Does Beta Move with News?

Firm-Specific Information Flows and Learning about Profitability*

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Abstract

We investigate whether the betas of individual stocks vary with the release of firm-specific news. Using daily firm-level betas estimated from intra-day prices for all constituents of the S&P 500 index, we find 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. The increase in betas is greater for announcements with larger positive or negative earnings surprises, with greater analyst forecast dispersion, and occurring earlier in the earnings season. Furthermore, the increase in betas is greater for stocks with higher turnover and analyst coverage and for stocks whose fundamentals are more connected with market-wide fundamentals. These findings are consistent with a framework of information spillovers in which investors learn about the profitability of a given firm by using information on other firms.

Keywords: Realized covariance, realized volatility, earnings announcements, comovement, information spillovers, high-frequency data.

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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. Prior empirical studies find significant evidence of variation in beta at monthly or quarterly frequencies, typically associated with variables related to the business cycle or with stock fundamentals.[1]

Empirical work on variations in betas at higher frequencies has been hampered by a lack of reliable data and by the econometric difficulties of studying such betas. However, the ability to detect variations in individual betas at higher frequencies is crucial to understand the effect of information flows on the covariance structure of stock returns. Furthermore, it can be valuable in many applications such as the implementation of trading strategies that involve tracking portfolios or hedging market risks at high frequencies.

In this paper we draw on recent advances in econometric theory to investigate whether the *daily* betas of *individual* stocks vary with the release of firm-specific news.[2] The central question that we ask is whether firm-specific information can affect the market risk of a stock. We find that it does. We then exploit the rich cross-sectional and time-series heterogeneity in our estimates of daily betas to study whether an information spillover mechanism may be driving market-wide comovement in returns around firm-specific information flows. We focus on quarterly earnings announcements, which represent regular and well-documented information disclosures and are ideal for investigating comovement related to firm-specific news on fundamentals. 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 uncover statistically significant and economically important variations in betas around news announcements. These variations are short-lived, and are thus difficult to detect using lower frequency methods. 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 0.16 (with a t-statistic of 8.08) on announcement days. Be-

[1] See Robichek and Cohn (1974), Rosenberg and Guy (1976), Ferson, *et al.* (1987), Shanken (1990), Ferson and Harvey (1991), Ferson and Schadt (1996) and Lewellen and Nagel (2006), amongst others.

[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.

tas drop by 0.03 on the day after the earnings announcement (with a t-statistic of -3.21), before reverting to their average level about five days after the announcement. In a battery of robustness checks we show that our results are not sensitive to the choice of sampling frequency, variations in liquidity around announcements, or the possible presence of cross autocorrelations or jumps.

Our results are surprising, as they suggest a mechanism in which firm-specific information flows can spur market-wide return comovement. To better understand the mechanism that may generate this comovement around earnings announcements, we exploit the cross-sectional and time series heterogeneity in our beta estimates. Our estimation methodology enables us to detect daily movements in beta for individual stocks, allowing us to perform a disaggregated analysis of the behavior of beta across stocks with different characteristics and across announcements taking place in different information environments. The results that we obtain turn out to all be consistent with a framework in which investors use the information disclosure of a given firm not only to update their beliefs on the profitability of the announcing firm, but also to update their beliefs about the remaining non-announcing firms in the market. We first describe our disaggregated results in detail, and then formalize our intuition using a simple learning model.

We examine the behavior of betas around earnings announcements with different information content, measured in three different ways. Firstly, we use the earnings surprise relative to the consensus forecast. We find that betas increase significantly for both positive and negative earnings surprises, while they increase only moderately for announcements with little information content. The spike in beta is 0.25 and 0.22 for good and bad news respectively, and is only 0.10 when earnings surprises are close to zero. This result is consistent with an information spillover effect caused by learning: if news about a stock represents partial news for the remaining stocks in the market, then the covariance between the returns of the announcing stock and the market returns increases, regardless of whether the news is positive or negative, as investors incorporate the information contained in the announcement in the price of non-announcing stocks. Also consistent with learning from information flows, we find that the increase in beta on announcement days is larger for stocks characterized by higher dispersion in analyst forecasts of earnings (0.27 vs. 0.10). Dispersion can be viewed as ex-ante uncertainty about the fundamentals 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 soon after the end of the fiscal quarter (0.20 for early announcers) compared with the middle of the earnings season

(0.11).[3]

We also find that changes in beta on announcement days are larger for stocks with higher turnover (0.27 vs. 0.11) and broader analyst coverage (0.25 vs. 0.12), indicating that information releases about more visible stocks imply greater comovement with other stocks' returns. These findings suggest that investors learn more when the information comes from "bellwether" stocks, i.e. from stocks that are closely followed by traders and analysts, and whose earnings are taken to represent information on the prospects of other firms in the market. Finally, we show that the spikes in realized betas on earnings announcement days are larger for companies whose fundamentals are more highly correlated with aggregate fundamentals (about 0.11 vs. 0.20), where the degree of correlatedness across stocks is measured by analyst earnings betas. This finding lends support to our hypothesis that the return comovement captured by changes in realized betas is driven by the propagation of fundamental information across stocks.

To interpret this rich set of disaggregated results, we propose a simple and rational framework of learning that can give rise to the patterns observed in the data. The intuition is as follows: Since firms only announce their earnings once per quarter, on the intervening days investors must infer the profitability of a given firm (and thus the value of the stock) from other available information. 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 the firm using the earnings announcements of other firms. 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 and in turn drives up the beta of the announcing stock. In line with our empirical findings, simulations from our model show that 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. Thus while we do not rule out that there may be other channels, rational or behavioral, leading to changes in market betas around announcements, we note that any alternative hypothesis also needs to predict the patterns that we find in

[3] These results complement the evidence on lead-lag effects in stock returns (Hou, 2007), documenting gradual information diffusion across stocks. The higher frequency nature of our analysis allows us to detect patterns in return comovement that would not be revealed at lower frequencies.

our disaggregated analysis, i.e., the differences in the behavior of betas across stocks with different characteristics and across announcements with different informational features.

We investigate the robustness of our results in a variety of different ways. First, we check that the changes in betas documented in our study are driven by changes in liquidity or trading intensity that occur around information flows. We expand our regression specification to include controls for a stock's lagged betas, firm volatility, market volatility, trading volume, and bid-ask spreads, and obtain results that are very similar to our baseline specification. We also test whether the behavior of betas around earnings announcements is related to cross-sectional differences or changes in liquidity commonality (see Hameed et al. (2010) and Karolyi et al. (2011)). Our findings show no evidence of significant changes in liquidity comovement around earnings announcements, nor any evidence that cross-sectional differences in realized betas may be driven by ex-ante differences in liquidity commonality across stocks. Using the econometric approach of Todorov and Bollerslev (2010), we further show that our results are not driven by jumps in prices occurring on announcement days. These robustness tests suggest that volatility, liquidity, or commonality in liquidity cannot be the main drivers of the increase in betas around earnings announcements.

We illustrate the economic importance of our findings through a portfolio management application. We first construct a set of portfolios representing either a number of randomly selected individual stocks, or popular long-short strategies based on stock characteristics such as market capitalization, value, and momentum. We then attempt to make these portfolios market neutral by taking a position in the market index to offset their beta. We obtain the predicted beta of the portfolios using different models, and compare their ability to yield market neutral portfolios. We find that a model that uses only information on changes in betas around earnings announcements is better able to yield market neutral portfolios, i.e. portfolios with betas that are closer to zero in absolute value. This realized beta model beats not only a model in which betas are set to unity (market-adjusted model), but also a model in which betas are allowed to vary slowly over the sample period without exploiting information from high frequency data or earnings announcement dates (rolling beta model).

Our paper is related to a number of empirical studies that examine changes in the covariance structure of returns around a firm-specific event. Ball and Kothari (1991) estimate a daily average cross-sectional beta around earnings announcements during the period 1980-1988, documenting a moderate increase in beta of about 6.7% over a three-day window around announcements and no significant change in beta on announcement days. Our methodology allows us to add to this study by obtaining precise estimates of *daily* betas for *individual* stocks, thus enabling us to perform a disaggregate analysis of the behavior of beta at higher frequencies. We can then link variations in beta to firm and event characteristics, to better understand the determinants of the dynamics of beta around information flows. Other papers investigating changes in the covariance of returns across stocks due to firm-specific events include analyses of additions to an index (Vijh (1994), Barberis *et al.* (2005), Greenwood (2008)) or stock splits (Green and Hwang (2009)).[4] In contrast to these papers, we can estimate daily changes in betas for an individual stock, rather than pre- and post-event betas estimated over long horizons.

Our paper also relates to the empirical literature on information spillovers and contagion. Several studies analyze return comovement across markets in relation to contagion or changes in macroeconomic conditions (e.g., Shiller (1989), Karolyi and Stulz (1996), Connolly and Wang (2003), Pindyck and Rotemberg (1990, 1993)). These comovements have been previously explained by common news on fundamentals, information asymmetry, cross-market portfolio rebalancing, wealth effects, category trading, preferred habitats, or non-informational trade imbalances (King and Wadhwani (1990), Fleming et al. (1998), Kyle and Xiong (2001), Kodres and Pritsker (2002), Yuan (2005), Barberis et al. (2005), Pasquariello (2007), Andrade et al. (2008)). Our paper adds to this literature by linking return comovement to the release of firm-specific, intermittent information flows, and by providing a rich set of disaggregated results on comovement conditional on stock characteristics and on the features of the information environment in which the disclosure takes place.

Finally, our study relates to previous papers on price discovery using high frequency data (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

[4] See also Albuquerque (2011) on earnings announcements and skewness.

describes the data used in our analysis and the construction of individual betas. Section 4 presents our main empirical results, and Section 5 contains a simple model of learning across stocks that illustrates the intuition behind our empirical results. Section 6 establishes the economic importance of our findings with a simple portfolio management application. Section 7 presents a variety of robustness tests, and we conclude in Section 8. Appendix A presents the theory underlying the use of high frequency data to estimate daily betas, and Appendix B presents the details of our learning model.

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.[5] Recent advances in the econometrics of high frequency data show that the beta of stock i on day t can be estimated using "realized betas" as follows:

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

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. This estimator was studied by Barndorff-Nielsen and Shephard (2004) in the absence of jumps, and by Jacod and Todorov (2009) and Todorov and Bollerslev (2010) in the presence of jumps. For our main analysis we assume the absence of jumps and rely on the theory of Barndorff-Nielsen and Shephard (2004). In Section 7 we consider the impact of jumps, using theoretical results from Todorov and Bollerslev (2010), and find that our empirical results are robust to possible jumps in our data.

When the sampling frequency is high (S is large), but not so high as to lead to problems coming from market microstructure effects (discussed in detail below), then we may treat our estimated

[5] Previous research employing high frequency data to estimate betas includes that of Bollerslev and Zhang (2003), Bandi, *et al.* (2006) and Todorov and Bollerslev (2010), 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.

realized betas as noisy but unbiased estimates of the true betas:

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

With the above result from Barndorff-Nielsen and Shephard (2004), 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 Barndorff-Nielsen and Shephard (2004). 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). We exploit this feature in a series of robustness checks in Section 7.[6]

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, a total of 2770 trading days. 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. We use the TAQ database to compute daily betas, sampling quoted prices every 25 minutes between 9:45am and 4:00pm. We combine these high-frequency returns with the overnight return, computed between 4:00pm on the previous day and 9:45am on the current day, to obtain a total of 16 intra-daily returns per day.[7]

We choose a 25-minute sampling frequency for intra-daily returns to balance the desire for reduced measurement error with the need to avoid the microstructure biases that arise at the highest frequencies. 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. One

[6] The one-factor market model is simple and widely-used, and the estimation method and high frequency econometric approach used in this paper both generalize to multi-factor models. The key difficulty in such an extension is empirical: one needs high frequency returns on all factors. If the factors are not frequently traded then this can cause problems in the estimation of realized covariances. Dealing with these empirical issues is an active area of research, see Hautsch, et al. (2010) and Bannouh, et al. (2011). Our use of the highly liquid SPDR exchange traded fund (described in the next section) avoids such difficulties.

[7] 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.

example of such an issue arises when estimating the beta of a stock that 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 Bollerslev *et al.* (2008) and Todorov and Bollerslev (2010), and is the one we follow in our main empirical analyses. In the robustness section we analyze betas that are computed from 5-minute returns, and betas that are obtained using the more sophisticated estimator of Hayashi and Yoshida (2005).

We use national best bid and offer quotes, computed by examining all exchanges offering quotes on a given stock.[8] 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 (2010).[9] 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 at or 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 will be reflected in the stock's price only on the following trading day. This means that "day 0" in

[8]Using national best bid and offer (NBBO) quotes 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 quotes is the computational difficulty in constructing them, given the need to handle quotes from all exchanges and maintain a rolling best pair of quotes.

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

our event window is the day in which investors trading on a US exchange can react to the earnings announcement.[10]

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 The behavior of beta around information flows

4.1 Estimation of variations in betas

We estimate changes in betas around earnings announcements for the entire sample of stocks and, given the disaggregated nature of our beta estimates, for a number of sub-samples of stocks sorted by variables related to firm or announcement characteristics. Using a panel regression approach, we regress realized betas on event day dummies using the following specification:

$$\begin{aligned} R\beta_{it} &= \delta_{-10} I_{i,t-10} + ... + \delta_0 I_{i,t} + ... + \delta_{10} I_{i,t+10} \\ &\quad + \bar{\beta}_{i1} D_{1t} + \bar{\beta}_{i2} D_{2t} + ... + \bar{\beta}_{i,11} D_{11,t} + \varepsilon_{it}, \end{aligned} \tag{3}$$

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 include firm-year fixed effects, through the parameters $\bar{\beta}_{i,y}$, to allow for differences in betas across stocks and to capture low-frequency changes in betas over time. The dummy variables D_{1t} to D_{11t} represent the 11 years in our sample (1996 to 2006).[11]

We estimate the panel regression by allowing the observations to be clustered on any given day, obtaining standard errors that are robust to heteroskedasticity and to arbitrary within-cluster

[10] About 33% of the announcements in our sample occur after 4:00pm, while 50% of announcements occur between midnight and 9:44am, a total of about 83% of announcements occurring outside of trading hours. 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 74.4% of the firms in their sample announce outside of trading hours.

[11] In Section 7 we confirm that our results are robust to including a number of control variables to this baseline regression specification.

correlation.[12] The estimation procedure allows for different cluster sizes, as is the case in our unbalanced sample, and yields consistent standard errors, since the number of clusters is large relative to the number of within-cluster observations (Wooldridge 2002, 2003). Our sample consists of about 500 firms per day over a sample period of 2,770 days.[13]

From our regression specification in equation (3), 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 allow beta to change through time), and the δ_j parameters capture 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 Empirical results on the behavior of beta around announcements

We first estimate the average change in beta around earnings announcements across all the stocks in our sample, and then perform a disaggregate analysis. In Table 2 and Figure 1 we present estimates of 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, as explained in Section 3.

The coefficient estimates on the event window dummy variables show no evidence of large deviations in beta from its average non-announcement level during the first few days of the event window. On average, beta experiences a slight increase on days -3 to -1, albeit relatively small in magnitude. On day 0, the earnings announcement day, beta experiences a sharp increase of 0.16 (with a t-statistic of 8.08), followed by an immediate drop on day 1, to 0.03 below its non-announcement average level. Beta remains lower on days 2 to 5, at 0.03 and 0.02 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.

Our estimate of the average change in beta around earnings announcements is comparable to

[12] The mean number of announcements per day is 6.6, and the median is 2.

[13] For robustness we use several alternative techniques to estimate the standard errors, and we obtain similar results. We cluster the residuals by firm, thus allowing for a given firm's observations to be correlated over time. We also cluster the residuals along two dimensions, by firm and year, following the two-way clustering technique proposed by Petersen (2009) and Thompson (2006). Finally, we compute standard errors that are adjusted for heteroskedasticity and autocorrelation according to Newey and West (1987).

the change in beta experienced by stocks added to the S&P 500: Vijh (1994) finds that betas increase by 0.08 during the 1975-89 sample period, and Barberis et al. (2005) find an increase in beta of 0.15 during the period 1976-2000. Our aggregate results can also be broadly compared to Ball and Kothari (1991), who find an increase of 0.067 in their estimate of cross-sectional beta over a 3-day window around earnings announcements for the period 1980-1988. However, such an aggregate result masks the degree of cross-sectional heterogeneity in the behavior of *individual firm* betas around announcements.

To illustrate the degree of heterogeneity in changes in beta across individual stocks, and to motivate the disaggregate analysis below, we estimate regression (3) for two individual stocks, Hewlett-Packard (HPQ) and the New York Times Company (NYT). The results are plotted in Figure 2. This figure shows that the beta of HPQ increases, on average, by almost 2.4 on the day of its earnings announcement, then reverts to slightly below its average level for the subsequent three days, before returning to normal. The beta for NYT, on the other hand, does not significantly change on its announcement dates, and is effectively constant throughout its announcement window. The contrast between the results for HPQ and those for NYT reveal how much information can be lost by looking at average changes in beta across stocks, and prompts our disaggregated analysis.

We consider two types of variables to investigate the heterogeneity in the reaction of market betas to firm-specific news announcements. The first type of variables characterizes the information environment of the earnings announcement, such as the magnitude and sign of the earnings surprise, the degree of ex-ante uncertainty or disagreement about the earnings figure, and the delay with which a company announces its earnings after the end of the fiscal quarter. The second type of variables includes stock characteristics, such as measures of stock liquidity, visibility, and the degree of ex-ante correlatedness in fundamentals across firms.

4.2.1 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 first examine whether changes in betas during information flows are affected by the sign and the magnitude of new information. To answer this question we sort stocks into quintiles based on earnings surprise, defined as the scaled 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 scale the surprise using the firm's stock price measured 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.

Table 3 and Figure 3 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. Deviations of beta from its non-event level are, on average, 0.22 for bad news, 0.10 for no news, and 0.25 for good news (with t-statistics of 3.24, 2.82, and 4.47 respectively). 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 cause a smaller change in the degree of covariation of returns across stocks in the market index.

Next, we analyze cross-sectional differences in the behavior of beta related to investors' ex-ante uncertainty or disagreement about future earnings, measured by the dispersion in analyst forecasts of earnings before the announcement date:

$$disp_{i,t} = \frac{\sqrt{V_{t-1}\left[e_{i,t}\right]}}{\left|E_{t-1}\left[e_{i,t}\right]\right|},$$

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.

We find strong evidence that the increase in beta on announcement days is larger for stocks characterized by higher forecast dispersion, as can be seen from Table 4 and Figure 4. Stocks with low dispersion of forecasts experience an increase in beta of 0.10, while stocks with large forecast dispersion show a change in beta of 0.27. Consistent with the predictions of our model in Section 5, learning is stronger for announcements that resolve more ex-ante uncertainty, and is reflected in a significant increase in realized beta.[14]

Third, we test whether firms that announce their earnings soon after the end of the fiscal quarter exhibit different changes in betas than firms that announce later. Our conjecture is that early announcements carry more information than late announcements and thus represent greater updating and learning opportunities for investors. We should then observe a greater increase in betas for stocks that disclose information early in the earnings season. This analysis is related to the literature on the lead-lag effect in stock returns and gradual information diffusion. For example, Hou (2007) finds a significant intra-industry lead-lag effect between big and small firms and relates it to post-announcement drift of small firms following earnings releases of big firms. The higher frequency of our investigation allows us to complement this evidence by capturing patterns in return comovement that may not be revealed at lower frequencies.[15]

To avoid confusing late announcers and early announcers with different fiscal quarter-ends (e.g., a late announcing December quarter-end firm and an early announcing January quarter-end firm), we use the sub-sample of firms with March, June, September or December fiscal quarter-end for this analysis.[16] The average "delay" between the fiscal quarter-end and the announcement date for each quintile of stocks is 15, 20, 23, 27, and 36 calendar days, respectively. Table 5 presents the regression results, and Figure 5 illustrates the patterns in betas. The average change in beta is 0.20 for early announcers, and decreases gradually for firms that announce later in the earnings

[14] We find further support for these results when we use an alternative measure of ex-ante uncertainty about a firm's earnings, namely the standard deviation of the growth rate of quarterly earnings. Earnings growth is measured by the log change of a firm's quarterly earnings, scaled by analyst coverage; the standard deviation is computed each quarter over the previous six quarters. We find that, as the standard deviation of earnings growth increases, the spike in beta increases from 0.10 (bottom quintile of earnings uncertainty) to 0.24 (fourth quintile), and drops back to 0.15 for the fifth quintile.

[15] Hou and Moskowitz (2005) show that market frictions related to investor recognition drive the delay with which stock prices react to market-wide news. In contrast, our analysis focuses on the delay with which companies release firm-specific information, and on the differential degree of learning that such delay implies across stocks.

[16] These firms represent the bulk of the earnings announcements in our sample (85%). Estimating our baseline specification on this sub-sample of firms yields very similar results to those in Table 2, confirming that the two samples of firms do not present any systematic difference in the behavior of betas around earnings announcements.

season, with firms in the middle quintile of "delay" experiencing a modest increase in beta of 0.11. Interestingly, the latest announcers exhibit relatively large changes in beta of 0.18, which is difficult to explain via a pure learning story. We repeat this test by considering only announcements of December quarter-end earnings. We find that the spike in beta on announcement days is 0.37 for the earliest announcers, decreases to 0.03 for firms in the middle quintile, and becomes 0.19 for the latest announcers. Overall, these findings suggest that investors learn more from the disclosures that come earliest in the earnings season.

4.2.2 Results by characteristics of the firm

We next examine cross-sectional differences in the behavior of realized beta around earnings announcement conditional on several characteristics of the firm. First, we investigate whether changes in betas differ across companies with different degrees of visibility and investor recognition (Merton, 1987). We use share turnover and analyst coverage as proxies for visibility and liquidity of a stock (see, for example, Gervais et al. (2001) and Korajczyk and Sadka (2008) for turnover, and Brennan *et al.* (1993) for analyst coverage). Our conjecture is that information releases of more visible and followed companies imply a larger degree of updating across stocks by investors, leading to greater changes in betas around earnings announcements. We sort stocks into quintiles based on share turnover, measured during a period of two months prior to the earnings announcement window, and we analyze cross-sectional differences in realized betas around announcement days. Table 6 and Figure 6 show that turnover is strongly associated with changes in beta: Low turnover stocks show a smaller increase in beta (0.11, with a t-statistic of 3.68) than stocks characterized by high turnover (0.27, with a t-statistic of 5.07). These findings are consistent with the intuition that high turnover stocks, being more visible and liquid, are more likely to be followed by investors and thus to present the characteristics of bellwether stocks, from which investors learn about other stocks in the market.[17]

As a second variable of stock visibility we consider analyst coverage. Since the number of analysts covering a stock is well-known to be positively correlated with a stock's market capitalization,

[17] Here we use turnover as an ex-ante proxy for a firm's visibility, and in Section 7.6 we analyze the impact of liquidity on our results. Gervais, Kaniel, and Mingelgrin (2001) and Kaniel, Ozoguz and Starks (2011) show that the high-volume return premium is not explained by liquidity premia.

we control for market cap by estimating each quarter the following cross-sectional regression:

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

where $na_{i,t}$ is the number of 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 measured 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". The estimates in Table 7 and Figure 7 reveal that the change in beta on news announcement days is 0.12 (t-statistic of 3.02) for stocks with low analyst coverage, and 0.25 (t-statistic of 4.73) for stocks in the top quintile of residual coverage. This finding is consistent with the intuition that information releases on stocks that are more visible and more followed by analysts imply a larger degree of learning by investors across the market.[18]

Finally, we examine differences in the behavior of betas around earnings announcements for stocks whose fundamentals exhibit different degrees of connectedness with market-wide fundamentals. If investors use a company's earnings announcements to update their beliefs about the prospects of the other companies in the market, then firms with stronger links to market-wide fundamentals should provide investors with a greater opportunity to learn. We measure the link in fundamentals between a given firm and the market by estimating the firm's analyst earnings beta, to capture the degree of correlation of the firm's cashflow innovations with those of the market.[19] We compute revisions in consensus quarterly forecasts as changes in consensus between a given quarter and the same quarter in the previous year, to account for seasonalities, and scale them by stock price. Aggregate revisions are computed as the weighted average of all individual revisions in each quarter. We estimate analyst earnings betas by regressing individual quarterly forecast

[18] Since both turnover and analyst coverage are imperfect proxies for a stock's visibility, we also consider a third proxy. We construct a measure of a stock's breadth of ownership by computing the fraction of institutional investors that hold a given stock in a given quarter (in the spirit of Sias et al. (2006) and Chen et al. (2002). Each quarter we sort stocks into quintiles based on their breadth of ownership, and we estimate differences in the behavior of realized betas around earnings announcement across these quintiles. We find that betas increase by 0.137 and 0.123 for stocks with breadth of ownership in the first two quintiles, and exhibit increasing spikes that reach 0.194 for stocks with more diffused institutional ownership (top quintile).

[19] We use betas computed from analyst forecasts of earnings, rather than from actual earnings, because the quarterly realized earnings for an individual firm contain more noise (also due to potential reporting errors or missing values). Da and Warachka (2009) also use analyst earnings betas, although they use a different procedure to compute cashflow innovations, and do not face issues related to noise in firm-specific earnings or forecast series as they aggregate stocks into portfolios and use the more numerous forecasts of annual earnings rather than quarterly earnings. Carrying out our analysis using firm-specific earnings betas, rather than analyst earnings betas, does not lead to significant patterns in our results.

revisions on aggregate forecast revisions:

$$\Delta C_{i,t} = a_i^E + b_i^E \ \Delta C_{M,t} + \varepsilon_{i,t},$$

where $\Delta C_{i,t}$ is the revision in firm i's consensus forecasts between quarters $t-4$ and t, and $C_{M,t}$ is the weighted average of $\Delta C_{i,t}$ with weights that reflect a company's market capitalization. Table 8 and Figure 8 report the coefficient estimates from these regressions. The results suggest that, consistent with our learning interpretation, firms whose fundamentals are more strongly correlated with market fundamentals experience larger increases in realized betas around earnings announcements. The increase in beta on announcement days is 0.098 and 0.116 for firms in the lower two quintiles of analyst earnings beta (with t-statistics of 2.75 and 2.46), rises to 0.147 for firms with a medium level of analyst earnings beta (t-stat of 3.56), and almost doubles to 0.193 and 0.203 for firms with higher analyst earnings betas (t-statistics of 3.71 and 4.44). These results lend further support to the hypothesis that the return comovement documented in our analysis can be explained by a learning channel: Investors use information on the announcing firm to learn about the rest of the market. As a consequence, stocks whose fundamentals are more connected with aggregate fundamentals offer greater opportunities to learn and trigger greater comovement.[20]

Overall, our results show that the increase in beta around announcement days shows a considerable degree of heterogeneity across stocks. Changes in beta are greatest when the announcement appears to convey more information (bigger surprise component, greater ex-ante analyst dispersion, or occurring earlier in the earnings season), when the firm is more widely watched by investors (greater analyst coverage or higher turnover), and when the fundamentals of the firm are more correlated with market fundamentals. One possible explanation for these disaggregated results is a framework in which firm-specific information signals can generate comovement in returns through an information spillover mechanism based on learning "across stocks". We formalize our intuition in the next section by presenting a simple model of earnings announcements and learning which can match our average results, together with some comparative statics which can match our disaggre-

[20] We also use an alternative and more indirect measure of a company's ex-ante correlatedness with aggregate fundamentals, namely the R^2 from a market model regression of a firm's returns on the market's returns during a pre-event window of about 40 days. Each quarter we rank firms based on this measure of ex-ante connectedness, and we estimate panel regressions of realized betas on event day dummies during a 21-day window around earnings announcements. The results from this test confirm those obtained using analyst earnings betas: Realized betas increase by 0.13 and 0.10 in the first two R^2 quintiles, and they increase by 0.21 and 0.20 in the top two R^2 quintiles.

gated results. This learning channel is not the only possible source of comovement, as information spillover and contagion effects have been previously attributed to a number of different hypotheses, based on rational or behavioral arguments. In the robustness section we show that channels related to volatility or liquidity cannot be the main drivers of our results. While we do not test explicitly for other potential alternative hypotheses that may lead to an increase in market betas around earnings announcements, we note that any alternative hypothesis would also need to predict the patterns in betas that we find in our disaggregated analysis based on the characteristics of the announcing firms and the features of the information environment in which the earnings disclosures take place.

5 A model of earnings announcements and learning

We now consider a simple model to illustrate how learning about the profitability of a given firm from the earnings announcements of other firms can lead to the patterns in betas around earnings announcements that we observe in the data. We start by assuming that the daily returns of a given stock are driven by changes in expectations of earnings, according to the following relation:

$$R_{i,t} = \left(E_t\left[\log X_{i,t}\right] - E_{t-1}\left[\log X_{i,t-1}\right]\right) + \varepsilon_{i,t} \tag{4}$$

where $X_{i,t}$ is the level of earnings of stock i on day t.[21] That is, the return on day t is driven by the change in investors' expectations of the earnings of the firm from day $t-1$ to day t, plus other effects reflected in the residual. The earnings of firm i are only observable on its announcement days, and in between those days investors form expectations of the current level of earnings using previous earnings on firm i and from information on the current and lagged earnings of other firms.

How these expectations vary through time and across firms is key to determining whether this channel can explain the observed behavior in betas around earnings announcement dates. Unfortunately, more structure is required to model the evolution of these expectations, and in Appendix B we outline a simple Kalman filter to model investors' expectations through time. We then simulate this model to see whether it can match key features observed in the data. Matching our empirical work, the simulated model generates $S = 16$ returns per trade day (corresponding to

[21] The equation above is equivalent to the well-known relation between returns and realized unexpected earnings (see Ball and Brown (1968) and Collins and Kothari (1989) among many others).

the 25-minute sampling frequency we use in the empirical analysis) which are then used to compute realized betas.

There are three key parameters in this model: the variability of the earnings process (more volatile earnings means more information is revealed on announcement dates thus resolving more uncertainty); the proportion of variability in returns explained by changes in expectations about future earnings (a closer link between earnings expectations and returns means larger reactions in returns for a given update in earnings expectations); the correlation of a firm's earnings innovations with aggregate earnings innovations (more correlated earnings processes mean that the announcement of a given firm is more revealing of the prospects of other firms, thus offering investors more potential for learning across firms). In our simulation we fix these parameters as follows: The volatility of the earnings process is set at the median value observed in our sample of 733 firms. We set the proportion of variability in observed returns that is explained by changes in expectations about future earnings at 2%, which is close to the figure presented by Imhoff and Lobo (1992) who studied this relation. To model correlation between earnings processes we assume a simple one-factor model for earnings; we set the proportion of variation in earnings that is attributable to the common component, denoted R_z^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.

Figure 9 presents the changes in beta for this stylized model. 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. This increase in beta 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 moves 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.[22]

The drop in beta immediately after the announcement date, and its slow increase on subsequent

[22] Kothari *et al.* (2006) document a negative quarterly correlation between aggregate earnings growth and market returns. Our evidence of an increase in the covariance of an announcing stock with the market return is not inconsistent with their findings, as the daily variations in beta that we uncover are not detectable at quarterly frequencies.

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 expectations for firm i by less than on an average day, 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 estimates of earnings are then less precise, and more open to revisions from day to day. While the reaction in beta to earnings announcements presented in Figure 9 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.

In Figure 10 we consider the patterns that would arise if no learning, or more learning, was possible, by varying the proportion of earnings variation that is explained by the common factor. In the left panel of Figure 10 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 (a "mechanical" component). The magnitude of the change in beta (around 0.5 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 larger spike in beta (around 0.9) with only a part of this being attributable to the "mechanical" component. Thus more correlated earnings processes, which allow for more cross-stock learning, lead to larger responses in betas to earnings announcements. This result is consistent with our cross-sectional test on the ex-ante correlation in fundamentals.

In Figure 11 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 the left panel, with low variance of the earnings innovation process, we see a smaller change in beta on announcement dates, around 0.2. In the right panel, with a high value for the earnings innovation variance, we observe a much larger spike in beta, around 0.95. Thus more volatile earnings processes lead to larger spikes in beta. This result confirms our cross-sectional test on analyst forecast dispersion (Table 4), which shows that firms with larger dispersion in analyst forecasts of earnings, thus greater ex-ante uncertainty about fundamentals, experience a larger increase in realized betas on earnings announcement days.

Some additional comparative statics are presented in Appendix B, along with technical details for this model.

6 Application to market neutral portfolios

In this section we show that the statistically significant variations in beta documented in Section 4 have economically significant implications for portfolio decisions. Consider the problem faced by a portfolio manager or hedge fund manager who wishes to incorporate into her portfolio a trading strategy devised by one of her traders, but who has a pre-determined target for her exposure to a broad market index. If the returns generated by the trader's strategy are not zero beta, then incorporating that strategy into the portfolio will move its beta away from the target. Worse, if the beta of the trading strategy is time-varying, then the beta of the overall portfolio may change in ways that do not line up with the portfolio objectives. This problem can be overcome if it is possible to make the trading strategy market neutral, by taking a position in the market index that offsets the beta of the strategy (this is related to the construction of so-called "portable alpha" strategies). We use this example to illustrate the importance of capturing daily variations in beta attributable to information flows around quarterly earnings announcements.

In this analysis we consider both completely random trading strategies (which are unlikely to be profitable, but which represent a varied set of strategies for us to attempt to neutralize) and simple trading strategies based on size, value and momentum. For the random strategies, we consider strategies that involve $N = 2$, 5, 10 or 25 stocks (thus ranging from a simple pairs-trading strategy, up to a more sophisticated strategy involving dozens of stocks), and we randomly select the N stocks from our universe of 733 stocks, and then assign each stock an equal weight or a random weight, uniform on the interval $[0, 2/N]$. For the simple characteristic strategies, we sort stocks into quintiles based on their market capitalization, book-to-market ratio, or past 12 months performance, and then randomly select 10 stocks from the top quintile to hold long and 10 stocks from the bottom quintile to hold short. We form the quintiles at the start of each year and rebalance at that time. In all studies, if a given stock is not in the sample on a particular day then we re-allocate its weight across the remaining stocks. We repeat the random draws of stocks and weights 1000 times.

We then attempt to make each portfolio "beta neutral" by taking a position in the market to offset the predicted beta of this portfolio. The predicted beta for the portfolio comes from one of four models. The first two beta models we consider are the "Zero beta" and the "Unit beta" models, which assume that the portfolio beta is identically zero, or identically one, on every day. The former case corresponds to not neutralizing the portfolio at all, while the latter case corresponds to a simple "market-adjusted model", in which the portfolio is neutralized by simply subtracting the market return. The third model is the familiar "Rolling beta" model, where the beta for each stock is estimated via a regression using the most recent 100 daily returns. This allows beta to vary slowly over the sample period but does not exploit information from high frequency data or earnings announcement dates. Our fourth model is the "Realized beta" model, where the daily beta for each stock is allowed to vary within a window of 10 days around earnings announcements, as in equation 3. If the dates of information flows, such as earnings announcements, were unimportant for beta then this model would simply return a constant beta for each stock, and we would expect to see no improvement in the market neutralization from using the Realized beta model relative to the Rolling beta model. If, on the other hand, the changes in beta documented in Section 4 are important for market neutralization, then we would expect to see this reflected in a "more neutral" portfolio based on the Realized beta model.[23]

We evaluate the performance of each model by computing the realized beta of each market neutral portfolio and comparing it with that of the Rolling beta market neutral portfolio. Better models should lead to market neutral portfolios with betas that are closer to zero in absolute value. We test whether a given model is better than the Rolling beta model by using a Diebold and Mariano (1995) test on the difference in absolute realized betas. We run this test for each of the 1,000 replications, and report the proportion of times that a given model was significantly better, or significantly worse, than the Rolling beta model at the 5% level.

The results of this analysis are reported in Table 9. This table reveals that the Rolling beta model significantly outperforms the Zero beta (no neutralization) model: across portfolio sizes (N) the Zero beta model almost never beats the Rolling beta model, and it is significantly beaten by the Rolling beta model in almost all cases. This is true for the equal-weighted, random-weighted, and the characteristic-based portfolios. A similar result is also found for the Unit beta model:

[23] Note that the "Realized beta" model used here contains only indicator variables (for whether day t is an event day or not) and does *not* contain lagged betas, lagged volatility, or any of the other variables that might be useful for predicting future betas, see Andersen, *et al.* (2006b) for example. Including these variables would most likely improve the "Realized beta" model performance, but would hinder our ability to determine whether changes in beta around information flows are important. Thus we limit our attention to this simple indicator-variable model, and leave a more detailed study of beta predictability to separate research.

the Unit beta model outperforms the Rolling beta model in only 1-3% of cases, whereas it significantly underperforms in 87-100% of cases. These results reveal that the Rolling beta model is a serious benchmark model for constructing market neutral portfolios: it represents a substantial improvement on these two simple neutralizing methods.

Table 9 shows that the Realized beta model significantly outperforms the Rolling beta model in almost all of the replications: it "neutralizes" the portfolios significantly better than the Rolling beta model in around 80-90% of cases, and underperforms in less than 1% of cases. The outperformance of the Realized beta model holds across all choices of portfolio size (2, 5, 10 and 25 stocks), across equal-weighted and random-weighted strategies, as well as the characteristic strategies. This finding offers strong empirical support for the importance of changes in beta around times of information flows. Note also that these results average across *all* stocks in our sample, including those with characteristics (such as low trading volume, low analyst dispersion, or low correlatedness of fundamentals) that tend to lead to smaller changes in beta. The outperformance of the "Realized beta" model in this market neutralization application would presumably be even greater if we focused on trading strategies involving stocks with characteristics associated with larger changes in beta.

7 Robustness tests

In this section we perform a series of robustness tests of the changes in beta that we report in Section 4. First, we check the sensitivity of our results to the choice of sampling frequency and to the methodology used in constructing realized betas. We then modify our regression specification to include controls for lagged realized betas, realized volatility, trading volume and bid-ask spreads. Furthermore, we check the robustness of our results to a modified measure of beta that is constructed after excluding the announcing stock from the market index. We also consider the impact of potential jumps in prices on our estimates of realized betas. Finally, we investigate whether comovement in liquidity before and during earnings announcements could give rise to the pattern in realized betas that we uncover in this study. In unreported tests, we verify that our results are robust to the clustering of earnings announcements on event days,[24] and to the potential

[24] When we control for the number of other announcements occurring on any given day, the increase in realized betas on day 0 is 0.169, compared with 0.162 in our baseline results. When we exlude from the sample all days with a number of announcements higher than 4 (the median number of announcements on days with at least one

cross-listing of S&P 500 stocks on non-US markets.[25]

7.1 Higher frequency beta

In our main set of empirical results we follow earlier research on estimating covariances and betas from high frequency data, see Bollerslev *et al.* (2008) and Todorov and Bollerslev (2010) 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 10 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 (0.12 vs. 0.16). The similarity of our results for 5-minute and 25-minute betas is likely to be related to our focus on *deviations* of beta from its average level, which provides some built-in protection against level biases arising from market microstructure effects.

7.2 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) (henceforth HY) 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.[26] 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

announcement) the increase in beta is 0.218. This result is also consistent with our learning story: on days with many announcements, the unique information content of any given announcement is lower, leading to less learning from any single announcement. In contrast, if the announcing company is the only announcer on a given day, then there is more potential for learning from that individual firm, leading to a bigger change in its beta.

[25] To control for the potential influence of cross-listing on our results on comovement (Bailey, Karolyi and Silva (2006), Gagnon and Karolyi (2009)) we replicate our analysis after excluding from our sample those stocks that are also traded in foreign exchanges. We obtain the dataset of foreign equity listings used by Sarkissian and Schill (2004, 2009), which comprises cross-listings in international markets as of December 1998. We match the list of companies in their dataset with our sample of S&P500 companies, and find an overlap of 126 firms (about 17% of our sample). We re-estimate our panel regression of realized betas around earnings announcements after excluding these stocks. We find that the behavior of betas around earnings announcements is very similar to our baseline case, with a spike in realized beta of 0.17 on announcement days.

[26] 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.

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 10. 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 smaller relative to our main empirical results (0.14 versus 0.16 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.

7.3 Adding control variables

We check the robustness of our results on 25-minute beta by adding a number of control variables in the regression specification. First, we include lagged realized betas in the regression to account for autocorrelation in realized betas, see Andersen, et al. (2006b) for example. We include five lags of daily realized betas. The results from this estimation are presented in Table 10 (Lags), and are similar to those obtained in our baseline specification. The change in beta on day 0 is 0.17, with a t-statistic of 7.62.

Next, we add realized firm volatility, realized market volatility, trading volume, and adjusted spreads (described in Section 7.6 below) as further control variables in the regression specification. We control for firm volatility given the existing empirical evidence that volatility can affect covariance estimates (Forbes and Rigobon (2002)). We also control for potential variations in market volatility over the event window, caused by clustering of earnings announcements or other factors. We control for volume given the evidence that non-synchronous trading can cause a downward bias in realized covariances (see Epps (1979), Scholes and Williams (1977), Dimson (1979) and Hayashi and Yoshida (2005)). 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 may be important to account for the possibility that an observed increase in realized beta on announcement dates is due to a decrease in the bias related to non-synchronous trading. We control for this effect by including a stock's trading volume in our regression specification. We also include the square and cube of volume as control variables, allowing for a nonlinear relation between volume and any biases present in the beta estimates. Table 10 (V Controls) shows that the estimates of beta are similar to our base specification (with a day 0 change of 0.12), providing further confidence in our empirical results.

7.4 A modified measure of beta

In this section we estimate the behavior of beta around earnings announcements using a modified measure of beta. This new measure, labeled $\beta_{it}^{(i)}$, is the beta of stock i with a re-weighted market index that places zero weight on stock i and only uses the remaining $N-1$ stocks. Given that the firms in our sample are constituents of the index used as the market portfolio (the S&P500 index), an increase in the return variance of a given stock can mechanically increase its beta with the market. We thus compute this new measure of beta to exclude any possible mechanical variations in beta due to using a market portfolio that places non-zero weight on the announcing stock. To obtain this modified measure of beta we first define $r_{mt}^{(i)}$, the re-weighted market index which places zero weight on stock i, as a simple function of the return on the original market index, the return on stock i, and the weight on stock i:

$$r_{mt}^{(i)} \equiv \frac{1}{1-\omega_{it}} \sum_{j=1, j\neq i}^{N} \omega_{jt} r_{jt} = \frac{1}{1-\omega_{it}} \left(r_{mt} - \omega_{it} r_{it} \right). \tag{5}$$

The beta of stock i with respect to this re-weighted market index is then given by

$$\beta_{it}^{(i)} \equiv \frac{Cov\left[r_{it}, r_{mt}^{(i)}\right]}{V\left[r_{mt}^{(i)}\right]} = \frac{(1-\omega_{it})}{1-\omega_{it}\left(\beta_{it}+\beta_{it}^{(cov)}\right)} \beta_{it}^{(cov)}, \tag{6}$$

where $\beta_{it}^{(cov)}$ is defined as

$$\beta_{it}^{(cov)} = \sum_{j=1, j\neq i}^{N} \omega_{jt} \frac{Cov\left[r_{it}, r_{jt}\right]}{V\left[r_{mt}\right]} = \beta_{it} - \omega_{it} \frac{V\left[r_{it}\right]}{V\left[r_{mt}\right]}. \tag{7}$$

The penultimate column in Table 10 presents estimates of our baseline panel regression using this modified measure of beta. The results show that the pattern documented in this paper for the behavior of beta around earnings announcements does not depend on the mechanical component that is related to the weight of the announcing stock in the market index. Beta spikes upward on announcement days by 0.14, a magnitude that is very similar to our baseline result.

7.5 Possible jumps in prices

We use the recent work of Todorov and Bollerslev (2010) to consider the impact of potential jumps in prices on our main findings. Like us, Todorov and Bollerslev (2010) consider a one-factor model, and they decompose the factor return into a part attributable to a continuous component and a part attributable to jumps. In the most general case, each of the factor components has a separate loading (β^c and β^d), and when these two loadings are equal the model simplifies back to a standard one-factor model. Todorov and Bollerslev (2010) provide a method for estimating the continuous and jump betas, which we implement here. The first step in their analysis is to test for the presence of a jump in the market price on each day,[27] and we do so using the same test (that of Barndorff-Nielsen and Shephard (2006)) and critical value (3.09) as Todorov and Bollerslev (2010). On days with no jumps in the market, the usual realized beta is an estimate of the continuous beta. On days with jumps in the market, one can use the estimator in Todorov and Bollerslev (2010) to estimate the jump and continuous betas separately, and then look at the reaction in each of these around earnings announcements. In our sample, however, we have too few jump days that intersect with earnings announcement days (less than one per firm on average) and so we do not attempt to estimate reactions in "jump betas". In contrast, we have sufficient observations to study the reactions in "continuous betas".

The test for jumps in the market factor reveals that on 4.04% of days we find a significant jump. Excluding these days from our analysis, and estimating the reaction of "continuous betas" around announcements yields results presented in the last column in Table 10. We see there that the results excluding jump days are very similar to our baseline results, with the spike in beta on announcement days estimated at 0.17 with a t-statistic of 8.43. In unreported analysis, we also consider using a less conservative critical value of 1.65 for the jump test, which leads to a proportion of 21.4% of days with a jump, and find very similar results to those presented in Table 10. Thus we conclude that our findings are not driven by the presence of jumps.

[27] There is no need to test for a jump in the individual stock price, as the estimates of the continuous and jump betas depend only on whether the *factor* was continuous or experienced a jump.

7.6 Comovement in liquidity

In this section we test whether the changes in realized beta around earnings announcements that we uncover can be driven by comovement in liquidity innovations. A large and growing literature shows evidence of commonality in stock liquidity (e.g., Chordia et al., 2000) and shows that comovement of a stock's liquidity with market liquidity is priced (Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006)). Recent work documents that liquidity comovement varies over time. For example, Hameed et al. (2010) find that the comovement in spreads tends to increase in down markets, while Karolyi, Lee and van Dijk (2011) show that commonality in liquidity is greater in countries and during times of high market volatility, larger presence of international investors, and more correlated trading activity. Our goal is to test whether comovement in liquidity has an effect on return comovement during the release of firm-specific information. To the extent that variations in the covariance of a stock's liquidity with market liquidity are priced and translate into a liquidity premium, they may also drive a stock's return comovement with the rest of the market and thus be captured by our measure of realized beta. We test whether comovement in liquidity is related to changes in realized beta around earnings announcements in two different ways. First, we test for variations in liquidity comovement during earnings announcements directly, using a proxy for daily comovement in liquidity. Second, we test for differences in the behavior of realized betas during earnings announcements across stocks with different ex-ante liquidity comovement.

We start by constructing a daily measure of liquidity for each stock in our sample using bid-ask spreads. We compute the daily proportional quoted spread (the difference between bid and ask quotes as a proportion of the midquote, in percent) from 5-minute bid and ask quotes. As in Hameed et al. (2010) and Chordia et al. (2005), we then adjust spreads for time-series variations due to seasonality and deterministic changes such as time trends and changes in tick size. We regress a stock's daily spread on day of the week dummies, month dummies, tick change dummies, and a trend variable capturing the age of the stock in our dataset.[28] The residuals that we obtain from this regression are the adjusted proportional quoted spreads, $ASPR_{it}$. Innovations in liquidity

[28] In particular, we estimate the following regression for each stock i in our sample:

$$QSPR_{i,t} = \sum_{k=1}^{4} \gamma_{i,k}^{1} Day_{k,t} + \sum_{k=1}^{11} \gamma_{i,k}^{2} Month_{k,t} + \gamma_i^3 Tick1_t + \gamma_i^4 Tick2_t + \gamma_i^5 Trend_t + \varepsilon_{i,t},$$

where $Day_{k,t}$ are day of the week dummies from Monday to Thursday; $Month_{k,t}$ are month dummies from January to November; $Tick1_t$ captures the tick change on 24 June 1997 and $Tick2_t$ captures the tick change on 29 January 2001; $Trend_t$ is the difference between the current year and the year in which the stock appears in our sample.

are defined as daily changes in adjusted spreads, $\Delta ASPR_{i,t} = ASPR_{it} - ASPR_{it-1}$, and market innovations in liquidity are obtained by averaging individual stock innovations on any given day.

To test whether liquidity comovement varies with the release of firm-specific news, we construct a proxy for the daily covariance of a stock's liquidity innovations with the market's liquidity innovations. This proxy is the product of the daily liquidity innovations for the stock ($\Delta ASPR_{i,t}$) and for the market ($\Delta ASPR_{M,t}$), scaled by the variance of the market innovations:

$$LC_{i,M,t} = \frac{\Delta ASPR_{i,t} \times \Delta ASPR_{M,t}}{V_{t-1}[\Delta ASPR_{M,t}]},$$

where $V_{t-1}[\Delta ASPR_{M,t}]$ is the variance of the market innovations in liquidity and is measured during the non-event days that precede the earnings announcement window. The results are presented in Panel A of Table 11. We find that liquidity comovement does not vary significantly on earnings announcement days: liquidity comovement is significantly lower than average during event days -6 to +1, on days +4 to +6, and again from day +8 onward. The lack of a clear change in comovement on the announcement day (day 0) suggests that daily variations in liquidity comovement cannot drive the pattern in realized betas that we uncover in this study.

As a second test of the impact of liquidity comovement we exploit the cross-sectional heterogeneity in realized betas in our sample and test whether stocks with different ex-ante levels of liquidity comovement exhibit different patterns in realized betas around announcements. We estimate ex-ante liquidity comovement using a method similar to Hameed et al. (2010). We regress daily individual liquidity innovations on daily market liquidity innovations during a pre-event window of about 40 trading days before the earnings announcement window: $\Delta ASPR_{i,t} = a_i^L + b_i^L$ $\Delta ASPR_{M,t} + \varepsilon_{i,t}$. The R^2 from this regression represents the measure of comovement in liquidity between stock i and the market. Each quarter we rank stocks into quintiles based on this ex-ante measure of liquidity comovement, and evaluate the behavior of realized betas around earnings announcements for these different portfolios. Panel B of Table 11 presents the results. We find that the increase in realized betas is similar across all quintiles of liquidity comovement. The lack of substantial differences in realized betas across stocks exhibiting different levels of liquidity comovement further confirms that commonalities in liquidity innovations, while time-varying and certainly of interest, do not drive the behavior of realized betas around firm-specific information flows.

8 Conclusions

In this paper we investigate variations in daily individual stock betas around 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 that we document are short-lived (lasting around two to five days) and thus difficult to detect using the lower frequency methods employed in most previous studies. Furthermore, the behavior of beta exhibits a large degree of cross-sectional heterogeneity.

We exploit information from our estimates of daily betas for individual stocks to perform a disaggregated analysis of the behavior of beta around information flows. We study cross-sectional differences in changes in beta for stocks with different characteristics, and for earnings announcements with different information content and different degrees of uncertainty. We find that changes in beta are strongest for earnings announcements that represent large (positive or negative) surprises, that resolve a larger amount of uncertainty (measured by analyst dispersion), or that occur earlier in the earnings season. We also find that changes in beta are greatest for stocks with higher turnover and greater analyst following, i.e. for more visible stocks. Furthermore, the increase in betas is greater for stocks whose fundamentals are more connected with market-wide fundamentals.

Our analysis contributes to the empirical literature on return comovement and information spillovers. While we do not explicitly test for all possible channels that may explain our empirical findings, we note that our results are all consistent with the intuition that investors form expectations about the profitability of a given company by using information on other companies. We propose a simple framework that formalizes this intuition: In the presence of intermittent earnings announcements and cross-sectional correlation in earnings, good (bad) news for announcing firms is interpreted as partial good (bad) news for other firms. Investors' updating process "across firms" 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. Our disaggregate empirical results confirm this interpretation, as the estimated changes in beta are generally strongest in cases where the most learning is possible.

Our findings are robust to using alternative measures of beta that address potential market microstructure biases, and are also robust to controlling for changes in firm volatility, market volatility, and for jumps in prices around announcements. Furthermore, the results in this paper appear not to be driven by changes in liquidity comovement before or during the announcement window. These robustness tests suggest that changes in volatility or commonality in liquidity around announcements cannot be the main drivers of the comovement that we document around earnings releases.

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. We provide a simple application to illustrate the relevance of our findings for neutralizing a portfolio's exposure to a market index. More generally, the analysis in this paper establishes that firm-specific information flows have a significant impact on the covariance structure of stock returns, thus contributing to our understanding of information spillover mechanisms and the process of incorporation of new information into prices.

Appendix

A Details on the estimation 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 $d \log \mathbf{P}(t)$:

$$\begin{aligned} d \log \mathbf{P}(t) &= d\mathbf{M}(t) + \Theta(t)\, d\mathbf{W}(t) \\ \Sigma(t) &= \Theta(t)\, \Theta(t)' \end{aligned} \tag{8}$$

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 process given above assumes the absence of jumps in the stock price process; this assumption can be relaxed using the framework of Todorov and Bollerslev (2010) as outlined below.

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":

$$ICov_t = \int_{t-1}^{t} \Sigma(\tau)\, d\tau. \tag{9}$$

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:

$$\beta_{it} \equiv \frac{ICov_{imt}}{IV_{mt}}, \tag{10}$$

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 β_{it} is the beta of asset i (sometimes known as the "integrated beta" in this literature).[29] 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:

$$RCov_t^{(S)} = \sum_{k=1}^{S} \mathbf{r}_{t,k}\mathbf{r}_{t,k}' \xrightarrow{p} ICov_t \quad \text{as } S \to \infty, \tag{11}$$

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:

$$\sqrt{S}\left(vec\left(RCov_t^{(S)}\right) - vec\left(ICov_t\right)\right) \xrightarrow{D} N\left(0, \Omega_t\right) \quad \text{as } S \to \infty, \tag{12}$$

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.[30] Combining the above asymptotic distribution result with

[29] 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 may differ from that defined in equation (10), see Dovonon, *et al.* (2008) for example. We elect to use the definition given in equation (10) as it fits directly into the theoretical framework of Barndorff-Nielsen and Shephard (2004) and Todorov and Bollerslev (2010).

[30] Recent extensions of the theory presented by Barndorff-Nielsen and Shephard include Bandi and Russell (2005),

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

$$\sqrt{S}\left(R\beta_{it}^{(S)}-\beta_{it}\right)\xrightarrow{D}N\left(0,W_{it}\right),\ \text{ as } S\to\infty \tag{13}$$

This can then be re-expressed as

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

as in equation (2).

To allow for the presence of jumps in the price process, Todorov and Bollerslev (2010) consider the following specification[31] for stock i :

$$d\log P_i\left(t\right)=\alpha_i d\left(t\right)+\beta_i^c\sigma_m\left(t\right)dW_m\left(t\right)+\beta_i^d J_m\left(t\right)+\sigma_i\left(t\right)dW_i\left(t\right)+J_i\left(t\right) \tag{14}$$

In this framework, $\left[\beta_i^c,\beta_i^d\right]$ is assumed constant throughout each day, but can change from day to day. Aggregating the above process to the daily frequency yields a very intuitive model for daily stock returns:

$$r_{it}=\alpha_i+\beta_{it}^c r_{mt}^c+\beta_{it}^d r_{mt}^d+\varepsilon_{it}$$

That is, the daily return on stock i has exposure to both the continuous part of the market return (r_{mt}^c) and the jump part of the market return $\left(r_{mt}^d\right)$, and has an idiosyncratic term (ε_{it}) which is also made up of a continuous and a jump component. When $J_m\left(t\right)=J_i\left(t\right)=0$ this framework collapses to that of Barndorff-Nielsen and Shephard (2004) described above. When $\beta_{it}^c=\beta_{it}^d$, this model collapses to the usual one-factor model for stock returns, but as Todorov and Bollerslev (2010) point out, there is no a priori reason to impose such a restriction. A key contribution of Todorov and Bollerslev (2010) is a method for consistently estimating β_{it}^c and β_{it}^d using high frequency data, and for conducting inference on these estimates.

Barndorff-Nielsen, *et al.* (2008) and Dovonon, *et al.* (2008).

[31] The notation here is simplified relative to that in Todorov and Bollerslev (2010); see their paper for a more general description.

B Details on the model

This appendix provides details on a simple model of investor learning from intermittent earnings announcements.

B.1 Intermittent earnings announcements

We specify the dynamics of the earnings process by assuming that log-earnings follow a random walk with drift.[32] We write the process in log-differences so that the left-hand side variable is stationary:[33]

$$\Delta \log X_{it} = g_i + w_{it}.$$

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}:

$$w_{it} = \gamma_i Z_t + u_{it} \tag{15}$$

where γ_i captures the importance of the common component for stock i.[34]

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:

$$y_{it} = \sum_{j=0}^{M-1} \Delta \log X_{i,t-j} + \eta_{it} \tag{16}$$

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

[32] 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.

[33] In line with an extensive literature in finance (see Kleidon (1986) and Mankiw, *et al.* (1991) for example), this relation can be derived by assuming that log-dividends follow a random walk with drift:

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

where $t = 1, 2, ..., T$ represents trade days and $i = 1, 2, ..., N$ represents different firms. Dividends can be linked to earnings by assuming that the dividend paid at time t is a fixed proportion of the earnings at time t, $D_{it} = \lambda_i X_{it}$. Therefore we have: $\log X_{it} = \log D_{it} - \log \lambda_i = g_i + (\log \lambda_i + \log X_{i,t-1}) + w_{it} - \log \lambda_i$, and so $\Delta \log X_{it} = g_i + w_{it}$.

[34] 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 (2009).

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, namely 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:

$$V\left[\eta_{it}|I_{it}\right] = \sigma^2_{\eta i} \cdot I_{it} + \sigma^2_I \left(1 - I_{it}\right) \tag{17}$$

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

$$\begin{aligned} \Delta \log \mathbf{X}_t &= \mathbf{g} + \boldsymbol{\gamma} Z_t + \mathbf{u}_t & (18) \\ \mathbf{y}_t &= \sum_{j=0}^{M-1} \Delta \log \mathbf{X}_{t-j} + \boldsymbol{\eta}_t & (19) \end{aligned}$$

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

$$V\left[\boldsymbol{\eta}_t|\mathbf{I}_t\right] = R \cdot \Gamma_t + \sigma^2_I \left(I_N - \Gamma_t\right) \tag{20}$$

where I_N is an $N \times N$ identity matrix, $R = diag\left\{\left[\sigma^2_{\eta 1}, \sigma^2_{\eta 2}, ..., \sigma^2_{\eta N}\right]\right\}$ and $\Gamma_t = diag\left\{\mathbf{I}_t\right\}$, where $diag\left\{\mathbf{a}\right\}$ is a diagonal matrix with the vector $\mathbf{a}$ on the main diagonal.

Expectations of future (and past) earnings can be estimated in this framework using a standard Kalman filter, see Hamilton (1994) for example, where the usual information set is extended to include both lags of the observed variable, $\mathbf{y}_t$, and lags of the indicator vector for announcement dates, $\mathbf{I}_t$, so $\mathcal{F}_t = \sigma(\mathbf{y}_{t-j}, \mathbf{I}_{t-j}; j \geq 0)$. 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 $\sigma^2_{\eta i}$), while in between announcement dates it will efficiently combine information on firm i's earlier announcements with information on announcements by other firms.

There are numerous models for linking expectations about future dividends and earnings to stock prices, see Campbell, *et al.* (1997) for a review. For example, using a standard present-value relation for stock prices, we can express daily returns the change in expectations of the log-earnings process:

$$R^*_{i,t+1} \equiv \log P_{i,t+1} - \log P_{it} = \hat{E}_{t+1}[\log X_{it+1}] - \hat{E}_t[\log X_{it}]. \tag{21}$$

B.2 High frequency returns

To match our use of high frequency returns in our empirical analysis, we now consider simulating this model to obtain S observations per trade day, and then computing realized betas from the resulting simulated returns. To do this, we assume that each intra-daily return is comprised of a component arising from the revision in expectations about earnings and a "noise" component, $\varepsilon_{i,t}$, that is unrelated to earnings information. We assume that the noise component for the j^{th} intra-daily period obeys:

$$\varepsilon_{i,j} \sim iid\ N\left(0, \sigma^2_\varepsilon / S\right), \quad j = 1, 2, ..., T \times S,$$

so that the variance of the noise cumulated over one day is equal to σ^2_ε. To simplify the computations, we assume that all earnings announcements take place during the "overnight" period (in our data, 83% of announcements occur during the overnight period, so this assumption is not unreasonable.) Thus the simulated return for the j^{th} intra-daily period follows:

$$R_{i,j} = R^*_{i,j} + \varepsilon_{i,j}$$

and the realized beta for stock i on day t is computed as:

$$R\beta_{i,t} = \frac{\sum_{j=1}^{S} R_{i,(t-1)S+j} R_{m,(t-1)S+j}}{\sum_{j=1}^{S} R^2_{m,(t-1)S+j}}$$

With the simulated realized betas and the earnings announcement indicator variables, we can run the regressions described in Section 4 on the simulated data and conduct comparative static analyses by varying some of the key parameters of this model.

Our empirical analysis is based on 25-minute returns, which provides us with $S = 16$ observations per day. In the simulation we make the simplifying assumption that all S intra-daily periods are of equal length, and abstract away from the fact that in practice the overnight period is longer than the other intra-daily periods. Allowing for a "longer" overnight period could be accommodated by increasing the variance of the noise term for that period. As we show in Figure 13 below, increasing the variance of the noise reduces the magnitude of the change in beta around announcements, but does not affect the shape of the changes in beta through the event window, thus this assumption is not critical to the results of this simulation study.

B.3 Numerical results and analysis

The nature of the 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.

We set the number of firms (N) to 100 and the number of days between earnings announcements (M) to 25.[35] Below we also present the reactions in beta to news when $M = 12$ and $M = 6$ to see how this choice affects the results. In all cases we simulate $T = 1000$ days, each with $S = 16$ observations per day, 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.

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

[35] 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.

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. As noted in Section 5, 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. We set σ_ε^2 (the variance of the component of returns that is *not* attributable to changes in expectations about earnings) so that 2% of the variability in returns is explained by changes in expectations about future earnings. We vary this parameter between 0.01 and 0.04 in comparative statics.[36] 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 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.

The results from the base case simulation, presented in Figure 9, are discussed in Section 5, as are the results related to variations in the amount of learning from other firms' earnings announcements and the results on variations in the variance of the earnings process. We discuss here two other comparative statics. In Figure 12 we vary the number of days between earnings announcements. We are computationally constrained to keep M no larger than 25, and in Figure 12 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 larger "lumps".

Finally, in Figure 13 we present the results from changing the amount of variation in returns that is explained by variation in earnings expectations. In the left panel, with a low value of noise, we observe a larger spike in beta on announcement dates, around 1.6 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

[36] Straightforward calculations 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. See Karolyi (1992) for a study applying shrinkage methods to obtain better forecasts of betas.

future earnings, the response of beta to earnings announcements is smaller, around 0.6 in this simulation.

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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 cross-sectional medians of variables measured before earnings announcements, by year, 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

Table 2: Changes in beta around information flows

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. The estimates are obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Event day	**Beta**	**Event day**	**Beta**	**Event day**	**Beta**
-10	0.007	-3	0.022	4	-0.024
	(0.78)		(2.60)		(-2.77)
-9	0.014	-2	0.022	5	-0.017
	(1.47)		(2.77)		(-2.18)
-8	0.019	-1	0.027	6	-0.012
	(2.22)		(2.97)		(-1.53)
-7	-0.015	0	0.162	7	-0.005
	(-1.76)		(8.08)		(-0.68)
-6	0.008	1	-0.031	8	-0.006
	(1.06)		(-3.21)		(-0.71)
-5	0.018	2	-0.031	9	0.002
	(2.35)		(-4.05)		(0.30)
-4	0.009	3	-0.034	10	-0.007
	(1.02)		(-4.39)		(-0.96)

Table 3: Changes in beta around information flows
By Earnings Surprise

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of earnings surprise, where earnings surprise is defined as the difference between actual quarterly earnings and the consensus analyst forecast, scaled by price. The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	**1 (low)**		**2**		**3**		**4**		**5 (high)**	
-10	0.051	(1.58)	-0.006	(-0.43)	-0.017	(-1.22)	0.006	(0.41)	0.016	(0.96)
-9	0.029	(1.49)	-0.002	(-0.14)	-0.028	(-1.82)	0.032	(2.00)	0.041	(1.25)
-8	0.046	(2.11)	-0.004	(-0.27)	0.027	(1.90)	0.000	(-0.01)	0.033	(1.88)
-7	-0.005	(-0.26)	-0.001	(-0.08)	-0.022	(-1.61)	-0.022	(-1.33)	-0.023	(-1.34)
-6	0.013	(0.74)	-0.007	(-0.48)	0.003	(0.18)	0.004	(0.24)	0.047	(2.60)
-5	0.048	(2.57)	0.009	(0.63)	-0.010	(-0.68)	0.005	(0.37)	0.032	(2.01)
-4	0.006	(0.33)	0.018	(1.22)	0.012	(0.86)	0.012	(0.79)	-0.004	(-0.23)
3	-0.016	(-0.92)	0.019	(1.30)	0.036	(2.37)	0.059	(3.67)	0.014	(0.77)
2	0.051	(2.61)	0.016	(1.05)	0.010	(0.69)	0.007	(0.44)	0.031	(1.81)
1	0.048	(2.06)	0.019	(1.22)	0.003	(0.21)	0.016	(0.93)	0.059	(2.88)
0	0.216	(3.24)	0.144	(3.80)	0.104	(2.82)	0.135	(3.21)	0.250	(4.47)
1	-0.035	(-1.53)	-0.040	(-2.29)	-0.040	(-2.60)	-0.033	(-1.76)	-0.009	(-0.45)
2	-0.019	(-1.06)	-0.062	(-4.50)	-0.033	(-2.25)	-0.025	(-1.68)	-0.012	(-0.65)
3	-0.020	(-1.11)	-0.025	(-1.84)	-0.043	(-2.96)	-0.025	(-1.69)	-0.035	(-2.25)
4	-0.024	(-0.82)	-0.046	(-3.33)	-0.036	(-2.87)	-0.031	(-2.02)	0.014	(0.88)
5	-0.018	(-0.98)	-0.021	(-1.58)	-0.010	(-0.74)	-0.026	(-1.81)	-0.002	(-0.10)
6	-0.012	(-0.75)	-0.015	(-1.01)	-0.027	(-2.12)	0.008	(0.57)	-0.008	(-0.51)
7	0.008	(0.45)	-0.017	(-1.24)	-0.001	(-0.05)	-0.008	(-0.58)	-0.012	(-0.69)
8	-0.002	(-0.12)	-0.001	(-0.07)	0.010	(0.80)	-0.014	(-0.79)	-0.022	(-1.30)
9	0.030	(1.78)	0.005	(0.39)	-0.019	(-1.16)	-0.010	(-0.62)	0.011	(0.62)
10	0.015	(0.91)	-0.020	(-1.60)	-0.010	(-0.76)	0.000	(-0.04)	-0.007	(-0.41)

Table 4: Changes in beta around information flows
By Forecast Dispersion

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of forecast dispersion, where forecast dispersion is defined as the coefficient of variation of analyst forecasts of quarterly earnings (the ratio of the standard deviation of forecasts to the absolute value of their mean). The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	**1 (low)**		**2**		**3**		**4**		**5 (high)**	
-10	-0.002	(-0.16)	0.013	(0.90)	-0.030	(-1.87)	0.013	(0.85)	0.049	(1.47)
-9	-0.019	(-1.37)	0.015	(1.07)	-0.005	(-0.31)	0.039	(1.22)	0.039	(1.71)
-8	0.008	(0.58)	0.022	(1.56)	0.009	(0.51)	0.027	(1.41)	0.039	(1.68)
-7	-0.011	(-0.73)	0.002	(0.14)	0.009	(0.60)	-0.046	(-2.55)	-0.030	(-1.29)
-6	0.002	(0.16)	0.017	(1.16)	0.030	(1.93)	0.002	(0.11)	0.007	(0.34)
-5	-0.009	(-0.70)	0.005	(0.35)	0.015	(1.00)	0.028	(1.76)	0.048	(2.18)
-4	0.004	(0.29)	0.010	(0.67)	-0.001	(-0.05)	0.023	(1.39)	0.002	(0.11)
-3	0.030	(2.13)	0.038	(2.29)	0.041	(2.58)	0.018	(1.05)	-0.003	(-0.16)
-2	0.002	(0.17)	0.012	(0.78)	0.003	(0.18)	0.045	(2.48)	0.054	(2.59)
-1	0.026	(1.70)	0.023	(1.42)	0.013	(0.67)	0.039	(2.12)	0.053	(2.24)
0	0.101	(2.93)	0.119	(2.56)	0.187	(4.45)	0.167	(3.80)	0.270	(5.07)
1	-0.021	(-1.29)	-0.060	(-3.63)	-0.027	(-1.51)	-0.012	(-0.58)	-0.026	(-1.02)
2	-0.031	(-2.38)	-0.039	(-2.69)	-0.030	(-1.95)	-0.032	(-1.75)	-0.017	(-0.87)
3	-0.007	(-0.52)	-0.021	(-1.61)	-0.024	(-1.58)	-0.032	(-1.97)	-0.065	(-3.19)
4	-0.045	(-3.31)	-0.030	(-2.23)	-0.026	(-1.79)	-0.015	(-0.93)	-0.010	(-0.33)
5	0.001	(0.10)	-0.017	(-1.23)	0.001	(0.04)	-0.029	(-1.81)	-0.027	(-1.45)
6	-0.009	(-0.64)	-0.013	(-1.08)	-0.010	(-0.71)	-0.011	(-0.73)	-0.016	(-0.88)
7	-0.023	(-1.67)	0.008	(0.60)	-0.020	(-1.35)	0.006	(0.35)	-0.010	(-0.49)
8	-0.010	(-0.80)	0.003	(0.21)	-0.026	(-1.55)	0.023	(1.41)	-0.007	(-0.33)
9	-0.002	(-0.14)	0.000	(-0.02)	-0.030	(-2.14)	0.023	(1.31)	0.020	(1.05)
10	-0.009	(-0.76)	0.012	(1.02)	-0.007	(-0.45)	-0.013	(-0.82)	0.002	(0.13)

Table 5: Changes in beta around information flows
By Announcement Delay

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of announcement delay. Announcement delay is defined as the number of days between the end of a given fiscal quarter and the earnings announcement day. The sample is limited to firms with fiscal quarter-end corresponding to a calendar quarter. The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	1 (early)		2		3		4		5 (late)	
-10	-0.012	(-0.64)	0.032	(0.86)	0.010	(0.55)	-0.017	(-0.83)	-0.013	(-0.67)
-9	-0.005	(-0.23)	0.015	(0.79)	0.018	(0.55)	0.010	(0.49)	0.036	(2.02)
-8	0.004	(0.22)	0.026	(1.15)	-0.005	(-0.25)	0.010	(0.43)	0.031	(1.59)
-7	0.013	(0.81)	-0.040	(-2.05)	-0.023	(-0.99)	-0.029	(-1.34)	-0.029	(-1.39)
-6	-0.041	(-2.36)	0.011	(0.51)	0.020	(1.01)	-0.009	(-0.46)	0.011	(0.63)
-5	0.010	(0.51)	0.005	(0.24)	0.015	(0.84)	0.024	(1.39)	0.009	(0.52)
-4	-0.021	(-1.08)	0.025	(1.35)	-0.018	(-0.88)	0.060	(2.67)	0.006	(0.26)
-3	0.022	(1.17)	0.020	(0.89)	0.012	(0.61)	0.038	(2.02)	0.003	(0.13)
-2	0.014	(0.74)	0.017	(0.94)	0.028	(1.37)	-0.014	(-0.69)	0.034	(1.84)
-1	0.065	(2.73)	-0.007	(-0.31)	-0.009	(-0.46)	0.036	(1.78)	0.025	(1.12)
0	0.203	(4.67)	0.171	(3.22)	0.110	(2.47)	0.128	(3.32)	0.175	(3.51)
1	-0.041	(-1.88)	-0.037	(-1.57)	-0.040	(-1.80)	-0.023	(-0.84)	0.014	(0.61)
2	-0.038	(-2.15)	-0.051	(-2.71)	-0.039	(-2.25)	0.005	(0.25)	-0.022	(-1.16)
3	-0.049	(-2.95)	-0.047	(-2.48)	-0.032	(-1.95)	-0.002	(-0.11)	-0.029	(-1.35)
4	-0.050	(-3.21)	-0.011	(-0.65)	-0.023	(-1.19)	0.023	(1.05)	-0.013	(-0.73)
5	-0.034	(-1.89)	-0.010	(-0.57)	-0.014	(-0.66)	0.003	(0.15)	0.004	(0.23)
6	-0.032	(-1.75)	-0.008	(-0.45)	-0.007	(-0.40)	0.003	(0.18)	0.018	(0.97)
7	-0.015	(-0.78)	0.001	(0.06)	0.002	(0.10)	0.032	(1.48)	0.009	(0.51)
8	-0.008	(-0.40)	0.026	(1.42)	0.021	(0.92)	-0.005	(-0.24)	-0.008	(-0.38)
9	-0.014	(-0.77)	-0.018	(-0.93)	0.014	(0.75)	0.044	(2.06)	-0.013	(-0.70)
10	0.005	(0.26)	0.011	(0.62)	-0.005	(-0.29)	-0.004	(-0.19)	-0.019	(-1.17)

Table 6: Changes in beta around information flows
By Average Turnover

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of average turnover, defined as the average daily turnover during the two months that precede the earnings announcement month. The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	**1 (low)**		**2**		**3**		**4**		**5 (high)**	
-10	0.012	(0.99)	0.012	(0.88)	0.009	(0.59)	-0.017	(-1.18)	0.020	(0.58)
-9	-0.009	(-0.70)	0.016	(1.14)	0.025	(0.83)	0.010	(0.55)	0.026	(1.09)
-8	0.000	(0.00)	0.003	(0.17)	0.019	(1.33)	0.018	(1.02)	0.053	(2.11)
-7	-0.001	(-0.09)	-0.009	(-0.69)	-0.023	(-1.47)	-0.021	(-1.27)	-0.022	(-0.94)
-6	0.003	(0.25)	0.009	(0.69)	-0.029	(-2.01)	0.029	(1.92)	0.029	(1.29)
-5	-0.003	(-0.21)	0.012	(0.87)	-0.001	(-0.11)	0.041	(2.55)	0.041	(1.68)
-4	-0.005	(-0.37)	0.004	(0.33)	0.011	(0.85)	0.011	(0.67)	0.021	(0.84)
-3	0.020	(1.45)	-0.001	(-0.04)	0.026	(1.82)	0.032	(1.92)	0.029	(1.24)
-2	0.006	(0.46)	0.027	(2.05)	0.017	(1.16)	0.018	(1.03)	0.042	(1.83)
-1	0.010	(0.76)	0.029	(1.91)	0.006	(0.34)	0.025	(1.28)	0.069	(2.71)
0	0.113	(3.68)	0.092	(2.42)	0.156	(3.93)	0.176	(3.67)	0.275	(5.07)
1	-0.008	(-0.58)	-0.014	(-0.74)	-0.056	(-3.14)	-0.033	(-1.76)	-0.044	(-1.65)
2	-0.009	(-0.71)	-0.049	(-3.46)	-0.028	(-2.02)	-0.040	(-2.30)	-0.029	(-1.29)
3	-0.018	(-1.52)	-0.025	(-1.89)	-0.023	(-1.53)	-0.053	(-3.13)	-0.053	(-2.33)
4	-0.019	(-1.56)	-0.026	(-2.00)	-0.025	(-1.75)	-0.036	(-2.32)	-0.015	(-0.45)
5	-0.023	(-1.85)	-0.023	(-1.70)	-0.020	(-1.53)	-0.029	(-2.00)	0.010	(0.48)
6	0.010	(0.81)	-0.016	(-1.20)	-0.035	(-2.56)	-0.005	(-0.34)	-0.013	(-0.62)
7	0.005	(0.37)	-0.023	(-1.72)	-0.002	(-0.15)	-0.002	(-0.11)	-0.005	(-0.24)
8	0.000	(0.03)	-0.013	(-0.74)	-0.004	(-0.33)	-0.025	(-1.59)	0.015	(0.63)
9	0.008	(0.59)	-0.016	(-1.21)	0.020	(1.37)	0.000	(-0.02)	0.000	(-0.02)
10	0.005	(0.39)	-0.030	(-2.37)	-0.009	(-0.71)	-0.018	(-1.21)	0.018	(0.87)

Table 7: Changes in beta around information flows
By Residual Analyst Coverage

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of residual analyst coverage, defined as the residual from a cross-sectional regression of analyst coverage on market capitalization. The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	**1 (low)**		**2**		**3**		**4**		**5 (high)**	
-10	0.008	(0.55)	0.010	(0.70)	0.032	(1.08)	0.008	(0.53)	-0.012	(-0.58)
-9	0.025	(1.81)	-0.023	(-1.60)	0.039	(1.31)	0.020	(1.18)	0.010	(0.44)
-8	0.016	(1.13)	0.016	(0.99)	0.013	(0.82)	0.011	(0.61)	0.044	(1.95)
-7	0.006	(0.44)	0.006	(0.38)	-0.015	(-0.90)	-0.041	(-2.50)	-0.030	(-1.44)
-6	0.036	(2.53)	-0.019	(-1.37)	0.013	(0.81)	-0.008	(-0.47)	0.037	(1.85)
-5	0.001	(0.09)	0.008	(0.59)	-0.010	(-0.71)	0.007	(0.39)	0.077	(3.69)
-4	0.012	(0.83)	-0.005	(-0.32)	0.007	(0.49)	0.010	(0.65)	0.020	(0.96)
-3	0.027	(1.96)	0.011	(0.65)	0.028	(1.90)	0.027	(1.66)	0.020	(1.03)
-2	0.002	(0.14)	0.022	(1.42)	0.019	(1.27)	0.017	(1.06)	0.052	(2.74)
-1	-0.011	(-0.58)	0.033	(2.12)	0.036	(2.08)	0.037	(1.88)	0.048	(2.11)
0	0.124	(3.02)	0.112	(2.77)	0.142	(3.45)	0.216	(5.82)	0.248	(4.73)
1	-0.015	(-0.70)	-0.030	(-1.76)	-0.036	(-1.92)	-0.041	(-2.22)	-0.037	(-1.72)
2	-0.038	(-2.46)	-0.007	(-0.45)	-0.044	(-3.23)	-0.032	(-2.31)	-0.031	(-1.46)
3	-0.015	(-1.04)	-0.004	(-0.24)	-0.040	(-2.93)	-0.046	(-3.09)	-0.043	(-2.22)
4	-0.024	(-1.71)	-0.022	(-1.64)	-0.047	(-1.73)	0.010	(0.67)	-0.042	(-2.14)
5	-0.008	(-0.60)	-0.011	(-0.83)	-0.007	(-0.54)	-0.034	(-2.35)	-0.016	(-0.84)
6	0.002	(0.12)	-0.034	(-2.50)	0.012	(0.89)	-0.016	(-1.17)	-0.018	(-0.99)
7	0.002	(0.14)	-0.024	(-1.69)	0.013	(0.93)	-0.014	(-0.93)	-0.007	(-0.36)
8	-0.020	(-1.04)	-0.020	(-1.21)	0.006	(0.42)	-0.016	(-0.92)	0.021	(1.06)
9	0.017	(1.21)	-0.009	(-0.65)	-0.006	(-0.39)	-0.004	(-0.25)	0.017	(0.78)
10	-0.014	(-1.09)	-0.014	(-1.01)	0.011	(0.77)	-0.008	(-0.56)	0.002	(0.08)

Table 8: Changes in beta around information flows
By correlatedness in fundamentals

This table presents the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. Beta is estimated for stocks grouped into quintiles of analyst earnings beta. Analyst earnings beta is the slope coefficient from a regression of a firm's innovations in consensus quarterly earnings forecasts on aggregate innovations in consensus forecasts. The estimated beta is obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Day	**1 (low)**		**2**		**3**		**4**		**5 (high)**	
-10	-0.027	(-1.42)	-0.003	(-0.22)	-0.046	(-3.09)	0.011	(0.68)	0.067	(1.91)
-9	0.041	(2.36)	0.007	(0.20)	-0.001	(-0.06)	0.004	(0.23)	0.021	(0.93)
-8	-0.020	(-1.25)	0.006	(0.37)	0.006	(0.35)	0.026	(1.39)	0.043	(1.90)
-7	-0.022	(-1.28)	-0.013	(-0.94)	-0.009	(-0.44)	-0.012	(-0.68)	-0.046	(-2.10)
-6	-0.022	(-1.41)	-0.017	(-1.18)	0.008	(0.57)	0.035	(1.89)	-0.008	(-0.38)
-5	0.009	(0.55)	0.000	(-0.02)	0.005	(0.32)	0.007	(0.38)	0.054	(2.43)
-4	0.019	(1.05)	-0.002	(-0.12)	0.021	(1.21)	0.002	(0.14)	0.010	(0.46)
-3	0.036	(2.04)	0.001	(0.10)	0.015	(0.91)	0.029	(1.58)	0.011	(0.50)
-2	0.031	(1.93)	-0.020	(-1.38)	0.033	(1.87)	0.008	(0.46)	0.029	(1.27)
-1	0.060	(3.14)	-0.016	(-1.02)	-0.014	(-0.73)	0.024	(1.26)	0.044	(1.72)
0	0.116	(2.46)	0.098	(2.75)	0.147	(3.56)	0.203	(4.44)	0.193	(3.71)
1	-0.015	(-0.71)	-0.019	(-1.13)	-0.038	(-1.84)	-0.079	(-4.18)	0.016	(0.62)
2	-0.008	(-0.42)	-0.038	(-2.73)	-0.051	(-3.35)	-0.008	(-0.41)	-0.035	(-1.64)
3	-0.009	(-0.45)	-0.032	(-2.26)	-0.048	(-3.11)	-0.018	(-1.09)	-0.063	(-3.05)
4	-0.010	(-0.57)	-0.022	(-1.51)	-0.040	(-2.97)	-0.004	(-0.23)	0.000	(0.01)
5	-0.016	(-0.99)	-0.004	(-0.30)	-0.023	(-1.58)	0.005	(0.27)	-0.022	(-1.16)
6	-0.018	(-1.11)	-0.024	(-1.67)	-0.020	(-1.31)	0.006	(0.34)	0.028	(1.47)
7	0.008	(0.45)	-0.006	(-0.43)	-0.012	(-0.77)	0.019	(1.20)	0.021	(0.95)
8	0.025	(1.52)	0.010	(0.71)	0.006	(0.35)	-0.015	(-0.84)	-0.003	(-0.13)
9	0.012	(0.68)	0.005	(0.25)	-0.006	(-0.44)	0.005	(0.30)	-0.005	(-0.26)
10	-0.004	(-0.26)	0.003	(0.19)	-0.008	(-0.52)	-0.003	(-0.16)	-0.010	(-0.55)

Table 9: Market neutral portfolio application

This table presents the results of a market neutral portfolio application. In the top two panels we randomly choose N stocks to include in a portfolio (with N=2, 5, 10 or 25) and we assign each stock either an equal weight (top panel) or a random weight (middle panel), in both cases imposing that the weights sum to unity. In the lower panel we consider long-short portfolios based on market capitalization (size), book-to-market ratio (value) or past performance (momentum), with 10 stocks long from the top quintile and 10 stocks short from the bottom quintile, all with equal weights. We then attempt to make each portfolio "beta neutral" by taking a position in the market to offset the predicted beta of this portfolio. The predicted beta for the portfolio comes from one of four models: "Rolling beta", where the beta for each stock is estimated via a regression using the most recent 100 daily returns; "Zero beta", where all portfolios have identically zero beta, and so no neutralization is needed; "Unit beta", where all portfolios have identically unit beta; "Realized beta", where the daily beta for each stock is allowed to vary within a window of 21 days around earnings announcements. We then compute the realized beta of the "market neutral" portfolio constructed using each of these four beta models, which should be near zero for a well-specified model of beta. We consider 1,000 random portfolios for each case. For each beta model we report the proportion of the 1,000 random portfolios for which a Diebold-Mariano (1995) test rejects the null, at the 5% level, of equal absolute beta in favor of the Rolling beta model vs. each of the other three models. For example, for N=2, the "Zero beta" model significantly beats the "Rolling beta" model in only 0.3% of cases, while it is significantly beaten by the "Rolling beta" model in 99.3% of cases.

	Equal weights				Random weights						
	N=2	N=5	N=10	N=25	N=2	N=5	N=10	N=25	Size	Value	Mom
Zero beta beats Rolling beta	0.3%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Zero beta loses to Rolling beta	99.3%	100.0%	100.0%	100.0%	99.3%	100.0%	100.0%	100.0%	100.0	99.9%	98.9%
Unit beta beats Rolling beta	2.9%	2.2%	1.6%	0.8%	3.2%	2.9%	1.9%	0.9%	0.0%	0.0%	0.0%
Unit beta loses to Rolling beta	87.5%	87.2%	90.8%	91.7%	87.3%	86.9%	87.2%	87.6%	100.0%	100.0%	99.5%
Realized beta beats Rolling beta	91.6%	95.2%	94.9%	93.7%	91.7%	95.7%	94.6%	91.8%	84.5%	80.2%	89.2%
Realized beta loses to Rolling beta	0.6%	0.7%	0.1%	0.1%	0.6%	0.5%	0.3%	0.0%	0.1%	0.2%	0.0%

Table 10: Robustness tests

This table presents robustness results for the estimated beta on 21 days around quarterly earnings announcements, computed as the difference with respect to the average non-announcement beta. In the baseline specification the estimates are obtained from a panel regression of daily realized betas on dummy variables for each of 21 days around quarterly earnings announcements. Event day 0 is the earnings announcement date. In the first regression (5-min Beta) the dependent variable is the realized daily beta computed from 5-minute returns. In the second regression (HY Beta) the dependent variable is the realized daily beta computed from computed with the Hayashi-Yoshida (2005) method, where the tick frequency is optimized for individual stocks. In the third regression (Lags) the dependent variable is the 25-minute realized beta as in Table 2; the specification includes five lags of realized beta. In the fourth regression (V Controls) the dependent variable is the 25-minute realized beta as in Table 2; the specification adds controls variables which include five lags of realized beta, realized firm volatility, trading volume, the square and cube of trading volume, adjusted daily bid-ask spread, and realized market volatility. In the fifth regression (Beta$^{(i)}$) the dependent variable is a modified measure of beta computed as the beta of stock i with respect to a market index which excludes the return of stock i. In the last regression (Jumps) we test the robustness of changes in realized betas to the possible presence of jumps in prices around announcement days. The regressions 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.

Day	5-min Beta		HY Beta		Lags		V Controls		Beta$^{(i)}$		Jumps	
-10	0.003	(0.51)	0.007	(0.79)	0.009	(0.85)	0.007	(0.67)	0.008	(0.76)	0.008	(0.81)
-9	0.007	(0.91)	0.010	(1.14)	0.015	(1.44)	0.013	(1.24)	0.019	(1.50)	0.017	(1.71)
-8	0.013	(2.05)	0.012	(1.30)	0.015	(1.62)	0.013	(1.38)	0.019	(2.15)	0.018	(2.02)
-7	-0.017	(-2.62)	-0.016	(-1.77)	-0.017	(-1.82)	-0.019	(-1.99)	-0.016	(-1.84)	-0.015	(-1.70)
-6	0.007	(1.08)	0.010	(1.16)	0.008	(0.90)	0.005	(0.64)	0.008	(1.01)	0.011	(1.40)
-5	0.018	(2.83)	0.016	(1.82)	0.017	(2.02)	0.014	(1.65)	0.018	(2.30)	0.022	(2.76)
-4	-0.002	(-0.23)	0.002	(0.25)	0.003	(0.36)	0.001	(0.07)	0.008	(0.95)	0.009	(0.99)
-3	0.015	(2.35)	0.019	(2.11)	0.019	(2.19)	0.017	(1.90)	0.021	(2.48)	0.020	(2.39)
-2	0.019	(3.04)	0.026	(2.76)	0.019	(2.16)	0.015	(1.75)	0.020	(2.53)	0.023	(2.76)
-1	0.014	(2.07)	0.025	(2.62)	0.027	(2.69)	0.019	(1.89)	0.025	(2.68)	0.029	(3.07)
0	0.125	(7.47)	0.136	(7.43)	0.171	(7.62)	0.122	(5.48)	0.142	(7.00)	0.172	(8.43)
1	-0.034	(-4.68)	-0.028	(-2.94)	-0.036	(-3.50)	-0.042	(-4.10)	-0.034	(-3.51)	-0.030	(-3.10)
2	-0.031	(-5.13)	-0.022	(-2.77)	-0.037	(-4.33)	-0.037	(-4.41)	-0.031	(-4.09)	-0.030	(-3.89)
3	-0.030	(-4.81)	-0.018	(-2.00)	-0.032	(-4.01)	-0.032	(-4.00)	-0.035	(-4.48)	-0.034	(-4.26)
4	-0.020	(-2.73)	-0.014	(-1.73)	-0.026	(-2.71)	-0.026	(-2.72)	-0.024	(-2.78)	-0.022	(-2.50)
5	-0.017	(-3.02)	-0.014	(-1.74)	-0.018	(-2.18)	-0.018	(-2.18)	-0.017	(-2.15)	-0.016	(-2.00)
6	-0.014	(-2.58)	-0.008	(-1.03)	-0.007	(-0.80)	-0.007	(-0.79)	-0.012	(-1.51)	-0.012	(-1.50)
7	-0.016	(-2.69)	-0.002	(-0.21)	0.002	(0.19)	0.002	(0.27)	-0.006	(-0.72)	-0.004	(-0.47)
8	-0.012	(-1.86)	0.003	(0.33)	-0.002	(-0.21)	-0.001	(-0.15)	-0.006	(-0.74)	-0.006	(-0.74)
9	0.001	(0.17)	0.006	(0.67)	0.003	(0.38)	0.004	(0.46)	0.002	(0.26)	0.002	(0.21)
10	-0.013	(-2.32)	-0.011	(-1.32)	-0.008	(-1.06)	-0.007	(-0.96)	-0.007	(-0.96)	-0.006	(-0.88)

Table 11: Robustness tests
Controlling for liquidity comovement

This table presents robustness tests to control for the effect of liquidity comovement. Panel A reports estimates of liquidity comovement around announcement days, defined as the product of individual stock daily liquidity innovations and market daily liquidity innovations, scaled by the variance of market liquidity innovations. Liquidity innovations are computed from daily adjusted bid-ask spreads. Panel B presents estimated realized betas for stocks grouped into quintiles of ex-ante liquidity comovement, computed as the R^2 from regressions of individual daily liquidity innovations on market liquidity innovations during a 40-day window before earnings announcements. Event day 0 is the earnings announcement date. The regressions 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.

Panel A

Day			Day			Day		
-10	-0.067	(-0.62)	-3	-0.230	(-2.33)	4	-0.208	(-2.00)
-9	0.055	(0.40)	-2	-0.299	(-3.14)	5	-0.226	(-2.45)
-8	-0.069	(-0.53)	-1	-0.280	(-2.59)	6	-0.199	(-2.08)
-7	-0.127	(-1.27)	0	-0.413	(-4.23)	7	-0.106	(-0.93)
-6	-0.352	(-4.20)	1	-0.351	(-3.25)	8	-0.252	(-2.60)
-5	-0.389	(-4.28)	2	-0.170	(-1.51)	9	-0.275	(-2.99)
-4	-0.229	(-2.48)	3	-0.166	(-1.37)	10	-0.316	(-3.90)

Panel B

Day	1 (low)		2		3		4		5 (high)	
-10	0.021	(1.19)	0.004	(0.14)	0.004	(0.30)	0.006	(0.38)	0.005	(0.32)
-9	-0.001	(-0.05)	0.016	(1.01)	0.007	(0.48)	0.017	(0.58)	0.030	(1.76)
-8	0.023	(1.12)	0.031	(1.83)	0.034	(2.10)	0.015	(0.88)	-0.004	(-0.28)
-7	-0.037	(-1.94)	-0.014	(-0.87)	-0.022	(-1.41)	-0.008	(-0.52)	0.005	(0.36)
-6	0.019	(1.13)	0.001	(0.08)	0.026	(1.67)	-0.001	(-0.07)	-0.001	(-0.08)
-5	-0.001	(-0.04)	0.010	(0.61)	0.030	(2.01)	-0.006	(-0.43)	0.055	(3.23)
-4	0.022	(1.37)	0.008	(0.48)	-0.001	(-0.09)	0.008	(0.47)	0.010	(0.66)
-3	-0.001	(-0.06)	-0.002	(-0.11)	0.042	(2.69)	0.040	(2.61)	0.026	(1.59)
-2	-0.005	(-0.28)	0.016	(0.90)	0.041	(2.70)	0.007	(0.46)	0.051	(2.87)
-1	0.030	(1.52)	0.011	(0.55)	0.025	(1.40)	0.029	(1.80)	0.040	(2.39)
0	0.182	(3.54)	0.167	(3.96)	0.161	(4.16)	0.167	(4.34)	0.142	(3.49)
1	-0.030	(-1.39)	-0.025	(-1.43)	-0.044	(-2.53)	-0.033	(-1.76)	-0.025	(-1.43)
2	-0.042	(-2.37)	-0.033	(-2.02)	-0.020	(-1.28)	-0.041	(-2.81)	-0.022	(-1.42)
3	-0.041	(-2.67)	-0.039	(-2.72)	-0.031	(-2.15)	-0.043	(-2.96)	-0.016	(-0.87)
4	-0.028	(-1.87)	-0.058	(-2.08)	-0.001	(-0.04)	-0.033	(-2.40)	-0.002	(-0.16)
5	-0.017	(-1.08)	-0.025	(-1.69)	-0.007	(-0.48)	-0.024	(-1.68)	-0.012	(-0.87)
6	-0.035	(-2.13)	-0.008	(-0.58)	-0.019	(-1.35)	-0.002	(-0.14)	0.002	(0.11)
7	-0.015	(-0.88)	-0.004	(-0.23)	0.007	(0.51)	-0.019	(-1.32)	0.005	(0.33)
8	-0.002	(-0.10)	-0.012	(-0.71)	-0.007	(-0.41)	0.012	(0.83)	-0.018	(-1.10)
9	-0.034	(-1.78)	0.011	(0.77)	0.023	(1.64)	0.015	(0.93)	-0.002	(-0.13)
10	-0.003	(-0.22)	-0.011	(-0.76)	-0.001	(-0.05)	-0.001	(-0.08)	-0.017	(-1.25)

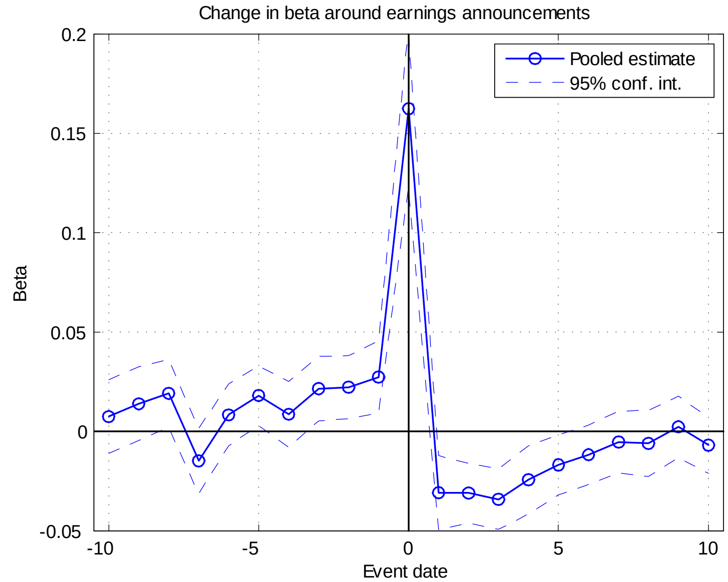

Figure 1: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) reported in Table 2. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed line.*

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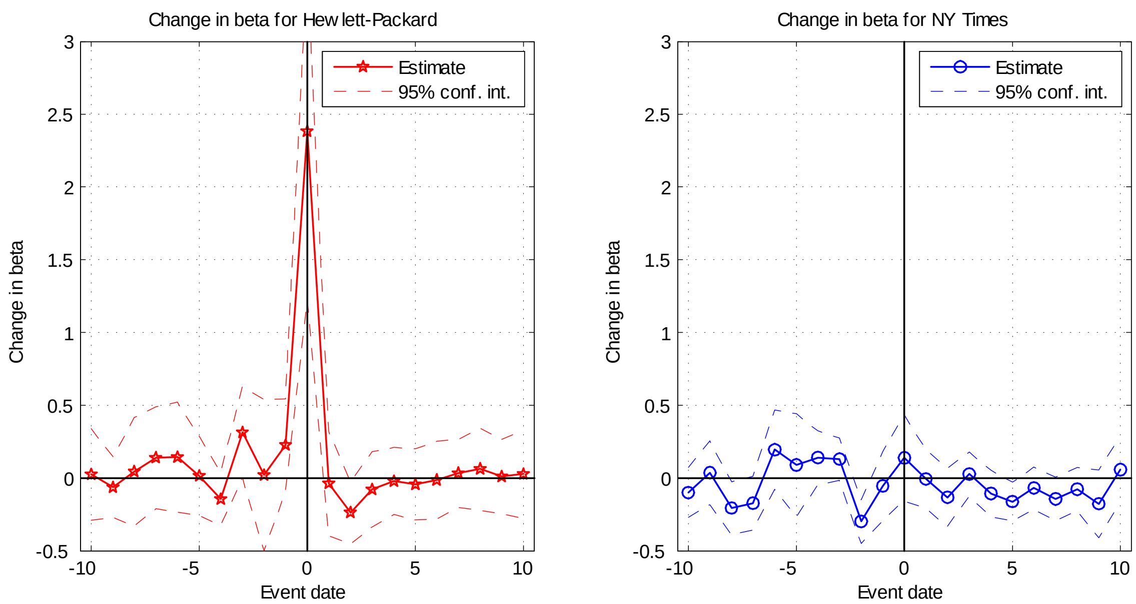

Figure 2: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day) for Hewlett-Packard and for New York Times. Point estimates are marked with a solid line, and 95% confidence intervals are marked with a dashed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

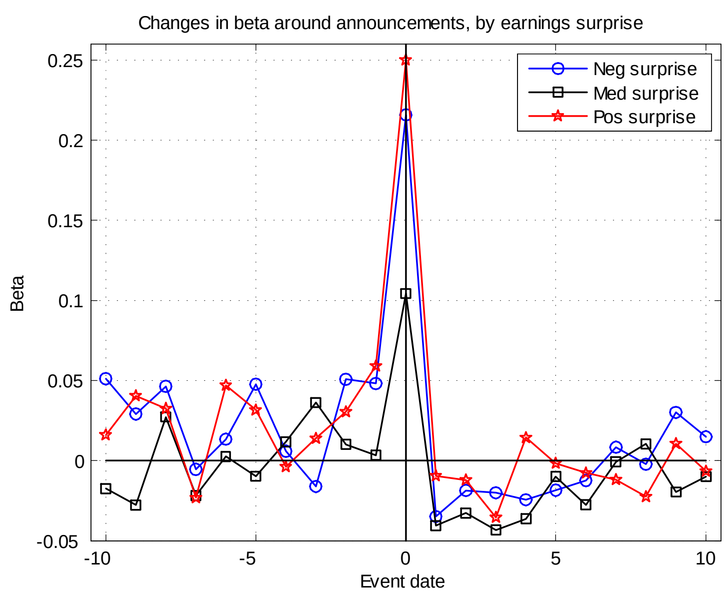

Figure 3: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by earnings surprise, as reported in Table 3.*

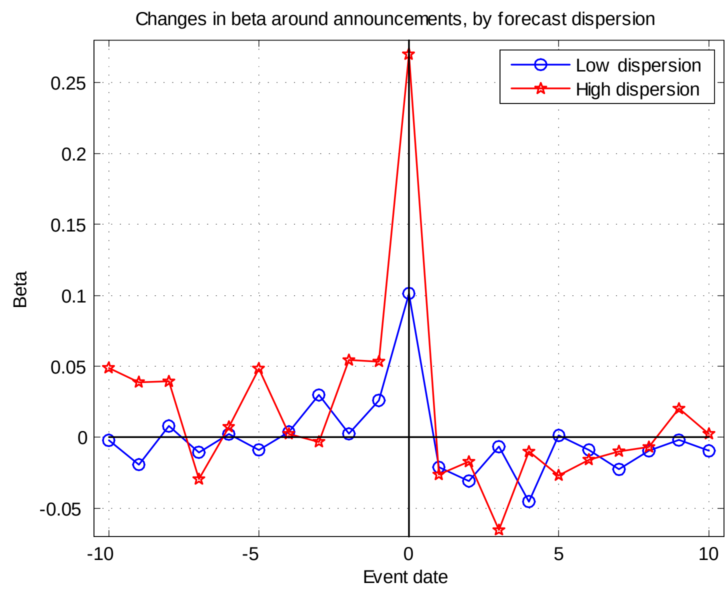

Figure 4: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles by analyst forecast dispersion, as reported in Table 4.*

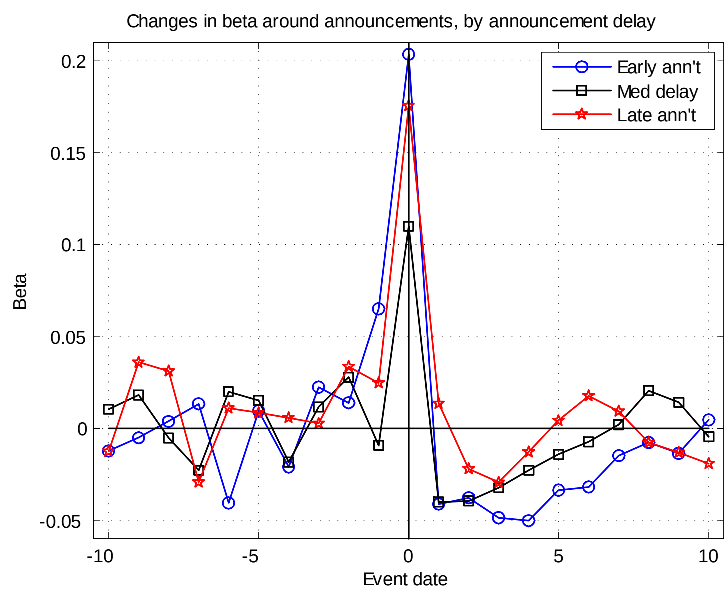

Figure 5: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest, middle, and highest quintiles of the number of days between the quarter-end and the announcement, as reported in Table 5.*

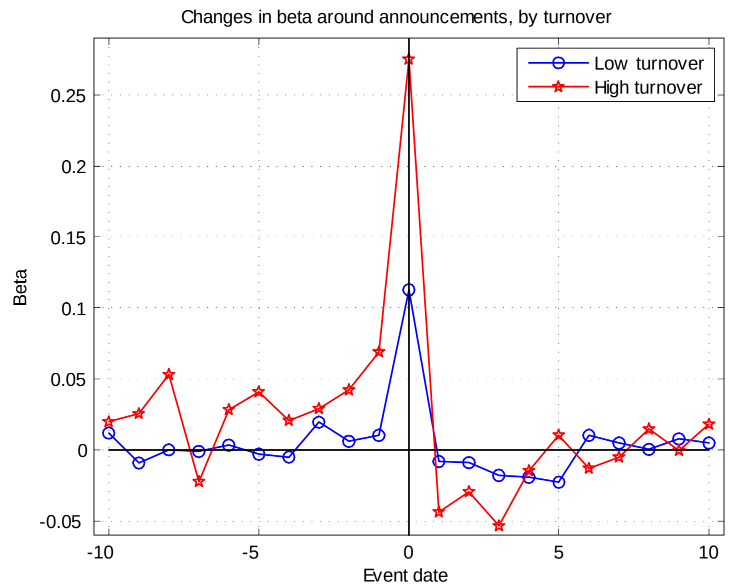

Figure 6: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by turnover, as reported in Table 6.*

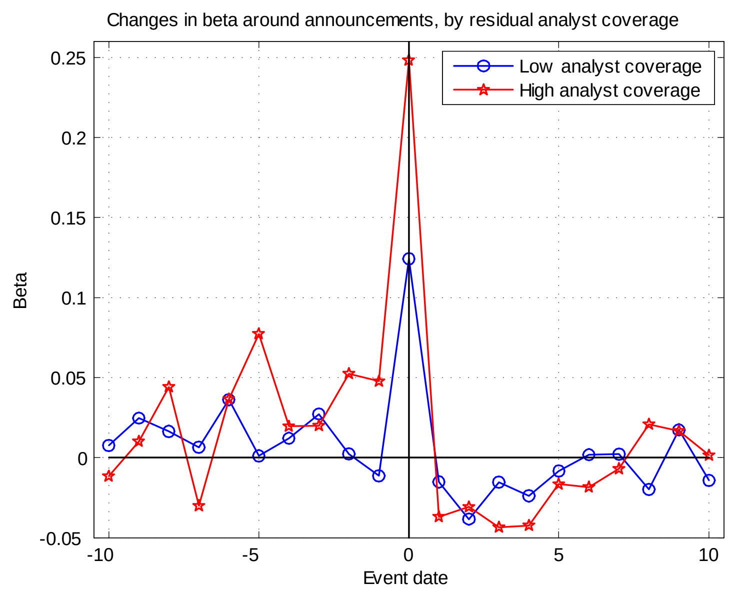

Figure 7: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by residual analyst coverage, as reported in Table 7.*

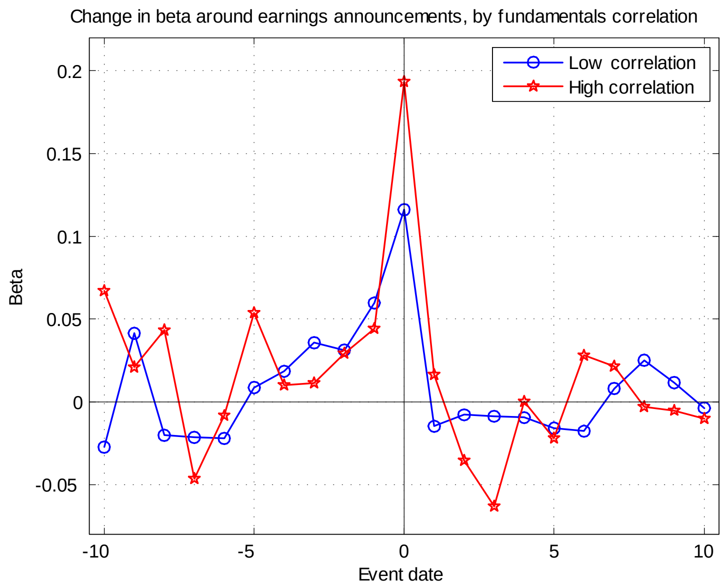

Figure 8: *This figure presents the estimated changes in beta on 21 days around quarterly earnings announcements (where event day 0 is the announcement day), for the lowest and highest quintiles by correlation of fundamentals, as reported in Table 8.*

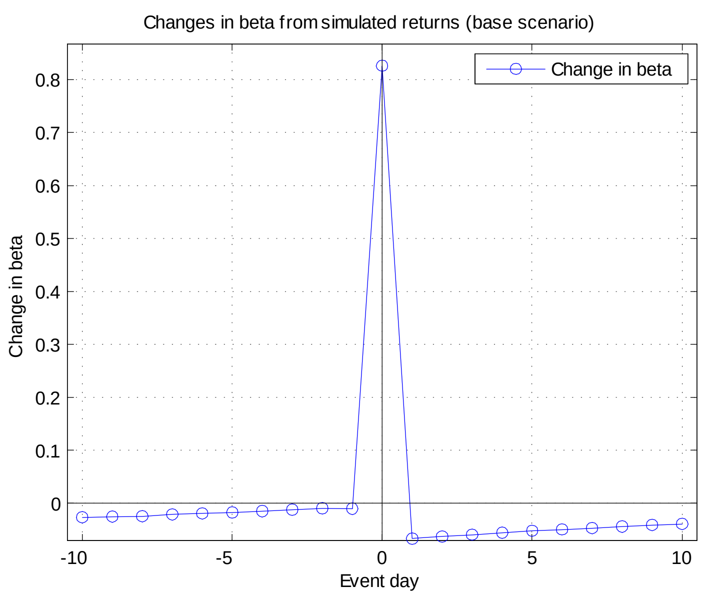

Figure 9: *Change in beta around event dates for benchmark scenario.*

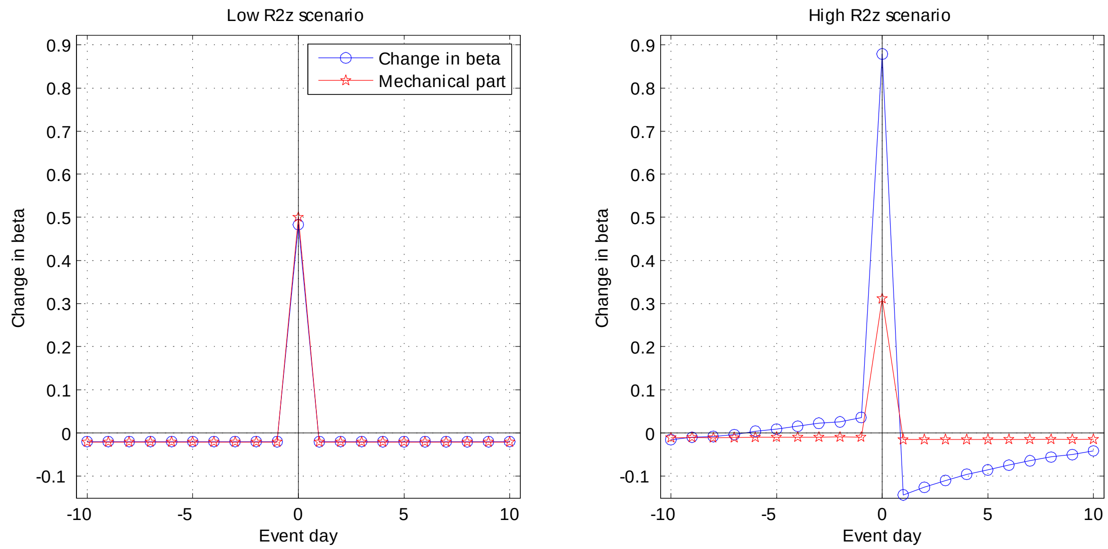

Figure 10: *Changes in beta around event dates for low and high values of the ratio of the variance of the common component in earnings innovations to total variance,* $R_z^2 = \sigma_z^2/\sigma_w^2$.

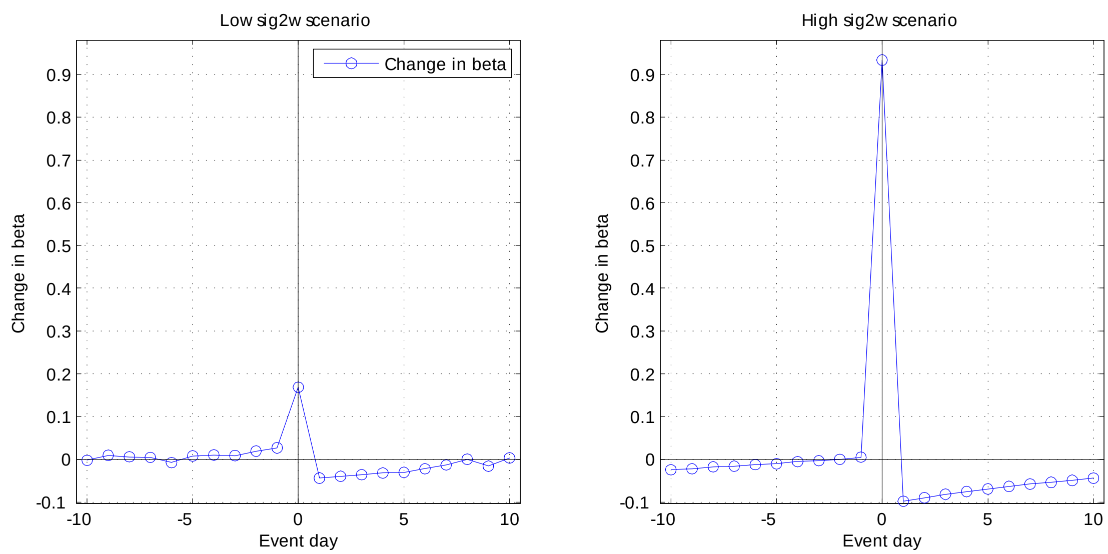

Figure 11: *Changes in beta around event dates for low and high values of the variance of earnings innovations,* σ_w^2.

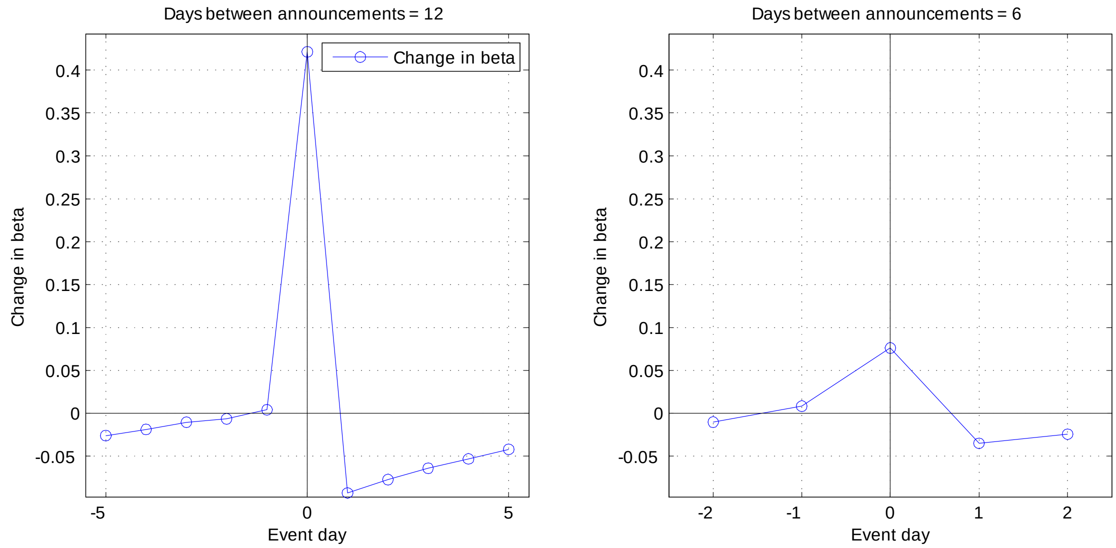

Figure 12: *Changes in beta around event dates when the number of days between announcements is decreased.*

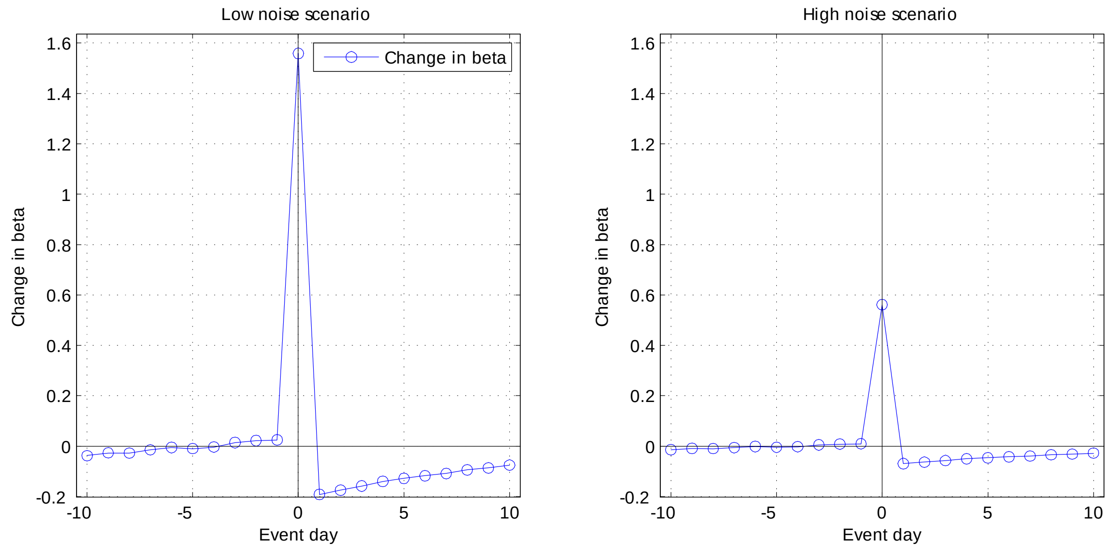

Figure 13: *Changes in beta around event dates for low and high values of the ratio of the variance of the part of daily returns* not *explained by changes in expectations about future earnings,* σ_e^2.