.35)	(2.34)	(1.99)	(-0.54)	(0.03)	(-0.52)	(2.29)	(1.92)
-1	0.012	0.009	0.005	0.032	0.043	0.009	0.007	0.003	0.028	0.040
	(0.78)	(0.53)	(0.26)	(1.69)	(1.76)	(0.56)	(0.41)	(0.14)	(1.54)	(1.65)
0	0.047	0.043	0.130	0.140	0.217	0.019	-0.002	0.089	0.107	0.194
	(1.41)	(0.99)	(3.19)	(3.21)	(4.09)	(0.58)	(-0.04)	(2.18)	(2.47)	(3.67)
1	-0.039	-0.076	-0.048	-0.024	-0.045	-0.040	-0.075	-0.050	-0.025	-0.046
	(-2.31)	(-4.47)	(-2.62)	(-1.16)	(-1.72)	(-2.38)	(-4.41)	(-2.73)	(-1.18)	(-1.77)
2	-0.039	-0.043	-0.037	-0.039	-0.017	-0.038	-0.041	-0.035	-0.038	-0.016
	(-3.03)	(-2.89)	(-2.39)	(-2.11)	(-0.82)	(-2.93)	(-2.80)	(-2.29)	(-2.08)	(-0.78)
3	-0.008	-0.025	-0.019	-0.028	-0.054	-0.008	-0.024	-0.018	-0.027	-0.054
	(-0.65)	(-1.88)	(-1.20)	(-1.70)	(-2.61)	(-0.61)	(-1.79)	(-1.17)	(-1.68)	(-2.61)
4	-0.048	-0.033	-0.026	-0.012	-0.003	-0.047	-0.031	-0.025	-0.011	-0.002
	(-3.43)	(-2.43)	(-1.74)	(-0.76)	(-0.11)	(-3.38)	(-2.33)	(-1.67)	(-0.71)	(-0.05)
5	0.000	-0.021	-0.004	-0.029	-0.026	0.001	-0.019	-0.002	-0.028	-0.025
	(-0.04)	(-1.48)	(-0.25)	(-1.80)	(-1.35)	(0.08)	(-1.36)	(-0.13)	(-1.70)	(-1.29)
6	-0.014	-0.012	-0.009	-0.011	-0.013	-0.013	-0.010	-0.007	-0.010	-0.012
	(-0.98)	(-0.92)	(-0.62)	(-0.72)	(-0.69)	(-0.95)	(-0.78)	(-0.50)	(-0.63)	(-0.67)
7	-0.026	0.011	-0.018	0.013	-0.002	-0.025	0.012	-0.019	0.013	-0.002
	(-1.89)	(0.80)	(-1.23)	(0.71)	(-0.11)	(-1.83)	(0.88)	(-1.27)	(0.76)	(-0.09)
8	-0.011	0.003	-0.024	0.025	0.000	-0.011	0.003	-0.024	0.025	0.000
	(-0.91)	(0.18)	(-1.45)	(1.53)	(-0.00)	(-0.93)	(0.23)	(-1.44)	(1.53)	(0.01)
9	-0.005	0.000	-0.034	0.025	0.019	-0.005	0.001	-0.033	0.025	0.020
	(-0.38)	(0.02)	(-2.33)	(1.34)	(0.96)	(-0.38)	(0.05)	(-2.30)	(1.37)	(1.00)
10	-0.010	0.013	-0.006	-0.008	0.004	-0.009	0.014	-0.005	-0.008	0.005
	(-0.79)	(1.03)	(-0.38)	(-0.53)	(0.23)	(-0.69)	(1.15)	(-0.32)	(-0.48)	(0.26)

Table 5: Changes in Beta by Announcement Delay

	Realized beta			Covariance component		
Day	1(early)	2	3(late)	1(early)	2	3(late)
-10	0.012	-0.005	-0.016	0.012	-0.006	-0.015
	(0.45)	(-0.34)	(-1.09)	(0.46)	(-0.42)	(-1.00)
-9	-0.002	-0.003	0.039	-0.002	-0.002	0.039
	(-0.11)	(-0.12)	(2.86)	(-0.11)	(-0.09)	(2.88)
-8	0.020	-0.013	0.014	0.020	-0.013	0.014
	(1.22)	(-0.75)	(0.90)	(1.23)	(-0.77)	(0.88)
-7	0.003	-0.040	-0.030	0.004	-0.040	-0.030
	(0.23)	(-2.17)	(-1.86)	(0.32)	(-2.16)	(-1.84)
-6	-0.015	0.008	-0.001	-0.015	0.008	-0.001
	(-1.01)	(0.51)	(-0.10)	(-0.99)	(0.54)	(-0.06)
-5	-0.006	0.030	0.009	-0.005	0.029	0.009
	(-0.40)	(1.95)	(0.71)	(-0.34)	(1.90)	(0.68)
-4	0.001	-0.009	0.023	0.003	-0.009	0.023
	(0.07)	(-0.54)	(1.36)	(0.17)	(-0.59)	(1.34)
-3	0.024	0.012	0.012	0.025	0.012	0.012
	(1.53)	(0.84)	(0.76)	(1.55)	(0.82)	(0.71)
-2	0.011	0.012	0.006	0.010	0.012	0.006
	(0.89)	(0.70)	(0.43)	(0.73)	(0.67)	(0.40)
-1	0.041	-0.022	0.023	0.041	-0.024	0.023
	(2.24)	(-1.41)	(1.33)	(2.24)	(-1.51)	(1.30)
0	0.165	0.099	0.086	0.133	0.074	0.056
	(4.86)	(2.72)	(2.37)	(3.92)	(2.04)	(1.50)
1	-0.063	-0.044	-0.021	-0.063	-0.046	-0.021
	(-3.58)	(-2.64)	(-1.03)	(-3.57)	(-2.77)	(-1.05)
2	-0.060	-0.032	-0.019	-0.062	-0.031	-0.021
	(-4.35)	(-2.16)	(-1.24)	(-4.28)	(-2.10)	(-1.30)
3	-0.053	-0.031	-0.006	-0.053	-0.030	-0.006
	(-3.77)	(-2.16)	(-0.40)	(-3.77)	(-2.13)	(-0.40)
4	-0.037	-0.019	0.011	-0.035	-0.018	0.011
	(-2.75)	(-1.26)	(0.70)	(-2.63)	(-1.23)	(0.72)
5	-0.028	-0.012	0.002	-0.025	-0.011	0.004
	(-2.07)	(-0.74)	(0.15)	(-1.82)	(-0.67)	(0.27)
6	-0.027	-0.003	0.010	-0.025	-0.002	0.011
	(-1.84)	(-0.19)	(0.72)	(-1.65)	(-0.12)	(0.76)
7	-0.016	0.005	0.030	-0.014	0.005	0.030
	(-1.05)	(0.31)	(2.00)	(-0.93)	(0.32)	(1.95)
8	0.002	0.017	-0.001	0.003	0.016	-0.003
	(0.16)	(1.01)	(-0.10)	(0.18)	(0.95)	(-0.20)
9	-0.019	0.005	0.012	-0.019	0.005	0.011
	(-1.24)	(0.37)	(0.77)	(-1.25)	(0.36)	(0.68)
10	-0.005	0.013	-0.017	-0.002	0.014	-0.015
	(-0.35)	(0.93)	(-1.21)	(-0.14)	(0.95)	(-1.08)

Table 6: Changes in Beta by Market Capitalization

	Realized beta					Covariance component				
Day	1(small)	2	3	4	5(big)	1(small)	2	3	4	5(big)
−10	-0.008	-0.005	0.012	0.004	0.007	-0.008	-0.005	0.013	0.005	0.005
	(-0.44)	(-0.34)	(0.41)	(0.31)	(0.45)	(-0.44)	(-0.33)	(0.43)	(0.37)	(0.34)
−9	0.029	0.007	-0.010	0.004	0.017	0.029	0.007	-0.010	0.003	0.018
	(1.43)	(0.44)	(-0.71)	(0.26)	(0.53)	(1.43)	(0.43)	(-0.69)	(0.22)	(0.59)
−8	0.016	0.021	0.006	0.002	0.021	0.015	0.020	0.006	0.002	0.019
	(0.65)	(1.23)	(0.36)	(0.12)	(1.41)	(0.64)	(1.22)	(0.35)	(0.11)	(1.40)
−7	-0.018	-0.023	-0.012	0.004	-0.028	-0.018	-0.023	-0.012	0.004	-0.030
	(-0.84)	(-1.31)	(-0.79)	(0.28)	(-1.90)	(-0.84)	(-1.32)	(-0.78)	(0.28)	(-2.06)
−6	-0.019	0.007	-0.003	0.032	0.003	-0.019	0.007	-0.003	0.033	0.003
	(-0.97)	(0.44)	(-0.18)	(2.05)	(0.23)	(-0.97)	(0.45)	(-0.18)	(2.08)	(0.19)
−5	0.013	0.015	0.012	0.029	0.004	0.013	0.015	0.012	0.030	0.003
	(0.70)	(1.05)	(0.67)	(1.91)	(0.27)	(0.71)	(1.06)	(0.67)	(1.96)	(0.24)
−4	-0.024	-0.014	0.026	0.020	0.006	-0.024	-0.014	0.026	0.020	0.005
	(-1.23)	(-0.83)	(1.63)	(1.45)	(0.46)	(-1.22)	(-0.84)	(1.62)	(1.48)	(0.35)
−3	-0.025	0.010	0.021	0.076	0.003	-0.025	0.010	0.021	0.076	0.002
	(-1.23)	(0.60)	(1.31)	(4.49)	(0.23)	(-1.23)	(0.58)	(1.28)	(4.49)	(0.14)
−2	0.000	-0.001	0.033	0.020	0.015	0.000	-0.001	0.032	0.020	0.008
	(0.00)	(-0.03)	(2.08)	(1.27)	(1.11)	(-0.01)	(-0.04)	(2.05)	(1.24)	(0.61)
−1	0.006	0.011	0.008	0.022	0.043	0.005	0.010	0.007	0.017	0.036
	(0.26)	(0.52)	(0.48)	(1.21)	(2.61)	(0.23)	(0.47)	(0.42)	(0.98)	(2.22)
0	0.148	0.093	0.099	0.095	0.138	0.139	0.078	0.081	0.066	0.040
	(2.55)	(2.25)	(2.45)	(2.46)	(4.03)	(2.40)	(1.89)	(2.02)	(1.73)	(1.14)
1	-0.041	-0.029	-0.056	-0.040	-0.069	-0.042	-0.030	-0.057	-0.042	-0.069
	(-1.58)	(-1.60)	(-3.00)	(-2.12)	(-4.56)	(-1.61)	(-1.64)	(-3.07)	(-2.20)	(-4.63)
2	-0.022	-0.047	-0.025	-0.044	-0.041	-0.023	-0.047	-0.025	-0.044	-0.036
	(-1.09)	(-2.82)	(-1.75)	(-2.74)	(-3.30)	(-1.12)	(-2.82)	(-1.74)	(-2.72)	(-2.96)
3	-0.051	-0.006	-0.024	-0.029	-0.048	-0.051	-0.006	-0.024	-0.029	-0.046
	(-2.43)	(-0.38)	(-1.63)	(-1.98)	(-3.97)	(-2.42)	(-0.38)	(-1.64)	(-2.01)	(-3.83)
4	-0.045	-0.014	-0.005	-0.015	-0.041	-0.045	-0.014	-0.005	-0.014	-0.037
	(-1.46)	(-0.87)	(-0.35)	(-1.03)	(-3.33)	(-1.46)	(-0.88)	(-0.32)	(-0.97)	(-3.06)
5	-0.036	-0.030	-0.004	0.013	-0.039	-0.036	-0.030	-0.003	0.014	-0.034
	(-1.84)	(-2.27)	(-0.26)	(0.92)	(-3.04)	(-1.82)	(-2.24)	(-0.22)	(0.99)	(-2.69)
6	-0.031	0.006	0.003	-0.013	-0.026	-0.031	0.007	0.004	-0.012	-0.022
	(-1.68)	(0.41)	(0.22)	(-0.91)	(-2.01)	(-1.68)	(0.43)	(0.24)	(-0.87)	(-1.70)
7	-0.002	-0.003	0.000	0.011	-0.021	-0.002	-0.003	0.000	0.011	-0.020
	(-0.10)	(-0.22)	(-0.02)	(0.77)	(-1.65)	(-0.10)	(-0.22)	(0.00)	(0.75)	(-1.54)
8	-0.008	-0.021	0.016	-0.007	-0.003	-0.008	-0.021	0.015	-0.006	-0.002
	(-0.36)	(-1.12)	(0.93)	(-0.49)	(-0.25)	(-0.37)	(-1.11)	(0.90)	(-0.47)	(-0.18)
9	0.004	0.006	0.004	0.000	-0.007	0.004	0.006	0.004	0.001	-0.007
	(0.15)	(0.34)	(0.26)	(0.00)	(-0.55)	(0.15)	(0.35)	(0.29)	(0.05)	(-0.50)
10	-0.002	0.006	-0.007	-0.004	-0.021	-0.002	0.006	-0.006	-0.004	-0.018
	(-0.10)	(0.39)	(-0.48)	(-0.31)	(-1.73)	(-0.10)	(0.42)	(-0.45)	(-0.25)	(-1.50)

Table 7: Changes in Beta by Book-to-Market Ratio

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
−10	0.017	-0.001	-0.011	0.007	0.000	0.017	-0.001	-0.010	0.006	0.001
	(0.53)	(-0.04)	(-0.65)	(0.41)	(0.02)	(0.52)	(-0.06)	(-0.64)	(0.39)	(0.03)
−9	0.007	-0.008	-0.011	0.052	0.002	0.006	-0.007	-0.010	0.052	0.003
	(0.41)	(-0.45)	(-0.64)	(1.58)	(0.12)	(0.37)	(-0.42)	(-0.60)	(1.58)	(0.16)
−8	0.035	0.016	0.003	0.018	0.000	0.033	0.015	0.003	0.018	0.000
	(1.96)	(0.96)	(0.17)	(1.01)	(0.00)	(1.95)	(0.94)	(0.16)	(1.03)	(0.02)
−7	-0.006	-0.018	-0.022	0.000	-0.031	-0.008	-0.019	-0.022	0.000	-0.031
	(-0.36)	(-0.92)	(-1.30)	(-0.01)	(-1.76)	(-0.53)	(-0.94)	(-1.27)	(-0.01)	(-1.76)
−6	-0.021	0.038	0.026	-0.008	-0.008	-0.022	0.038	0.026	-0.008	-0.008
	(-1.17)	(2.37)	(1.75)	(-0.54)	(-0.54)	(-1.22)	(2.39)	(1.74)	(-0.52)	(-0.53)
−5	0.015	0.012	-0.007	0.018	0.032	0.016	0.012	-0.007	0.017	0.032
	(1.06)	(0.79)	(-0.43)	(1.01)	(1.98)	(1.07)	(0.81)	(-0.47)	(1.01)	(2.00)
−4	0.011	0.014	0.004	-0.005	0.006	0.010	0.014	0.002	-0.005	0.006
	(0.69)	(0.89)	(0.25)	(-0.31)	(0.38)	(0.60)	(0.94)	(0.15)	(-0.31)	(0.41)
−3	0.019	0.027	0.001	0.036	0.019	0.018	0.026	0.001	0.036	0.018
	(1.05)	(1.71)	(0.07)	(2.16)	(1.16)	(0.99)	(1.63)	(0.08)	(2.15)	(1.13)
−2	0.000	-0.004	0.011	0.034	0.030	-0.004	-0.006	0.009	0.032	0.029
	(0.01)	(-0.24)	(0.67)	(2.08)	(1.50)	(-0.26)	(-0.36)	(0.59)	(2.00)	(1.48)
−1	0.009	0.028	-0.019	0.017	0.053	0.005	0.025	-0.020	0.014	0.051
	(0.52)	(1.56)	(-0.91)	(0.93)	(2.45)	(0.27)	(1.39)	(-0.99)	(0.77)	(2.40)
0	0.128	0.161	0.128	0.101	0.068	0.054	0.119	0.103	0.080	0.052
	(2.43)	(3.60)	(3.34)	(2.51)	(1.75)	(1.03)	(2.66)	(2.72)	(2.01)	(1.34)
1	-0.090	-0.065	-0.064	-0.027	0.006	-0.090	-0.065	-0.066	-0.028	0.005
	(-4.62)	(-3.42)	(-3.16)	(-1.46)	(0.28)	(-4.63)	(-3.44)	(-3.26)	(-1.52)	(0.24)
2	-0.062	-0.040	-0.030	-0.050	0.018	-0.058	-0.040	-0.029	-0.050	0.018
	(-3.66)	(-2.58)	(-1.86)	(-3.02)	(1.11)	(-3.54)	(-2.54)	(-1.81)	(-2.97)	(1.12)
3	-0.032	-0.055	-0.030	-0.010	-0.012	-0.030	-0.054	-0.030	-0.010	-0.012
	(-2.13)	(-3.55)	(-1.84)	(-0.70)	(-0.74)	(-2.07)	(-3.51)	(-1.87)	(-0.66)	(-0.73)
4	-0.034	-0.046	-0.046	0.005	0.028	-0.032	-0.045	-0.045	0.005	0.028
	(-2.23)	(-3.11)	(-3.23)	(0.30)	(1.63)	(-2.10)	(-3.04)	(-3.17)	(0.35)	(1.67)
5	-0.034	-0.039	-0.020	-0.025	0.015	-0.031	-0.038	-0.019	-0.024	0.016
	(-2.25)	(-2.75)	(-1.37)	(-1.66)	(0.96)	(-2.08)	(-2.64)	(-1.28)	(-1.64)	(1.01)
6	-0.030	-0.035	-0.027	0.020	0.010	-0.028	-0.034	-0.025	0.020	0.011
	(-1.89)	(-2.54)	(-1.81)	(1.30)	(0.65)	(-1.74)	(-2.47)	(-1.72)	(1.33)	(0.69)
7	-0.023	-0.011	-0.007	-0.002	0.016	-0.022	-0.010	-0.007	-0.002	0.016
	(-1.49)	(-0.74)	(-0.45)	(-0.11)	(0.93)	(-1.43)	(-0.65)	(-0.46)	(-0.13)	(0.93)
8	0.010	-0.012	-0.027	0.003	0.001	0.011	-0.012	-0.028	0.003	0.001
	(0.69)	(-0.78)	(-1.80)	(0.13)	(0.06)	(0.72)	(-0.75)	(-1.82)	(0.15)	(0.04)
9	0.009	0.000	-0.017	-0.009	0.042	0.010	0.000	-0.016	-0.009	0.043
	(0.55)	(0.03)	(-1.24)	(-0.49)	(2.67)	(0.60)	(0.01)	(-1.18)	(-0.48)	(2.71)
10	-0.003	-0.014	-0.009	0.000	-0.018	-0.002	-0.012	-0.008	0.000	-0.017
	(-0.18)	(-0.98)	(-0.65)	(-0.02)	(-1.15)	(-0.11)	(-0.86)	(-0.59)	(0.02)	(-1.09)

Table 8: Changes in Beta by Turnover

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	0.008	0.009	0.002	-0.020	0.011	0.009	0.008	0.002	-0.020	0.011
	(0.68)	(0.64)	(0.13)	(-1.36)	(0.32)	(0.71)	(0.57)	(0.12)	(-1.31)	(0.32)
-9	-0.012	0.014	0.024	0.003	0.016	-0.011	0.014	0.024	0.002	0.016
	(-0.95)	(0.95)	(0.78)	(0.15)	(0.68)	(-0.88)	(1.01)	(0.79)	(0.12)	(0.68)
-8	-0.008	-0.001	0.013	0.012	0.047	-0.007	-0.003	0.012	0.012	0.046
	(-0.56)	(-0.05)	(0.88)	(0.67)	(1.87)	(-0.49)	(-0.18)	(0.84)	(0.68)	(1.86)
-7	-0.001	-0.009	-0.020	-0.026	-0.023	-0.001	-0.008	-0.023	-0.025	-0.022
	(-0.08)	(-0.65)	(-1.33)	(-1.50)	(-0.94)	(-0.04)	(-0.64)	(-1.52)	(-1.49)	(-0.93)
-6	0.000	0.003	-0.032	0.024	0.026	0.000	0.003	-0.033	0.025	0.026
	(0.03)	(0.22)	(-2.19)	(1.57)	(1.14)	(0.03)	(0.26)	(-2.23)	(1.59)	(1.12)
-5	-0.011	0.009	-0.004	0.040	0.037	-0.011	0.009	-0.004	0.040	0.037
	(-0.82)	(0.62)	(-0.33)	(2.50)	(1.49)	(-0.84)	(0.63)	(-0.30)	(2.51)	(1.50)
-4	-0.012	0.000	0.005	0.005	0.015	-0.013	0.000	0.006	0.005	0.015
	(-0.86)	(0.02)	(0.39)	(0.30)	(0.61)	(-0.89)	(-0.02)	(0.41)	(0.32)	(0.60)
-3	0.018	-0.007	0.019	0.029	0.029	0.018	-0.008	0.019	0.028	0.028
	(1.28)	(-0.49)	(1.33)	(1.69)	(1.25)	(1.29)	(-0.56)	(1.33)	(1.67)	(1.21)
-2	-0.006	0.021	0.011	0.009	0.033	-0.007	0.019	0.009	0.007	0.032
	(-0.50)	(1.55)	(0.73)	(0.49)	(1.39)	(-0.59)	(1.38)	(0.58)	(0.39)	(1.37)
-1	0.002	0.020	0.000	0.007	0.055	0.001	0.017	-0.003	0.004	0.051
	(0.14)	(1.29)	(-0.02)	(0.36)	(2.08)	(0.09)	(1.12)	(-0.18)	(0.19)	(1.96)
0	0.066	0.048	0.094	0.137	0.186	0.027	0.013	0.068	0.106	0.156
	(2.34)	(1.32)	(2.28)	(2.92)	(3.35)	(0.94)	(0.36)	(1.64)	(2.28)	(2.82)
1	-0.022	-0.028	-0.072	-0.053	-0.068	-0.022	-0.029	-0.073	-0.053	-0.069
	(-1.52)	(-1.50)	(-3.83)	(-2.75)	(-2.56)	(-1.51)	(-1.53)	(-3.90)	(-2.76)	(-2.60)
2	-0.016	-0.054	-0.030	-0.049	-0.033	-0.014	-0.053	-0.029	-0.048	-0.032
	(-1.30)	(-3.70)	(-2.12)	(-2.74)	(-1.43)	(-1.10)	(-3.64)	(-2.09)	(-2.70)	(-1.40)
3	-0.016	-0.026	-0.026	-0.050	-0.040	-0.014	-0.025	-0.026	-0.049	-0.040
	(-1.31)	(-1.94)	(-1.73)	(-2.91)	(-1.75)	(-1.15)	(-1.90)	(-1.77)	(-2.88)	(-1.76)
4	-0.021	-0.027	-0.025	-0.034	-0.011	-0.020	-0.025	-0.025	-0.033	-0.010
	(-1.70)	(-1.97)	(-1.78)	(-2.21)	(-0.32)	(-1.59)	(-1.87)	(-1.74)	(-2.13)	(-0.29)
5	-0.025	-0.025	-0.022	-0.032	0.008	-0.023	-0.023	-0.021	-0.030	0.010
	(-2.00)	(-1.82)	(-1.68)	(-2.14)	(0.38)	(-1.82)	(-1.74)	(-1.60)	(-2.03)	(0.45)
6	0.012	-0.019	-0.037	-0.006	-0.008	0.014	-0.018	-0.036	-0.006	-0.007
	(0.94)	(-1.43)	(-2.66)	(-0.45)	(-0.36)	(1.05)	(-1.31)	(-2.60)	(-0.39)	(-0.32)
7	0.006	-0.022	-0.002	0.003	-0.001	0.006	-0.022	-0.002	0.004	0.000
	(0.45)	(-1.63)	(-0.13)	(0.21)	(-0.03)	(0.49)	(-1.60)	(-0.11)	(0.24)	(-0.02)
8	0.002	-0.017	-0.008	-0.021	0.023	0.003	-0.017	-0.009	-0.021	0.023
	(0.18)	(-0.96)	(-0.60)	(-1.31)	(0.99)	(0.24)	(-0.90)	(-0.63)	(-1.28)	(0.96)
9	0.005	-0.015	0.016	-0.001	0.004	0.005	-0.015	0.016	-0.001	0.004
	(0.35)	(-1.15)	(1.06)	(-0.07)	(0.15)	(0.36)	(-1.09)	(1.08)	(-0.05)	(0.19)
10	0.006	-0.030	-0.010	-0.018	0.026	0.007	-0.029	-0.009	-0.017	0.026
	(0.50)	(-2.35)	(-0.76)	(-1.16)	(1.21)	(0.59)	(-2.21)	(-0.66)	(-1.11)	(1.22)

Table 9: Changes in Beta by Average Ex-ante Beta

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	-0.044	-0.011	0.008	0.011	0.043	-0.043	-0.011	0.008	0.012	0.042
	(-2.82)	(-0.81)	(0.52)	(0.79)	(1.19)	(-2.76)	(-0.84)	(0.57)	(0.82)	(1.16)
-9	-0.001	-0.011	0.012	0.010	0.032	0.000	-0.011	0.012	0.011	0.032
	(-0.03)	(-0.66)	(0.84)	(0.61)	(1.22)	(0.00)	(-0.67)	(0.85)	(0.68)	(1.23)
-8	-0.024	-0.027	0.006	0.030	0.076	-0.024	-0.029	0.006	0.029	0.076
	(-1.68)	(-1.66)	(0.39)	(1.71)	(2.98)	(-1.65)	(-1.82)	(0.39)	(1.67)	(3.00)
-7	-0.048	-0.028	0.007	-0.012	0.001	-0.048	-0.027	0.007	-0.011	-0.003
	(-3.28)	(-2.08)	(0.48)	(-0.72)	(0.02)	(-3.24)	(-2.01)	(0.48)	(-0.67)	(-0.13)
-6	-0.008	-0.017	0.010	0.014	0.020	-0.007	-0.017	0.011	0.013	0.019
	(-0.59)	(-1.27)	(0.72)	(0.87)	(0.79)	(-0.53)	(-1.23)	(0.75)	(0.82)	(0.78)
-5	0.019	-0.015	-0.008	0.032	0.042	0.019	-0.014	-0.008	0.032	0.041
	(1.34)	(-1.14)	(-0.54)	(2.03)	(1.60)	(1.32)	(-1.05)	(-0.55)	(2.04)	(1.59)
-4	0.000	-0.025	-0.009	-0.005	0.052	0.000	-0.025	-0.010	-0.005	0.051
	(-0.03)	(-1.66)	(-0.66)	(-0.30)	(2.11)	(0.01)	(-1.63)	(-0.71)	(-0.28)	(2.08)
-3	0.000	-0.003	0.022	0.038	0.027	0.000	-0.002	0.022	0.037	0.024
	(-0.03)	(-0.19)	(1.58)	(2.20)	(1.03)	(-0.01)	(-0.12)	(1.57)	(2.13)	(0.94)
-2	0.004	-0.004	0.002	0.011	0.051	0.004	-0.005	0.002	0.010	0.045
	(0.25)	(-0.24)	(0.13)	(0.68)	(1.98)	(0.26)	(-0.33)	(0.12)	(0.63)	(1.76)
-1	-0.029	0.010	0.027	-0.011	0.080	-0.030	0.010	0.026	-0.013	0.071
	(-2.06)	(0.64)	(1.38)	(-0.59)	(2.97)	(-2.09)	(0.63)	(1.30)	(-0.70)	(2.71)
0	0.067	0.027	0.047	0.089	0.263	0.052	0.009	0.023	0.050	0.201
	(2.05)	(0.80)	(1.27)	(2.29)	(4.16)	(1.61)	(0.27)	(0.61)	(1.26)	(3.21)
1	-0.006	-0.048	-0.057	-0.051	-0.086	-0.007	-0.048	-0.057	-0.049	-0.088
	(-0.34)	(-2.80)	(-3.30)	(-2.77)	(-3.05)	(-0.37)	(-2.75)	(-3.31)	(-2.71)	(-3.10)
2	0.000	-0.025	-0.027	-0.022	-0.105	0.000	-0.024	-0.026	-0.020	-0.104
	(-0.02)	(-1.76)	(-1.80)	(-1.39)	(-4.40)	(0.02)	(-1.65)	(-1.72)	(-1.30)	(-4.34)
3	-0.009	-0.011	-0.005	-0.045	-0.087	-0.008	-0.010	-0.004	-0.043	-0.086
	(-0.63)	(-0.80)	(-0.35)	(-2.87)	(-3.48)	(-0.62)	(-0.75)	(-0.30)	(-2.78)	(-3.50)
4	-0.034	0.001	-0.006	-0.035	-0.044	-0.033	0.002	-0.006	-0.033	-0.042
	(-1.21)	(0.07)	(-0.46)	(-2.44)	(-1.95)	(-1.19)	(0.13)	(-0.40)	(-2.29)	(-1.89)
5	0.014	-0.015	0.007	-0.038	-0.060	0.014	-0.015	0.008	-0.036	-0.056
	(0.92)	(-1.17)	(0.50)	(-2.65)	(-2.66)	(0.95)	(-1.09)	(0.59)	(-2.54)	(-2.53)
6	0.028	-0.012	-0.014	0.002	-0.060	0.029	-0.011	-0.013	0.003	-0.058
	(2.07)	(-0.86)	(-0.97)	(0.11)	(-2.72)	(2.10)	(-0.78)	(-0.90)	(0.16)	(-2.65)
7	0.017	-0.013	-0.012	-0.002	-0.003	0.018	-0.012	-0.012	-0.003	-0.001
	(1.19)	(-0.98)	(-0.83)	(-0.13)	(-0.12)	(1.23)	(-0.95)	(-0.81)	(-0.17)	(-0.06)
8	0.017	0.001	-0.015	0.003	-0.026	0.017	0.001	-0.015	0.004	-0.026
	(1.10)	(0.05)	(-1.04)	(0.20)	(-1.00)	(1.09)	(0.09)	(-1.02)	(0.23)	(-1.02)
9	-0.010	0.014	0.002	0.003	0.000	-0.010	0.015	0.002	0.004	0.001
	(-0.64)	(1.06)	(0.10)	(0.22)	(-0.00)	(-0.63)	(1.07)	(0.13)	(0.26)	(0.03)
10	-0.005	0.007	-0.010	0.002	-0.020	-0.005	0.008	-0.010	0.004	-0.019
	(-0.37)	(0.54)	(-0.72)	(0.14)	(-0.97)	(-0.35)	(0.62)	(-0.69)	(0.27)	(-0.91)

Table 10: Changes in Beta by Residual Analyst Coverage

	Realized beta					Covariance component				
Day	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
-10	0.007	-0.001	0.023	0.006	-0.013	0.007	-0.001	0.022	0.004	-0.012
	(0.49)	(-0.10)	(0.75)	(0.35)	(-0.67)	(0.51)	(-0.07)	(0.72)	(0.28)	(-0.62)
-9	0.027	-0.030	0.038	0.021	-0.007	0.027	-0.029	0.039	0.022	-0.008
	(1.94)	(-2.00)	(1.23)	(1.31)	(-0.29)	(1.99)	(-1.98)	(1.23)	(1.37)	(-0.34)
-8	0.010	0.014	0.009	0.014	0.028	0.010	0.014	0.008	0.012	0.027
	(0.69)	(0.83)	(0.57)	(0.81)	(1.22)	(0.69)	(0.84)	(0.55)	(0.75)	(1.18)
-7	0.005	-0.003	-0.016	-0.037	-0.021	0.002	-0.002	-0.017	-0.036	-0.020
	(0.31)	(-0.18)	(-0.97)	(-2.17)	(-1.00)	(0.13)	(-0.17)	(-1.03)	(-2.15)	(-0.96)
-6	0.030	-0.027	0.008	-0.012	0.044	0.031	-0.026	0.007	-0.012	0.043
	(2.08)	(-2.07)	(0.49)	(-0.71)	(2.20)	(2.09)	(-2.00)	(0.46)	(-0.73)	(2.20)
-5	0.002	0.003	-0.014	0.006	0.069	0.003	0.004	-0.014	0.005	0.070
	(0.18)	(0.20)	(-0.97)	(0.38)	(3.33)	(0.19)	(0.26)	(-0.99)	(0.31)	(3.37)
-4	0.003	-0.015	0.016	0.000	0.014	0.004	-0.015	0.016	-0.001	0.013
	(0.23)	(-0.93)	(1.09)	(0.03)	(0.66)	(0.28)	(-0.95)	(1.08)	(-0.04)	(0.62)
-3	0.026	0.005	0.018	0.017	0.033	0.026	0.003	0.018	0.017	0.032
	(1.81)	(0.28)	(1.19)	(1.05)	(1.61)	(1.82)	(0.17)	(1.15)	(1.03)	(1.61)
-2	-0.011	0.008	0.018	0.014	0.041	-0.014	0.008	0.016	0.013	0.037
	(-0.66)	(0.52)	(1.20)	(0.88)	(2.10)	(-0.83)	(0.49)	(1.06)	(0.85)	(1.93)
-1	-0.015	0.019	0.022	0.020	0.049	-0.016	0.016	0.020	0.016	0.046
	(-0.72)	(1.16)	(1.25)	(1.00)	(2.14)	(-0.81)	(0.98)	(1.14)	(0.82)	(2.00)
0	0.074	0.057	0.077	0.142	0.243	0.046	0.027	0.036	0.108	0.206
	(1.83)	(1.39)	(1.78)	(3.95)	(4.69)	(1.14)	(0.66)	(0.82)	(3.00)	(4.01)
1	-0.038	-0.044	-0.046	-0.056	-0.060	-0.039	-0.045	-0.046	-0.057	-0.061
	(-1.77)	(-2.48)	(-2.46)	(-2.99)	(-2.77)	(-1.80)	(-2.51)	(-2.48)	(-3.07)	(-2.81)
2	-0.040	-0.021	-0.050	-0.035	-0.030	-0.040	-0.021	-0.048	-0.034	-0.028
	(-2.43)	(-1.42)	(-3.60)	(-2.47)	(-1.41)	(-2.40)	(-1.40)	(-3.47)	(-2.38)	(-1.32)
3	-0.003	-0.007	-0.043	-0.037	-0.045	-0.003	-0.006	-0.042	-0.037	-0.043
	(-0.24)	(-0.45)	(-3.10)	(-2.39)	(-2.24)	(-0.18)	(-0.43)	(-3.05)	(-2.39)	(-2.20)
4	-0.026	-0.028	-0.018	-0.023	-0.028	-0.025	-0.027	-0.017	-0.021	-0.027
	(-1.84)	(-1.92)	(-1.21)	(-0.82)	(-1.39)	(-1.82)	(-1.84)	(-1.16)	(-0.76)	(-1.31)
5	-0.013	-0.011	-0.018	-0.032	-0.010	-0.012	-0.010	-0.017	-0.031	-0.008
	(-0.97)	(-0.83)	(-1.41)	(-2.16)	(-0.51)	(-0.87)	(-0.72)	(-1.30)	(-2.06)	(-0.42)
6	-0.001	-0.029	0.004	-0.015	-0.013	0.000	-0.028	0.005	-0.014	-0.011
	(-0.06)	(-2.16)	(0.32)	(-1.10)	(-0.67)	(0.00)	(-2.06)	(0.35)	(-1.04)	(-0.56)
7	-0.003	-0.020	0.016	-0.014	0.004	-0.002	-0.020	0.016	-0.013	0.005
	(-0.19)	(-1.39)	(1.17)	(-0.85)	(0.20)	(-0.17)	(-1.39)	(1.16)	(-0.83)	(0.28)
8	-0.023	-0.022	0.003	-0.009	0.028	-0.024	-0.022	0.004	-0.008	0.029
	(-1.17)	(-1.36)	(0.24)	(-0.48)	(1.42)	(-1.20)	(-1.33)	(0.25)	(-0.46)	(1.46)
9	0.017	-0.003	-0.016	-0.007	0.022	0.017	-0.002	-0.017	-0.006	0.023
	(1.15)	(-0.20)	(-1.02)	(-0.45)	(0.99)	(1.18)	(-0.18)	(-1.04)	(-0.37)	(1.04)
10	-0.018	-0.009	0.013	-0.007	0.004	-0.017	-0.008	0.014	-0.007	0.005
	(-1.33)	(-0.66)	(0.92)	(-0.49)	(0.19)	(-1.24)	(-0.61)	(1.01)	(-0.44)	(0.26)

Table 11: Robustness tests

	5-minute beta		HY beta		Extra volume controls	
Day	**Realized beta**	**Covariance**	**Realized beta**	**Covariance**	**Realized beta**	**Covariance**
-10	0.002	0.002	0.006	0.006	0.003	0.003
	(0.36)	(0.34)	(0.74)	(0.72)	(0.27)	(0.26)
-9	0.010	0.010	0.009	0.009	0.009	0.010
	(1.44)	(1.47)	(0.98)	(1.00)	(0.98)	(1.02)
-8	0.013	0.013	0.011	0.011	0.014	0.013
	(2.00)	(1.97)	(1.28)	(1.26)	(1.54)	(1.50)
-7	-0.017	-0.017	-0.016	-0.017	-0.015	-0.015
	(-2.70)	(-2.71)	(-1.78)	(-1.79)	(-1.73)	(-1.75)
-6	0.007	0.006	0.010	0.010	0.005	0.005
	(1.08)	(1.07)	(1.17)	(1.17)	(0.58)	(0.58)
-5	0.017	0.017	0.015	0.015	0.015	0.015
	(2.69)	(2.72)	(1.75)	(1.77)	(1.91)	(1.92)
-4	-0.003	-0.003	0.002	0.002	0.003	0.003
	(-0.40)	(-0.42)	(0.19)	(0.17)	(0.39)	(0.36)
-3	0.015	0.014	0.019	0.018	0.018	0.017
	(2.27)	(2.21)	(2.06)	(2.03)	(2.15)	(2.09)
-2	0.017	0.015	0.025	0.024	0.014	0.012
	(2.70)	(2.47)	(2.61)	(2.47)	(1.70)	(1.49)
-1	0.012	0.009	0.022	0.019	0.018	0.016
	(1.67)	(1.34)	(2.25)	(2.02)	(1.96)	(1.72)
0	0.118	0.090	0.125	0.097	0.111	0.078
	(7.15)	(5.47)	(6.94)	(5.41)	(5.41)	(3.80)
1	-0.041	-0.041	-0.035	-0.035	-0.045	-0.046
	(-5.59)	(-5.65)	(-3.69)	(-3.75)	(-4.62)	(-4.78)
2	-0.031	-0.031	-0.023	-0.022	-0.034	-0.034
	(-5.16)	(-5.03)	(-2.83)	(-2.74)	(-4.36)	(-4.29)
3	-0.030	-0.030	-0.018	-0.018	-0.030	-0.030
	(-4.84)	(-4.79)	(-2.03)	(-1.99)	(-3.83)	(-3.83)
4	-0.020	-0.019	-0.014	-0.013	-0.023	-0.022
	(-2.71)	(-2.58)	(-1.73)	(-1.61)	(-2.56)	(-2.47)
5	-0.017	-0.016	-0.014	-0.013	-0.018	-0.017
	(-3.06)	(-2.83)	(-1.76)	(-1.61)	(-2.33)	(-2.17)
6	-0.014	-0.013	-0.008	-0.007	-0.011	-0.010
	(-2.60)	(-2.41)	(-1.01)	(-0.89)	(-1.45)	(-1.33)
7	-0.016	-0.016	-0.001	-0.001	-0.003	-0.002
	(-2.62)	(-2.55)	(-0.16)	(-0.12)	(-0.32)	(-0.28)
8	-0.012	-0.012	0.003	0.003	-0.004	-0.004
	(-1.93)	(-1.88)	(0.30)	(0.33)	(-0.52)	(-0.51)
9	0.001	0.001	0.006	0.006	0.002	0.002
	(0.14)	(0.23)	(0.66)	(0.72)	(0.24)	(0.28)
10	-0.013	-0.012	-0.010	-0.009	-0.005	-0.005
	(-2.35)	(-2.18)	(-1.29)	(-1.17)	(-0.74)	(-0.62)

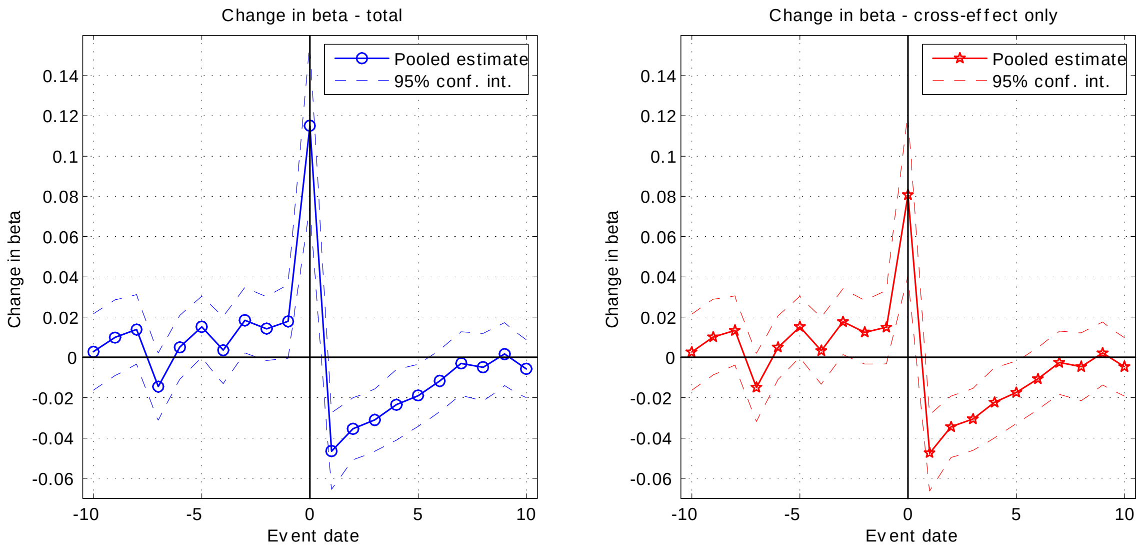

Figure 1: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) reported in Table 2. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed line.*

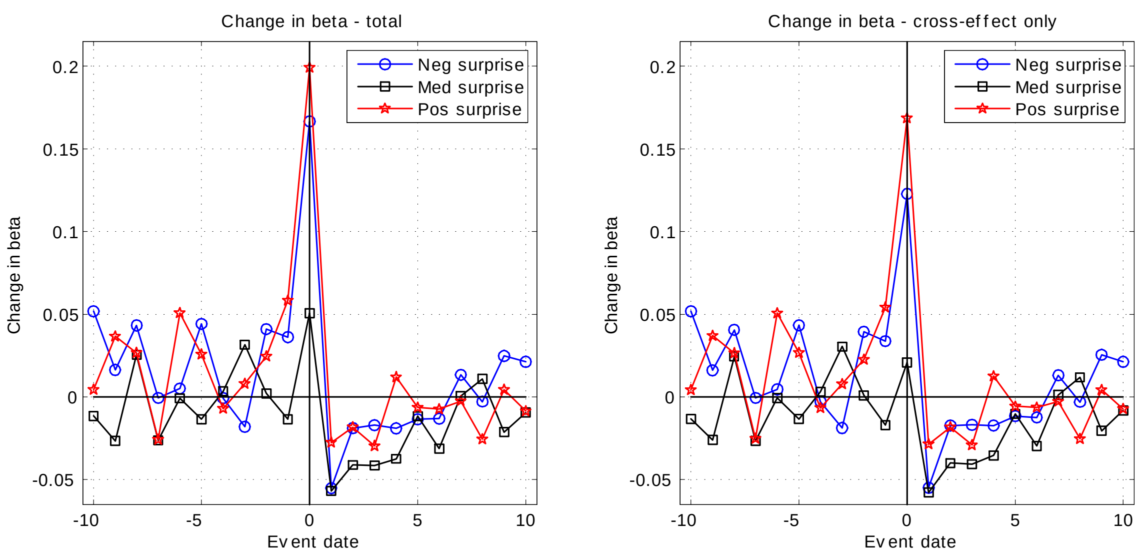

Figure 2: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by earnings surprise, as reported in Table 3.*

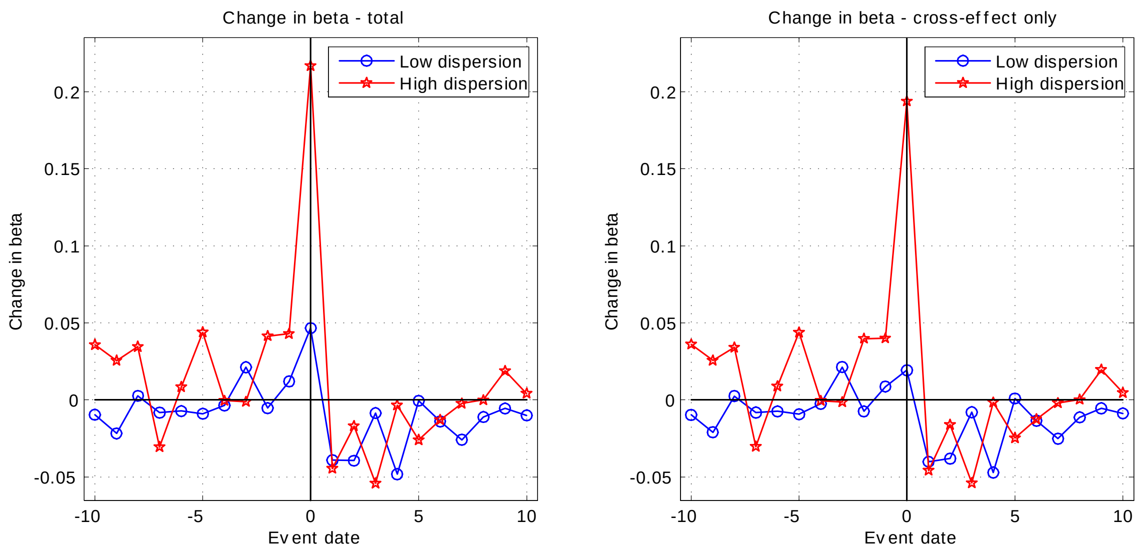

Figure 3: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by analyst forecast dispersion, as reported in Table 4.*

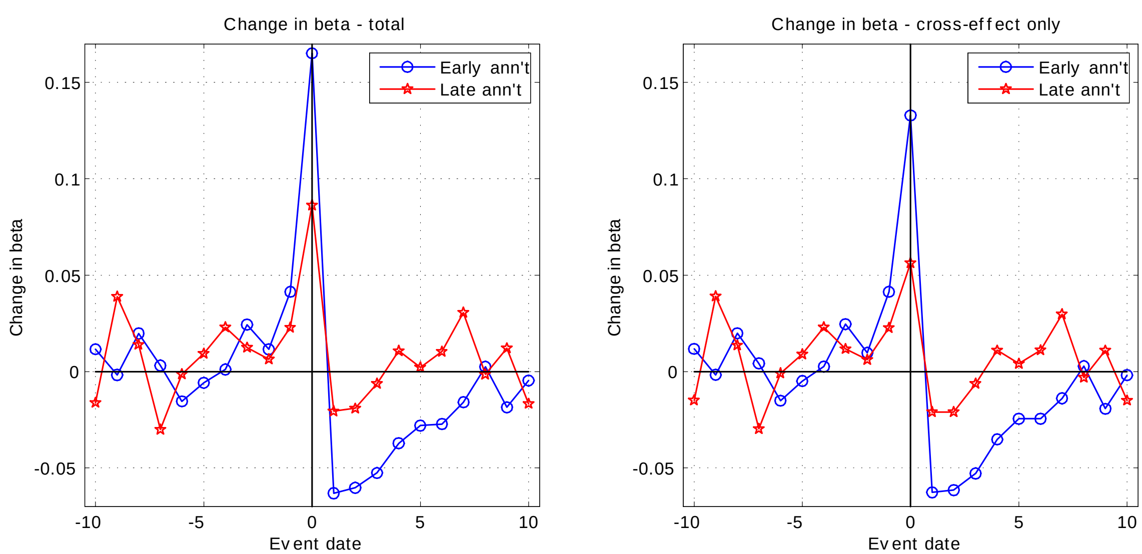

Figure 4: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for each of the tercile of the number of days between the quarter-end and the announcement, as reported in Table 5.*

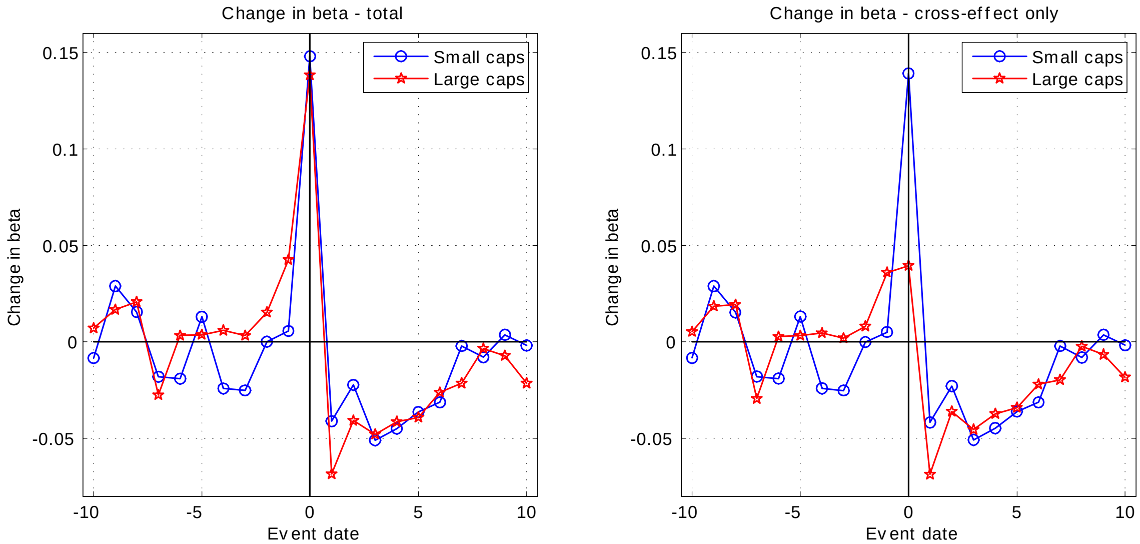

Figure 5: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the smallest and largest quintiles by market capitalization, as reported in Table 6.*

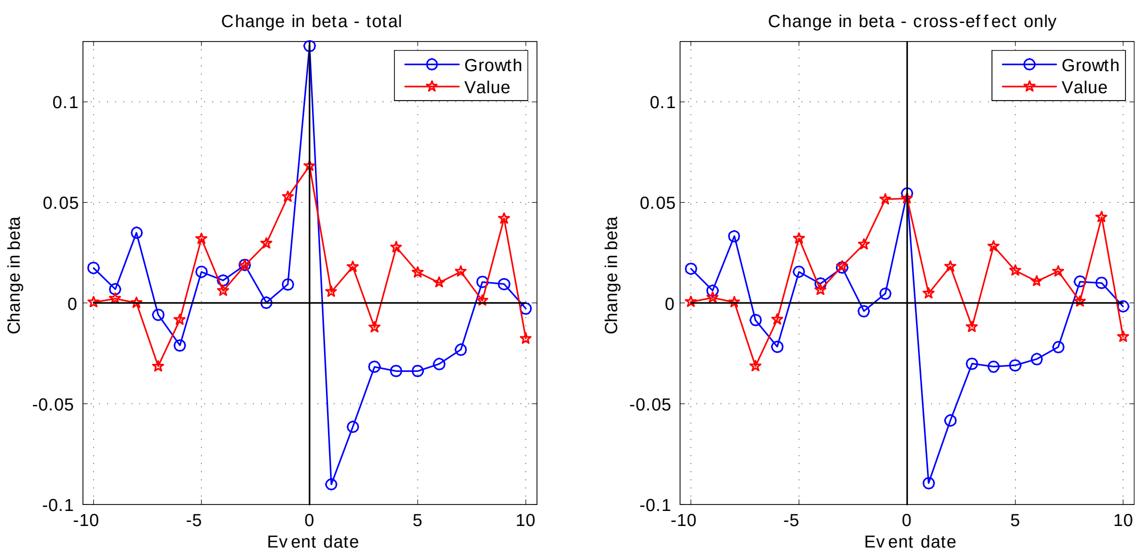

Figure 6: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by book-to-market ratio, as reported in Table 7.*

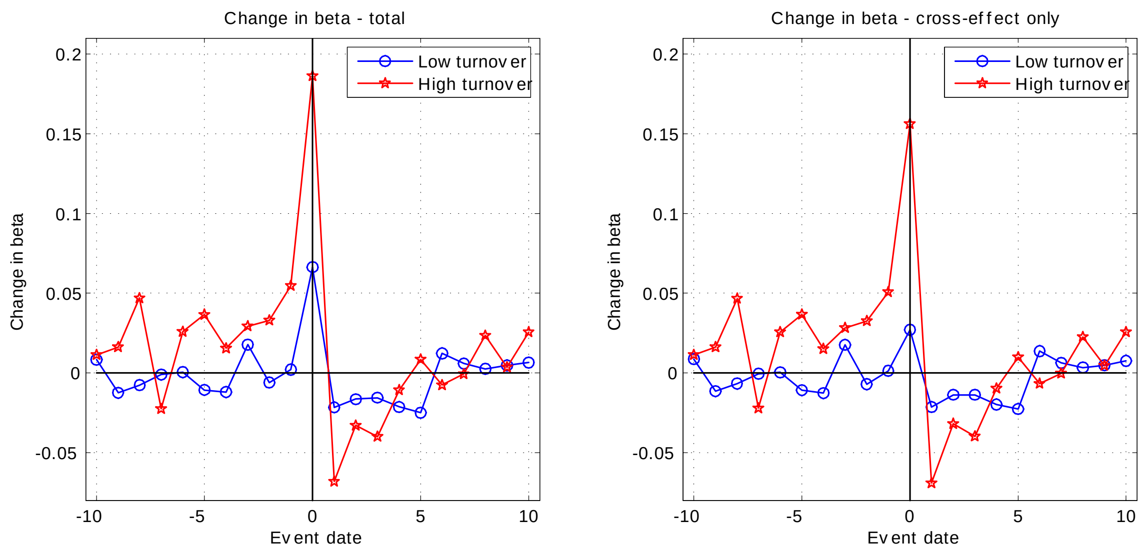

Figure 7: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by turnover, as reported in Table 8.*

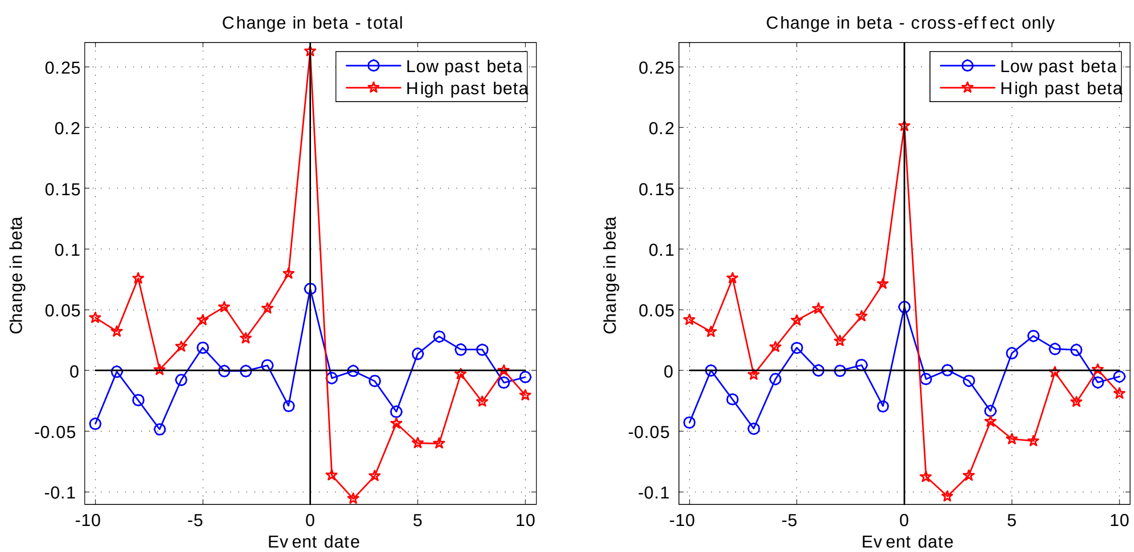

Figure 8: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by ex-ante beta, as reported in Table 9.*

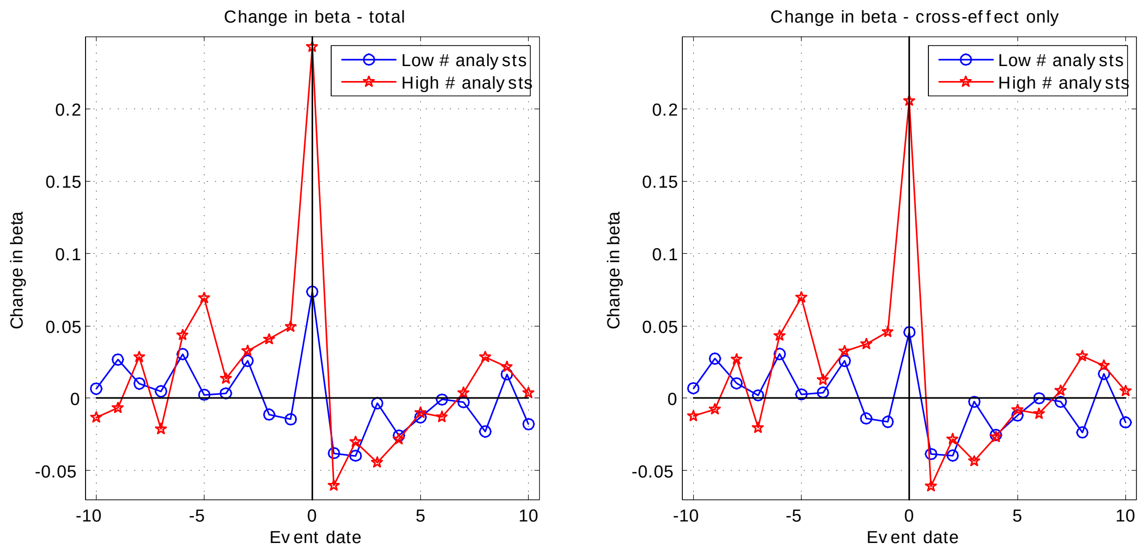

Figure 9: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by number of analysts, as reported in Table 10.*

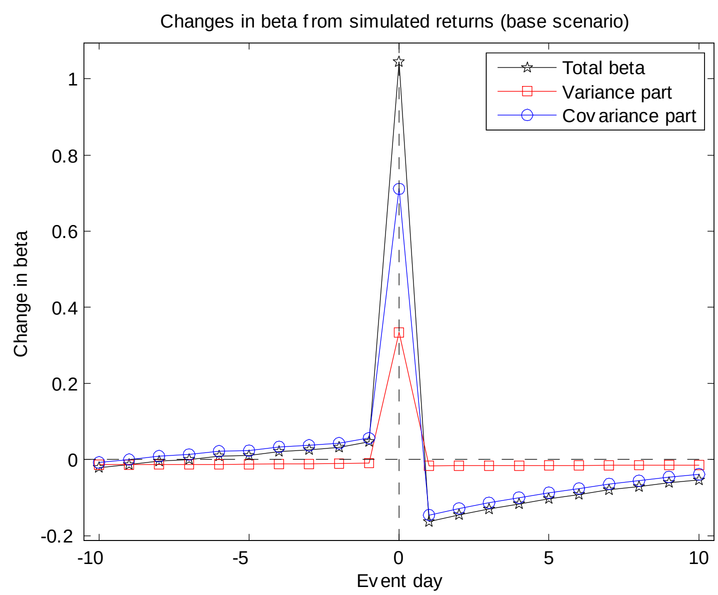

Figure 10: *Change in beta around event dates for benchmark scenario.*

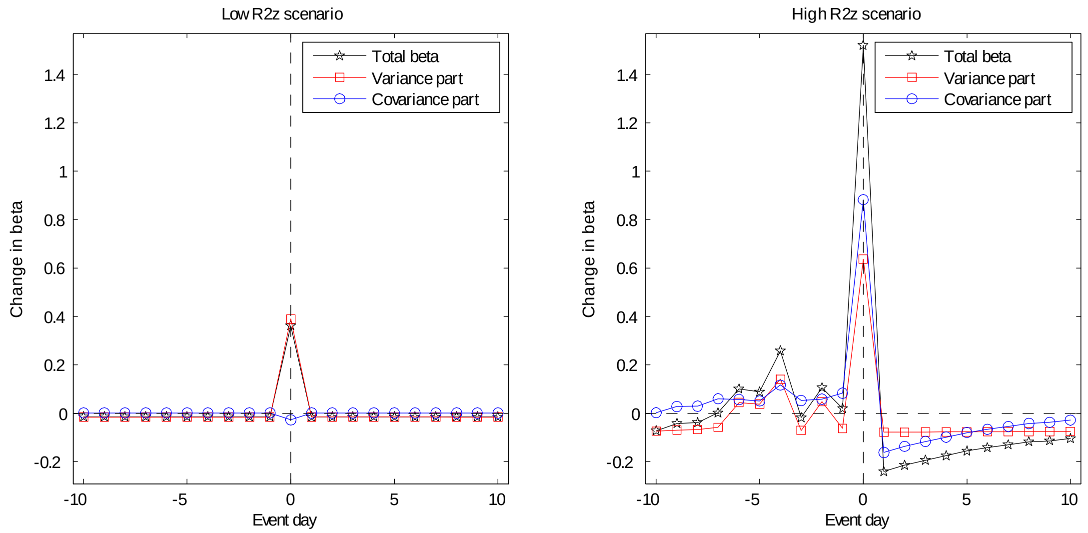

Figure 11: *Changes in beta around event dates for low and high values of the ratio of the variance of the common component in earnings innovations to total variance,* $R_z^2 = \sigma_z^2/\sigma_w^2$.

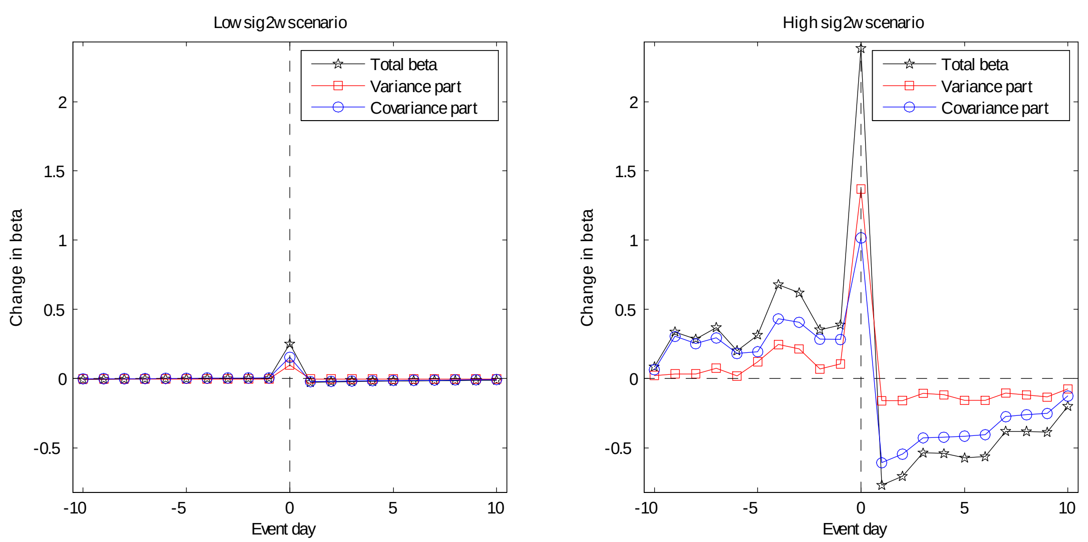

Figure 12: *Changes in beta around event dates for low and high values of the variance of earnings innovations,* σ_w^2.

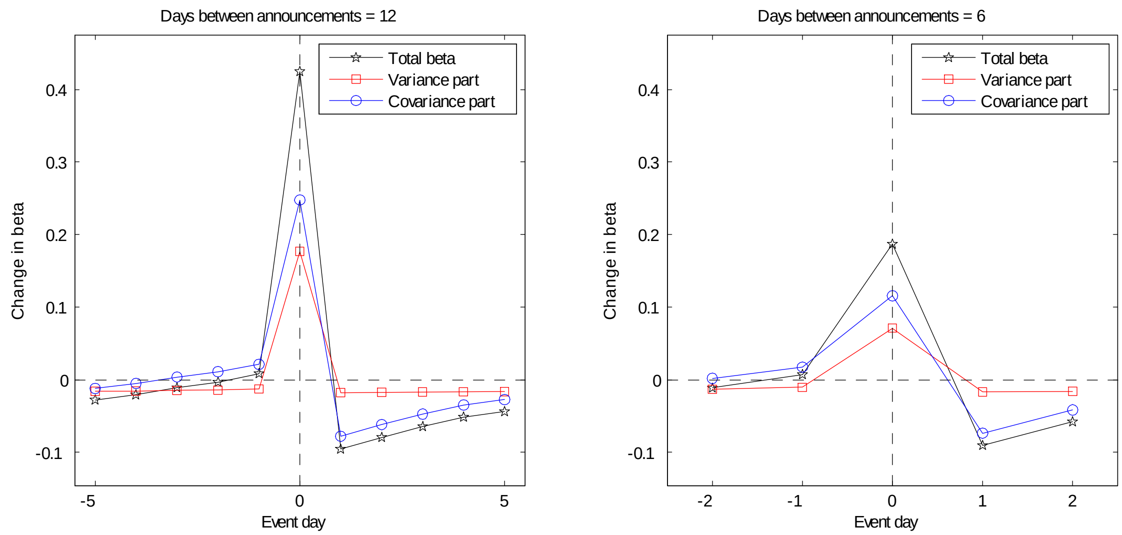

Figure 13: *Changes in beta around event dates when the number of days between announcements is lower.*

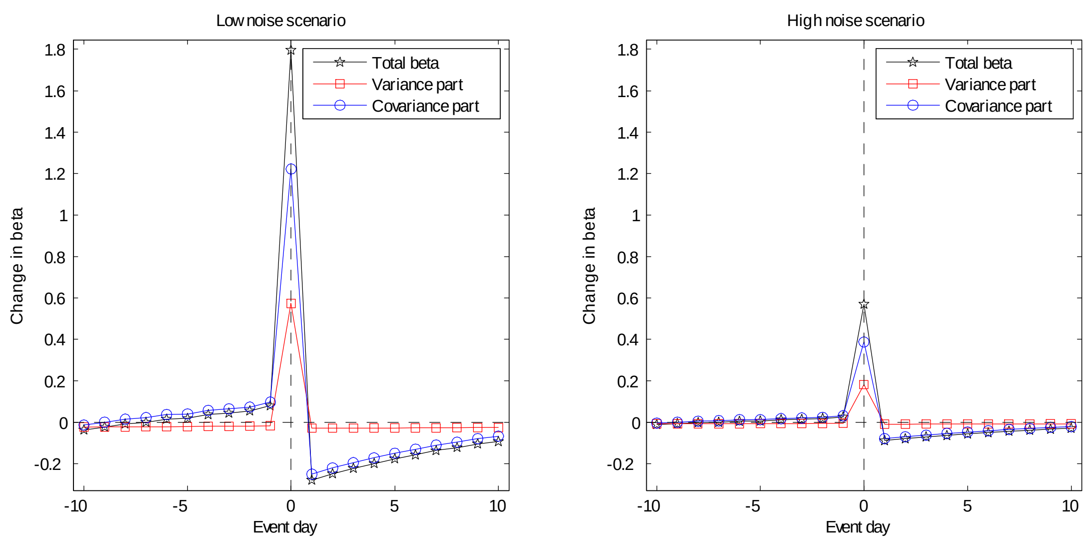

Figure 14: *Changes in beta around event dates for low and high values of the ratio of the variance of the part of daily returns* not *explained by changes in expectations about future earnings,* σ_e^2.