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WHEN ARE ANALYST RECOMMENDATION CHANGES INFLUENTIAL?

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ABSTRACT

Not all stock recommendation changes are equal. In a sample constructed to minimize the impact of confounding news, relatively few analyst recommendation changes are influential in the sense that they impact investors' beliefs about a firm in a way that could be noticed in that firm's stock returns. More than one-third of the stock-price reactions to analyst recommendation changes have the wrong sign and only approximately 10% have significant stock-price reactions at the 5% level using an extended market model. We find that the probability of an influential recommendation is higher for leader analysts, star analysts, away-from-consensus revisions, revisions issued contemporaneously with earnings forecasts, analysts with greater relative experience, and those with more accurate earnings estimates. Growth firms, small firms, high institutional ownership firms, and high prior turnover firms are also more likely to have influential stock recommendations. Strikingly, analyst recommendations are more likely to be influential after Reg FD and the settlement. Finally, influential recommendations are associated with increases in stock volatility and large absolute changes in consensus earnings forecasts.

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1. Introduction

Market observers at times attribute large stock price changes to analyst recommendation changes. For instance, according to the *Wall Street Journal*'s description, Kenneth Bruce from Merrill Lynch issued a recommendation downgrade on Countrywide Financial on August 15, 2007 questioning the giant mortgage lender's ability to cope with a worsening credit crunch. The report sparked a sell-off in Countrywide's shares, which fell 13% on that day. In another example, when Meredith Whitney (CIBC World Markets) downgraded Citigroup on November 1, 2007, the stock price dropped 6.9%, the CEO quit two days later, and she apparently received death threats.[4] Though the finance literature finds that significant average abnormal returns are associated with recommendation changes, the typical estimate associated with a recommendation change is too small to be considered a significant abnormal return for the stock of a firm when an analyst recommendation change is made. Consequently, with the typical recommendation change, investors following a firm could not distinguish the impact of the recommendation change from noise. However, at times a recommendation change, such as the Bruce call on Countrywide, is viewed by observers as having a large identifiable impact on the stock price. In this paper, we try to understand better when and why analyst recommendation changes at times appear to have a large stock price impact.

The question we address is different from the question typically answered in the analyst literature that tries to assess the impact of analyst recommendation changes. This literature focuses on average effects in large samples and generally investigates whether some type of analyst recommendation change has a significant average abnormal return. By averaging across a large number of announcements, the researcher hopes to eliminate the influence of confounding effects on the study and therefore to obtain an estimate of the "pure" recommendation change effect. At the same time, however, such an approach is of little use to evaluate claims about the

[4] The above examples are from the following articles: "Countrywide's woes multiply" by James R. Hagerty and Ruth Simon, *The Wall Street Journal*, August 17, 2007, and "CIBC analyst got death threats on Citigroup", by Jonathan Stempel, Reuters, November 4, 2007.

ability of analysts to impact stock prices of individual firms significantly. To wit, in our sample, the median abnormal return associated with a downgrade is roughly -1%. For the typical firm, a -1% abnormal return is noise. However, an abnormal return of the magnitude associated with the recommendation change of Bruce for Countrywide is a highly significant abnormal return for the typical firm.

The existing literature does not tell us whether analysts frequently make recommendation changes whose impact can be identified at the firm level rather than in large-scale samples. We identify recommendation changes that are impactful using a simple measure of significance at the firm level, namely the standard deviation of market model residuals, and we call such recommendation changes influential. To investigate whether recommendation changes are influential, it is important to focus on recommendation changes that occur on days without firm-specific news. Analysts often write reports on days of firm-specific news and recommendation changes on such days are more likely to be favorable if the firm has positive news. Though the traditional event study method reduces or even eliminates the impact of confounding news on the average abnormal return, it does so only when news and the probability of occurrence of the event are uncorrelated. In the case of analysts, there is no reason to believe that this condition holds. It is therefore important to construct a sample of recommendation changes where the impact of confounding firm-specific news is minimized. Eliminating firm-specific news days reduces the stock-price reaction to analyst recommendation changes, but the average stock-price reaction remains statistically significant. We find that roughly 10% of recommendation changes in our sample (that minimizes the impact of firm-specific news) are significant at the firm level and hence influential. However, one analyst in four never has an influential recommendation change. Conditional on an analyst having an influential recommendation change, one in five of the analyst's recommendation changes are influential.

Why is it that an analyst at times can make recommendations that are associated with a significant firm-level abnormal return? We believe that at times analysts can change how a corporation is viewed and that such "paradigm shifts" are responsible for the large impact of some recommendation changes. This perspective builds on Hong, Stein, and Yu (2007). Hong et al. study the implications of learning in an environment in which the true model of the world is a multivariate one, but agents update only over the class of simple univariate models. When sufficient evidence accumulates against the incumbent simple model, agents switch to another simple model, and prices in the underlying stock moves to reflect this paradigm shift. In this paper, we investigate whether influential analyst recommendation changes precipitate such paradigm shifts.

Meredith Whitney's Citigroup downgrade on Nov. 1, 2007 was associated with a drop in Citigroup's stock price of 6.1%. Yet, as a *Wall Street Journal* recently reported, other analysts in the weeks before downgraded the stock with reports that had similar content.[5] Consequently, a recommendation change is not influential simply because of its content—other factors must affect whether the recommendation change is influential. We use a probit model to investigate the factors that make it more likely that a recommendation change will be influential. In support of our "paradigm shift" hypothesis, we find that recommendations away from the consensus are more likely to be influential. The analysts who are likely to make influential recommendations are highly ranked analysts who have a history of being ahead of the crowd. It is harder for an analyst to have an influential recommendation when more analysts follow a firm and when the firm is larger. However, greater diversity of opinion about a firm makes it more likely that a recommendation change will be influential. This result is also consistent with the "paradigm shift" view, in that it is harder to change a paradigm when it is well-established.

When analyst recommendation changes are influential because they are associated with paradigm shifts, we should see them lead to much analyst activity and trading in the stock as investors adjust their holdings to the new paradigm. We find this is to be the case. Share turnover

[5] "When Meredith Whitney calls, should you listen?" by David Weidner, *The Wall Street Journal*, April 9, 2009.

is much larger in the three months following an influential analyst change than in the three months before. So is stock volatility. Analysts make more forecasts after an influential analyst recommendation change than before. Finally, forecast revisions by analysts following such a change are much larger than forecast revisions before such a change.

We are not the first study to examine the differential impact of stock recommendation changes. For instance, Stickel (1995) shows that recommendation changes of star analysts have more impact and Fang and Yasuda (2008) show that they are more profitable. Irvine (2004) provides evidence that the market reacts more strongly to initiations than to other recommendations. Ivkovic and Jegadeesh (2004) show that the timing of recommendation changes in relation to earnings announcements affects their impact. Asquith, Mikhail, and Au (2005) provide evidence that the impact of recommendation changes is affected by the content of analyst reports. Frankel, Kothari, and Weber (2006) examine whether firm characteristics affect the impact of earnings forecast revisions but they do not consider analyst characteristics or stock recommendations. Chen, Francis, and Schipper (2005) find that the average analyst recommendation or earnings forecast produces a price impact that is no different from the average stock price movement on non-recommendation days. Most recently, Altinkilic and Hansen (2008) report evidence that the average recommendation revision does not produce a statistically significant intra-day reaction after removing recommendations that piggyback on firm news such as earnings announcements. Both Altinkilic and Hansen and Chen et al. provide evidence to the effect that the average recommendation is not influential while our focus is to study which recommendations are influential and what makes them influential.

The rest of the study is organized as follows: Section 2 details the data and sample, Section 3 describes the average recommendation event abnormal return. Section 4 identifies which recommendations are influential and their characteristics and consequences, Section 5 investigates predictive variables for influential recommendations, Section 6 considers alternative definitions of influential, and Section 7 concludes.

2. Data and Sample

2.1. Recommendations data

The stock recommendations sample is from Thomson Financial's Institutional Brokers Estimate (I/B/E/S) U.S. Detail File, which contains stock recommendation ratings issued by individual analysts from 1993-2006. I/B/E/S reports ratings ranging from 1 (strong buy) to 5 (sell). To make the ratings more intuitive, we reverse the ratings (5 for strong buy and 1 for sell, etc.) so that higher ratings correspond to more favorable recommendations. The focus is on recommendation revisions and not levels since prior research confirms that recommendation changes are more informative than mere levels (e.g., Boni and Womack (2006) and Jegadeesh and Kim (2006)). The recommendation change *RECCHG* is computed as the current rating minus the prior rating by the same analyst. By construction, $RECCHG \in [-4,4]$. We exclude the recommendation if there is no outstanding prior rating from the same analyst (i.e., analyst initiations are excluded). A rating is always assumed to be outstanding if it is less than one year old and never if it is more than two years old; if the rating is between one and two years old, it is treated as outstanding only if there is an analyst forecast from the analyst in the one year window prior to the recommendation date (matching to the I/B/E/S Detail Earnings Forecast File).[6]

We also remove analysts coded as anonymous by I/B/E/S since it is not possible to track their recommendation revisions. Ljungqvist, Malloy, and Marston (2008) report that matched records in the I/B/E/S recommendations data were altered between downloads from 2000 to 2007. They also document that Thomson Financial, in response to their paper, has recently reinstated the

[6] The results are robust to using a stale criterion of one year. Most studies consider recommendations stale if they are more than one year old. This criterion is too stringent because in I/B/E/S, the average time it takes for an analyst to revise a recommendation is 274 days and 25% of the time it takes more than 360 days (Malmendier and Shanthikumar (2007) provide similar statistics). By refining the stale recommendation criterion, we avoid excluding outstanding recommendations that would be considered stale by other studies. The fact that the analyst issued a recent earnings forecast for the firm is consistent with continuing active coverage.

missing analyst names in the recommendation history file as of February 12, 2007. The dataset we use is dated March 15, 2007 and likely reflects these recent corrections by Thomson.

A portion of the sample period is affected by the introduction of Rule 2711 by the National Association of Securities Dealers (NASD). Part of the NASD 2711 rule required brokerages to report the distribution of stock ratings across its coverage universe. This rule was approved on May 8, 2002 with an implementation period ending September 9, 2002. Many brokers reissued stock recommendations in the implementation period. As a result, 2002 contains the most number of recommendations in I/B/E/S compared to any other sample year (see Barber, Lehavy, McNichols, and Trueman (2006)). To account for this structural break, we remove recommendation changes where the current recommendation is issued between May 8, 2002 and September 9, 2002 (inclusive) *and* the prior recommendation was issued before May 8, 2002. Such recommendation changes are likely to be motivated by adherence to the NASD 2711 rule rather than by stock selection.

Since we cannot determine the exact time of day of recommendation changes, we adopt a three-day event window to make sure that we incorporate the daily return reflecting the recommendation change. To compute the three-day (i.e., three trading days) cumulative buy-and-hold abnormal return (CAR) for a recommendation change i, we define

$$CAR_i = \prod_{t=-1}^{1}\left(R_{it}\right) - \prod_{t=-1}^{1}\left(R_{it}^{DGTW}\right). \tag{1}$$

R_{it} is the raw return of the stock on day t and R_{it}^{DGTW} is the return on a benchmark portfolio with the same size, book-to-market (B/M), and momentum characteristics as the stock (Daniel, Grinblatt, Titman, and Wermers (1997), thereafter DGTW).[7] Day 0 is the I/B/E/S reported recommendation date or the next trading day if the recommendation date is a non-trading day (for example, a Saturday). The DGTW portfolios are computed as follows. Every July, firms are first

[7] The results are similar when we use the sum of abnormal returns rather the buy-and-hold abnormal returns.

sorted into quintiles based on their market cap on June 30 of each year using break-points determined from NYSE stocks. Second, firms are then sorted within each size quintile into quintiles based on their B/M ratios. B/M ratios are computed as in Fama and French (2006). Third, firms within each size-B/M group are sorted into momentum quintiles every month based on the buy-and-hold return over the prior 12 months skipping the most recent month. Therefore the size and B/M rankings are updated every 12 months while the momentum rankings are updated monthly. Finally, the stocks within each characteristic portfolio are equally-weighted at the beginning of each month and the buy-and-hold average daily returns are computed.

2.2. Importance of removing recommendations made in response to firm news

If a stock recommendation has an immediate impact on a firm's stock price, it does so because it reveals information about the firm. In determining whether the analyst produced any material information, one should be careful to remove recommendations that merely repeat the information contained in firm-specific news releases. As already discussed, Altinkilic and Hansen (2008) go so far as to argue that once the impact of other news is removed, analyst recommendation changes do not have an impact. Malmendier and Shanthikumar (2007) and Loh (2007) report that 12-13% of stock recommendations occur in the three days around quarterly earnings announcements. Since there are 252 trading days in a year, one would expect only 4.8% of all recommendations to be issued around earnings announcements if the likelihood of a recommendation is uniformly distributed throughout the year. Therefore, not removing such earnings announcements recommendations falsely gives credit to the analyst recommendation for producing the earnings announcement price impact (see also, Frankel et al. (2006)). To apply this screen, we obtain quarterly earnings announcement dates from I/B/E/S.

Another type of firm-specific news release is earnings guidance issued by firms. Chen et al. (2005) suggest that such days should also be taken out when determining the price impact of stock recommendations. We obtain earnings guidance dates from the First Call Guidelines database. Finally, Bradley, Jordan, and Ritter (2007) contend that clustering in recommendation changes usually occur because of firm-specific news. Therefore we also identify days on which multiple analysts issue recommendations for the firm as potential firm-specific news events.

3. The average CAR of recommendations changes

In this section, we estimate the average CAR of recommendation changes to provide a benchmark for our later analysis and to show how minimizing the impact of firm-specific news affects the estimate of the average CAR of recommendation changes.

3.1. Descriptive statistics of recommendation changes

Our main sample contains 196,854 recommendation changes. Panel A of Table 1 shows the transition probabilities of recommendation changes. We see that recommendation levels are predominantly optimistic with sell and underperform ratings making up only a small percentage of all recommendations. Looking at rating changes where the prior rating was a hold (third column), we see that a hold is more likely to migrate to a buy recommendation (36% of the time). For rating changes where the prior rating was a buy, a downgrade to hold is very likely (49% of the time). Figure 1 plots the transition probabilities in Panel A of Table 1.

Next, Panel B summarizes the number of recommendations according to the sign and magnitude of the rating change. The two rating change groups that have the largest number of recommendations are one-point upgrades (+1) and one-point downgrades (–1). The +1 group contains 47,006 recommendations (23.9% of the sample) and the –1 group contains the 57,290 recommendations. Reiterations (rating change of 0) make up 21.7% of all recommendation changes. Looking at the diagonal cells in Panel A of Table 1, we observe that hold recommendations are the most likely to be reiterated, followed by buys and strong buys.

3.2. Histogram of recommendation CAR

Figure 2 plots the histogram of three-day CARs of recommendation changes for one- and two-point magnitude rating changes. The first two charts show the distribution of CARs for one- and two point upgrades. The mean CAR for a one-point upgrade is 2.687% and that for a two-point upgrade is 2.783%. The medians are much lower at 1.530% and 1.694% respectively. This reveals that the magnitude of the mean CARs are strongly influenced by outliers. Another piece of suggestive evidence that only a minority of recommendations are influential is that a sizable number of CARs fall into the zero bin. Note that each interval in the histogram is one percent so that the zero bin represents CARs between -0.5% and 0.5%. The distributions also do not appear to resemble a normal distribution given that there are more right tail observations than there are left tail observations for positive recommendation changes, implying positive skewness in the distribution. The opposite result holds for negative recommendation changes.

The last two charts in Figure 2 show the one- and two-point rating changes for downgrades. The charts here tell a similar story. The median CARs are much more attenuated compared to the mean CAR and there is evidence that tail observations have a large influence so that the typical downgrade CAR may be very different from the mean downgrade CAR.

3.3. Impact of firm news events and influential observations on mean CAR

The next analysis reports how the average CAR of recommendation changes is affected when recommendations issued together with firm news events are removed and when outlier recommendations are removed.

The nine panels of Table 2 show the distribution statistics of recommendation change categories by subsamples sequentially from -4 to +4. We begin by examining downgrades and focus on the fourth panel, the rating change of -1, which has the largest number of observations among all downgrade categories. Sample 1 is the full set of -1 downgrades. The average CAR is -3.786% with a trivially small associated p-value (reported as 0.000) based on standard errors clustered by calendar day. Although the average CAR is large, we see evidence that it could be driven by outliers because the median CAR is only -1.775% (p-value of 0.000 from a signed test). As we saw in the histogram earlier, the distribution of CARs does not appear normal and this is now confirmed with the negative skewness (many left tail outlier observations) and the large positive kurtosis (tails fatter than predicted by a normal distribution). We also report the

Kolmogorov-Smirnov D-statistic as a test of normality with the p-value in parentheses below the D-statistics. The null hypothesis is normality and we see that normality is soundly rejected.[8]

Further evidence that the mean gives a misleading view of the typical CAR can be seen in the mode of the various groups. Using 50 basis points (bps) intervals, we find that the modal CAR is -1%, which means that the interval containing the most values of CAR is [-1.25%, -0.75%]. Another interesting statistic (third column) is the percentage of positive-signed CARs. A positive CAR in this case shows that a -1 rating change was associated with a stock price movement in the opposite direction from the rating change. 33.48% of -1 rating changes actually had CARs with the wrong sign.

Next, we examine the impact of removing recommendations that are contaminated by firm news releases. First, we remove observations that fall in the three-day window around quarterly earnings announcements dates reported by I/B/E/S.[9] The impact of this removal is to reduce the average CAR to -3.246% (see sample 2). Next, we also remove from sample 2 the recommendations that fall in the three day window around management earnings guidance days and find that the average CAR drops dramatically to -2.030%. Finally, we remove days with multiple recommendations since these days could correspond to firm news releases that led multiple analysts to revise their ratings. The average CAR now becomes -1.623%. Although the average CAR is still statistically significant in sample 4, we see that moving from sample 1 to sample 4, the economic magnitude of the average CAR drops by more than half from -3.786% to -1.623%. The median CAR also falls from -1.775% to -1.074%. These results stress that a large fraction of the average recommendation CAR should be attributed to contemporaneous firm news

[8] It could be that stock returns are not normal so that the recommendation CARs are also not normal. However, all the results in Table 2 remain even when log abnormal returns (ln of 1+Eq. 1) are used in place of regular CARs.

[9] Quarterly earnings announcement dates can be obtained from either I/B/E/S or Compustat. DellaVigna and Pollet (2009) show that after 1994, earnings announcement dates provided both databases are equally accurate.

releases rather than to the recommendation itself and this is consistent with the findings in Chen et al. (2005) and Altinkilic and Hansen (2008).

Next, we consider the impact of removing outlier observations from this reduced sample of 38,515 recommendations. We consider two ways of removing outliers in sample 4. We note that sample 4 still has fat tails and negative skewness. The first method is to trim 5% from both tails of the sample distribution and we find that the average CAR reduces to -1.420% (see sample 5 row). The skewness and kurtosis drops significantly as a result of this filter. The second method is to identify outliers in an objective manner by using least trimmed squares (LTS) method (see for example, Knez and Ready (1997)). Specifically, we estimated a regression using LTS with the recommendation change CAR against a constant. This regression allows us to identify the observations that have the most influence on the coefficient estimate. We then compute the mean CAR by excluding the LTS-identified outliers and report the descriptive statistics from this new sample 6. The average CAR is now -1.194% and the median is -0.977%. Although the magnitudes are reduced dramatically from sample 1, we note that they are still statistically different from zero.

Other panels in Table 2 show similar patterns. First, the median CAR is roughly half of the mean CAR in absolute value, showing that outlier recommendations have a large influence on the mean. Second, removing all firm-news contaminated recommendations shaves off a sizable proportion (sometimes more than half) of the absolute value mean and median CARs, evidence that many recommendations do not add additional value but merely repeat information contained in firm news releases. Third, removing outliers from both tails further reduces the magnitude of the typical recommendation absolute value average CAR. Altogether, the results in this table show that the distributions of CARs are not normal. The CAR distributions are usually skewed and have fat tails, and outliers have an important impact on the mean CAR. Also, controlling for firm-specific news sharply reduces the average impact that a stock recommendation has on a firm's stock price.

Table 3 shows the sensitivity of the magnitude and statistical significance of the mean recommendation CAR when part of the influential tail is removed. The first row of the table shows the size and significance (with one, two, and three asterisks representing 10%, 5% and 1% statistical significance respectively) of the mean CAR when confounding firm-news events are removed. This is essentially the sample 4 from the panels of Table 2. The second row of the table "1%" reports the average CAR when 1% of the influential tail is removed. This means removing 1% of the left tail of a downgrade category or removing the 1% of the right tail of an upgrade category. When the average CAR becomes statistically insignificant after the removal of *x*% of the influential tail, the rows below are intentionally left blank. For example, rating changes of -4 have an average CAR of -1.803% but once we remove 3% of the left tail, the average CAR becomes a statistically insignificant -0.385%. Therefore in this rating change group, we label 3% of the observations of the left tail as influential and the other observations as non-influential.

The rest of Table 3 shows us that all four downgrade categories, removing up to 10% of the left tail removes the statistical significance of the mean CAR. The rating change group of -4 only requires removal of 3% of the tail and the rating change group of -3 already has an insignificant mean CAR without the removal of any tail observations. For the positive rating change groups, more of the positive tail needs to be removed before the mean CARs become insignificant. For the +2 group for example, 20% of the right tail needed to be removed before the mean CAR became insignificant. This table illustrates the importance of influential observations in the average price reaction to recommendations.

4. Influential versus non-influential recommendation changes

4.1. Methods for classifying recommendation changes

In this section, we identify recommendation changes that are influential and compare them with non-influential recommendation changes. We report results for two definitions of influential. We consider only rating changes in our analysis and exclude reiterations.

The first method classifies a recommendation change as an influential recommendation change if the CAR is greater than 1.96 times the standard deviation of the firm's prior three-month idiosyncratic return. We focus most of our discussion on this method and use the second method as a robustness test. This method is intuitive: it treats as influential recommendation changes accompanied by an abnormal return that is significant using the market model. Specifically, a recommendation change is influential if $CAR > 1.96 \times \sqrt{3} \times \sigma_{\varepsilon}$, where σ_{ε} is the standard deviation of firm residual returns in the prior three months ([-63,-2] days) from the recommendation change. We multiply by $\sqrt{3}$ since the CAR is a three-day CAR while the σ_{ε} is the standard deviation of residuals from a daily time-series regression of firm returns against market returns and the two Fama-French factors. This measure roughly captures recommendation changes that observers would judge to be influential, namely those recommendation changes that are associated with noticeable abnormal returns that may be attributable to the recommendation changes.

The second approach classifies a recommendation change as influential when its normalized CAR is more than 1.96 standard deviations better than the mean prior 12-month normalized CAR of the similar rating change category across all firms. A normalized CAR is simply the CAR scaled by the firm's prior idiosyncratic volatility. Recommendation changes are considered influential using this second approach based on historical recommendation change CARs rather than merely based on the prior idiosyncratic volatility of the firm. This second method identifies as influential recommendation changes that have an unusual impact relative to other similar recommendation changes. This definition may also capture what observers mean when they notice specific recommendation changes in that it selects recommendation changes with possibly large effects relative to typical recommendation changes. However, the stock-price reaction for these recommendation changes need not be significant at the firm level. We also use other definitions of influential (see Section 6) but our main tests focus on these two methods.

The first row of Table 4 reports the number of recommendations that are categorized into each dimension of success. We see that 10.0% (3.2%) of all recommendation changes are defined as influential using the first (second) definition.

4.2. Analyst and firm characteristics of influential recommendations changes

We now compare the average characteristics of influential recommendation changes versus non-influential changes for each rating change category. We examine the following analyst-related characteristics:

1) Forecast accuracy: Loh and Mian (2006) show that analysts who possess more accurate earnings forecasts issue more profitable contemporaneous stock recommendations. It is possible that such analysts have recommendations that also have a larger market impact since their recommendation changes are accompanied by more accurate concurrent earnings forecasts. We compute the forecast accuracy quintile of an analyst by sorting analysts within a firm year into quintiles using the last unrevised forecast of the analyst on the I/B/E/S Detail U.S. File. Only firms with at least five analysts are included. The forecast accuracy rank (1 being the most accurate) is assigned to the analyst for the recommendations that the analyst issues during the 12 month window that overlaps three months into the next fiscal year (following Loh and Mian). Overlapping the 12 month period into the next fiscal year allows the accuracy rank to be applied during the months when fiscal year's actual earnings are announced. Note that this accuracy rank is a perfect foresight rank and is not known at the time of the recommendation since actual earnings have not yet been announced.
2) Direction of recommendation relative to the consensus: Jegadeesh and Kim (2006) formulate a test for herding and contend that if analysts herd, recommendations that go toward the consensus would have a smaller price impact than those that go away from the consensus. Following their paper, we define recommendations that go away from the consensus as those where the absolute deviation of the new recommendation from the

consensus is larger than the absolute deviation of the prior recommendation from the consensus. The consensus recommendation is defined as the mean recommendation level that includes the most recent non-stale recommendation issued by all analysts covering the firm (see Section 2.1 for the definition of stale).

3) Star analyst: This is an indicator variable that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in the annual polls in the *Institutional Investor* Magazine. Analyst names in I/B/E/S are matched to *Institutional Investor* polls (published in the October issue) and an analyst maintains the star status for 12 months beginning the November after the polls. The star analyst indicator variable proxies for the reputation of the analyst and the market's attentiveness to the stock recommendation (the market could pay more attention to calls from star analysts).

4) Analyst experience: Mikhail, Walther, and Willis (1997) show that analysts improve their earnings forecast accuracy with experience. Hence, it is possible that experience could be related to the market impact of stock recommendation changes. Analyst experience is measured as the number of quarters since the analyst issued the first earnings forecasts or stock recommendation on I/B/E/S. If an analyst appears in both the earnings forecasts and the recommendation file, the earlier of the two dates is used. Two measures of experience are computed. The first is the analyst's overall experience, which is the number of quarters that he appeared on I/B/E/S. The second is the relative experience which is the number of quarters the analyst has covered that specific firm minus the average experience for all analysts covering the firm.

5) Concurrent earnings forecast: Michaely and Womack (2006) report that stock recommendations accompanied by forecast revisions are more profitable and have larger price reactions. Therefore, we include a concurrent earnings forecast indicator variable indicating whether the same analyst issued any type of earnings forecast in the three-day window around the recommendation change.

We compute the average of these analyst-specific variables for the different rating change groups. Table 4 reports the averages for observations where these variables can be computed. The first subsample analysis separates recommendation changes into influential and non-influential using the ratio of the CAR to the firm's prior idiosyncratic volatility. The average analyst forecast accuracy quintile of influential recommendation changes is 2.802 versus 2.769 for non-influential recommendations. The difference is statistically significant, but its economic importance seems limited. 58.2% of influential recommendation changes move away from the consensus while only 52.5% of non-influential recommendation changes move away from the consensus—the difference is significant. Also, a larger proportion of influential recommendation changes are issued by star analysts and analysts with higher overall experience and relative firm-specific experience. A larger proportion of influential recommendation changes have concurrent earnings forecasts issued together with the recommendation change. These differences are as predicted from the prior literature. Using the second definition of influential (based on prior distribution of recommendation CARs) yields similar patterns of differences. Influential recommendation changes are associated with higher analyst forecast accuracy, are issued away from the consensus, from star analysts, and have concurrently issued earnings forecasts. The benefit of having more relative firm-experience appears mixed across the two definitions of influential.

Next, in Panel B, we also consider firm characteristics because firm characteristics could create conditions that make it more likely that analysts could make significant recommendation changes. For example, analysts may add more value when the value of the firm depends more on growth options which are harder to value than assets-in-place. We examine the following firm characteristics.

1) Book-to-market ratio (B/M ratio) computed as in Fama and French (2006).
2) Size of the firm (lagged month market cap).
3) Institutional ownership (percent of shares owned by institutions as reported in Thomson 13f in the most recent quarter end).

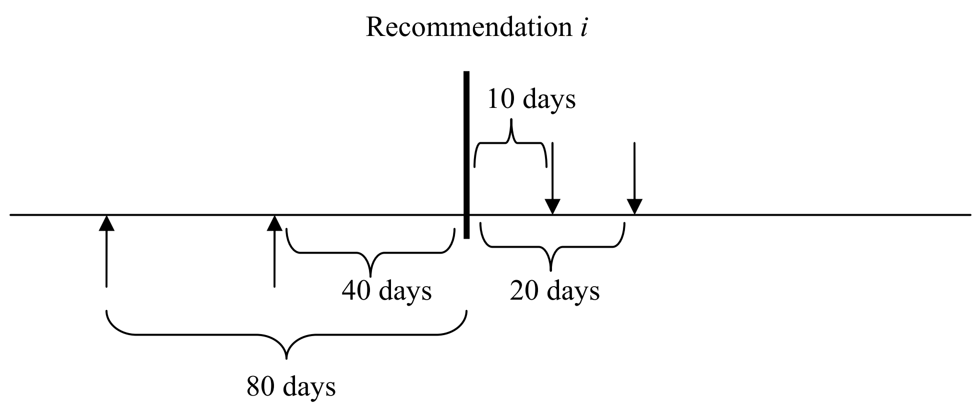
4) Dispersion is the standard deviation of the I/B/E/S Summary unadjusted file reported mean FY1 forecast divided by the absolute value of the mean forecast (following Diether, Malloy, and Scherbina (2002)).
5) # of forecasts is the number of forecasts (all horizons) issued by all analysts for the firm in the last three months ([-63,-2]).
6) Turnover is based on the last three-month average daily percentage of shares traded divided by total shares outstanding.
7) Idiosyncratic volatility is the standard deviation of the residuals from a time-series regression of past three-months' daily returns against the Fama-French three factors.
8) Total volatility is the standard deviation of prior three-month daily returns.

The results are reported in Panel B of Table 4. We first look at the first definition of influential. Influential recommendation changes tend to be issued on firms that are smaller, have higher institutional ownership, lower total and idiosyncratic volatility, lower turnover, and lower number of prior earnings forecasts. The second definition of influential yields similar results. These results are consistent with the paradigm change view of influential analyst recommendation changes. Analysts can more easily affect investors' beliefs about a firm when they are speaking in a smaller crowd. However, institutional investors are the main consumers of analyst reports, so that analysts are more likely to have a significant impact if a firm has more institutional ownership.

4.3. The effect of influential recommendation changes

Next, we consider changes in the firm environment. With the paradigm shift view, we would expect influential recommendation changes to be associated with important changes in the firm's expected performance and trading. Hong et al. (2007) propose that a paradigm shift is followed by increases in volatility. It is also possible that analyst activity and trading activity increase following a paradigm shift. We investigate changes in some firm-specific variables around the rating change event. The variables considered are:

1) The leader-follower ratio (LFR) is computed following Cooper, Day, and Lewis (2001) so as to gauge the extent to which the influential recommendation change leads other analysts to change their recommendations. The gaps between the current recommendation and the previous two recommendations from other brokers are computed and summed. The same is done for the next two recommendations. The leader-follower ratio is the gap sum of the prior two recommendations divided by the gap sum of the next two recommendations. Ratios larger than one show that other brokers issue new ratings quickly in response to the current analyst's recommendation. The schematic below illustrates the LFR of recommendation *i*: LFR_i=(80+40)/(20+10)=4, which is greater than one and hence the analyst associated with recommendation *i* is a leader analyst.



2) Change in volatility from the prior three months ([-63,-2] days) to the next three months ([2,63] days). The same horizon is used for the variables below.

3) Change in idiosyncratic volatility.

4) Change in analyst forecast dispersion.

5) Change in average daily turnover.

6) Change in number of earnings forecasts issued.

7) Change in the magnitude of monthly consensus FY1 and FY2 forecast revisions scaled by price, and long-term growth percentage forecasts.

Panel C of Table 4 reports the change in the above characteristics for the influential versus non-influential recommendation changes. The evidence strongly suggests a more significant change in the firm's information environment after influential recommendation changes. The LFR of influential recommendation changes is larger than the LFR of non-influential recommendation changes. Changes in idiosyncratic and total volatility are also larger for influential recommendation changes compared to non-influential recommendation changes. However, there is no difference in the change in dispersion. Finally, analyst and trading activity increase more following influential recommendation changes than non-influential recommendation changes.

An influential recommendation change would presumably change the way that investors view the future cash flows of the firm and this could show up in analyst forecast revisions. The change in the absolute value of FY1 and FY2 forecast revisions is significantly positive for influential recommendation changes. For example, the change in magnitude of FY2 forecast revisions for influential recommendation changes is 1.088% of price but only 0.075% of price for non-influential recommendation changes (first definition of influential). The difference of 1.012% is statistically significant. In contrast, there is little corroborating evidence for the magnitude of change in LTG forecasts.

4.4. Do influential recommendation changes come from only a subset of analysts?

Next, we investigate whether influential recommendation changes come only from a subset of analysts. Figure 3 plots the histogram of the proportion of an analyst's recommendation changes that are influential. We limit this analysis to analysts who made at least five recommendation changes in the sample period. If all analysts were equally capable of making influential recommendation changes, we would expect the distribution to peak around the average proportion of influential recommendation changes in the entire sample. The figure shows otherwise. The first chart uses the first definition of influential. Although the unconditional proportion of influential recommendation changes is 10% in the sample, about 25% of all analysts never issue a single influential recommendation change in their lifetimes. For the other definition of influential (based on past recommendation CARs), about 56% of analysts never issue an influential recommendation change. This skewed distribution indicates that only some analysts are influential and that there is a sizable proportion of analysts whose recommendation changes never have a noticeable stock-price impact.

Table 5 compares the characteristics of analysts who issue at least one influential recommendation change in the sample versus the other analysts. One would expect the "Ever influential" group to dominate the "Never influential" group in terms of skill, experience, star status, etc. Indeed this is the case. Analysts who issue at least one influential recommendation change in the sample have better average analyst earnings forecast accuracy ranks. They are also more likely to issue recommendations away from the consensus, have once been a star analyst, and have greater absolute and relative experience compared to "Never influential" analysts.

5. Predicting which recommendation changes will be influential

Section 4 provides evidence that influential recommendation changes are associated with specific analyst and firm attributes. Since many of these attributes are correlated, we use in this section a probit regression to assess the impact of these attributes on the likelihood that a recommendation will be influential. To make our approach predictive, we require the attributes to be known at the time of the recommendation change. All the variables used in the previous section are already based on past information except for forecast accuracy and the LFR. To make these two variables rely on past information, the forecast accuracy quintile is now the average quintile rank of the analyst for all the firms that he covers in the *prior* fiscal year and the LFR is now the average of the analyst's prior LFRs for the past 12 months. The definitions of the other attributes are the same as before. The probit regression is estimated for observations where all the required variables are available and the standard errors are clustered by analyst. We also add controls for the level of the recommendation, the absolute value of the recommendation change, an upgrade indicator variable, and indicator variables for the sample period after Reg FD (equals one from September 2000 onwards) and after the Global Analyst Settlement (equals one in 2003 and onwards).[10]

The dependent variable of the probit regression is equal to one if the recommendation change is influential. We report both coefficient estimates and marginal effects. [11] The results confirm the conclusions reached in the previous section. A recommendation change is more likely to be influential if it represents a move away from the consensus, it is from a star analyst,[12] from an analyst with more relative experience, has a contemporaneous earnings forecast, and from an analyst with high prior LFR. Firms that are more likely to receive impactful recommendation changes are growth firms, small firms, high institutional ownership firms, high prior turnover firms, less volatile firms, and low prior number of earnings forecasts firms.

The control variables also include indicator variables for Reg FD and the analyst settlement. After Reg FD was passed in August 2000, analysts were no longer allowed to get access to private information from firm executives. If such private information is one main source of influential recommendation changes, we would expect influential recommendation changes to abate after the passage of the law. For example, Gintschel and Markov (2004) show evidence that selective disclosure was curtailed after Reg FD and the absolute price impact of analyst output was reduced. We find, however, that the Reg FD dummy is significantly positive, implying that influential recommendation changes are even more likely after Reg FD.

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[10] In order to allow structural breaks to be identified, we compute the second definition of influential in a different manner compared to the earlier table. For the probit regression only, we compare the recommendation CAR against the distribution of similar rating change category CARs for the entire sample period instead of just using the prior 12 months.

[11] The marginal effect of a continuous variable x is the partial derivative with respect to x of the prediction function, evaluated at the mean value of y. If the independent variable is $\ln(x)$, the partial derivative will be $\delta y/\delta \ln(x)$, which is the partial derivative of y with respect to a 1% change in x. If x is a dummy variable, the marginal effect is the discrete change in y as the dummy variable changes from 0 to 1.

[12] The star analyst variable is a four point variable which we utilize their actual all American rank with higher numbers signifying a superior rank. We assign star=1 for runner-up ranks, up to star=4 for first place ranks.

For the settlement, Kadan, Madureira, Wang, and Zach (2009) find that after the settlement (their sample goes up to 2004 only), the overall informativeness of recommendations was reduced. Boni (2006) also finds similar evidence. Although, the overall informativeness of recommendations decreased, Kadan et al. also find that the falling number of optimistic recommendations could have caused optimistic recommendations to be become more informative. Our probit estimations find some evidence that a recommendation change is more likely to be influential after the settlement, especially for the first definition of influential. When we add an interaction variable upgrade×settlement to the estimations (unreported), we find that this interaction term is significant for the second definition of influential)—meaning that influential upgrades were more likely after the settlement. Altogether, our results suggest that although the overall impact of Reg FD and the settlement could have reduced the mean price impact of recommendations, the probability that a recommendation change is influential actually increased.

6. Alternative definitions of influential

We also use other methods of classifying recommendation changes as influential with generally similar results. One method is the one illustrated in Table 3 where influential tail observations are identified as those observations which, when removed, render the average recommendation change CAR insignificant. This method has a look-ahead bias since it relies on all future CARs in the entire sample period. Another method we also consider is whether recommendations returns beat twice the average CAR of same category rating changes that occurred in the last 12 months. We find that about 29.5% of them do.

Finally, we simply rely on the sign of the recommendation change CAR. One can view this as the lowest hurdle for the definition of influential since it only requires that the CAR has a correct sign. A correct recommendation change is one associated with a CAR that has the same sign as the direction of the recommendation change. Considering the sign of the recommendation change

CAR improves upon the methodology in some studies that evaluate recommendation changes based on only the absolute unsigned reaction magnitudes (example, Chen et al. (2005) and Frankel et al. (2006)).

7. Conclusion

Recommendation changes are sometimes associated with extremely large abnormal returns and these changes are typically the ones that the press focuses on. Such changes are associated with stock-price reactions that are quite different from the stock-price reaction of the typical recommendation change. The existing literature on analyst recommendation changes focuses on the average stock-price reaction. We show that the average stock-price reaction is small enough when proper care is taken to account for confounding news that for an individual stock it would not be identifiable with a firm-level event study. We call analyst recommendation changes with an identifiable impact at the firm level influential recommendation changes.

It is not surprising that some analyst recommendation changes will have a large impact. We argue that some analyst recommendation changes lead to a paradigm shift in how a firm is assessed by investors. We investigate the frequency of such recommendation changes, when a recommendation change is likely to be influential, and how the firm's information environment changes around influential recommendation changes. Using as our criterion for influential recommendation changes significance of the abnormal return in a firm-level event study, we find that roughly 10% of the recommendation changes in I/B/E/S after eliminating changes associated with confounding information are influential. Strikingly, a quarter of the analysts never have an influential recommendation change. We find that influential recommendations are more likely to be from analysts with larger leader-follower ratios, large brokers, away-from-consensus revisions, issued contemporaneously with earnings forecasts, and more experienced analysts. Further, growth firms, small firms, high institutional ownership firms, high prior turnover firms, and low prior number of earnings forecasts firms are more likely to be associated with influential recommendations. We also find evidence consistent with a paradigm shift for firms that experience influential recommendation changes: we find that if a firm has an influential recommendation change, its stock's turnover increases, its volatility increases, and analysts make more and bigger forecast changes. Overall our evidence is supportive of the view that influential analyst forecasts arise when analysts succeed in creating a paradigm shift, i.e., a significant change in how investors perceive a firm. However, analysts are like writers. Sometimes they have best-sellers, but the odds of writing a best-seller are low and whether a book is a best-seller depends on many factors that are not under the control of the writer.

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Table 1
Descriptive statistics of recommendation changes

The sample of recommendation (rec) changes are from I/B/E/S Detail U.S. File 1993 to 2006. Each rec change (or rating change) is an analyst's current rating minus his prior rating. Analyst initiations are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between -4 and 4. Firms with less than 3 analysts making up the consensus are excluded. Panel reports the transition probabilities of rec changes. For example in column 1, when the prior rec is a sell, it has a 4.6% probability of transiting an underperform. Panel B reports the frequencies of each rec change type.

Panel A: Transition probabilities of recommendation changes

Prior Rec \ Current Rec	1 Sell	2 Underperform	3 Hold	4 Buy	5 Strong Buy	Total
1 (Sell)	336	193	3,026	305	333	4,193
	8.0%	4.6%	72.2%	7.3%	7.9%	100%
2 (Underperform)	287	1,519	4,891	863	213	7,773
	3.7%	19.5%	62.9%	11.1%	2.7%	100%
3 (Hold)	3,243	5,834	17,246	24,067	16,508	66,898
	4.8%	8.7%	25.8%	36.0%	24.7%	100%
4 (Buy)	431	1,223	31,781	14,043	17,855	65,333
	0.7%	1.9%	48.6%	21.5%	27.3%	100%
5 (Strong Buy)	572	427	22,609	19,388	9,661	52,657
	1.1%	0.8%	42.9%	36.8%	18.3%	100%
Total	4,869	9,196	79,553	58,666	44,570	196,854

Panel B: Recommendation change categories

Rec Change	Frequency	Percentage
–4	572	0.3%
–3	858	0.4%
–2	27,075	13.8%
–1	57,290	29.1%
0	42,805	21.7%
+1	47,006	23.9%
+2	20,397	10.4%
+3	518	0.3%
+4	333	0.2%
Total	196,854	100%

Table 2
The impact of various filters on recommendation event percentage CAR

The sample of recommendation (rec) changes are from I/B/E/S Detail U.S. File. Each rec-change is an analyst's current rating minus his prior rating. Analyst initiations are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between -4 and 4. Firms with less than 3 analysts making up the consensus are excluded. Each panel reports summary statistics for the three-day buy-and-hold event CAR (in percent) of a rec-change group. P-values based on standard errors clustered by calendar day are reported in parentheses below the mean. Daily abnormal return is the raw return less the return on a size-B/M-momentum matched portfolio with CAR observations where the lagged price on day 0 is <$1 excluded. The mode column reports the midpoint of the 50bps interval modal group. P-value of the median is computed from a signed test. Kurt is excess kurtosis so that a normal distribution would have Kurt=0. KS is the Kolmogorov-Smirnov *D* statistic testing for the normality of the sample distribution where *, **, and *** represent that the null of normality is rejected at the 10%, 5%, and 1% levels respectively. No earnings annc refer to excluding rec-changes that occur in the three-day window around the firm's I/B/E/S reported quarterly earnings announcement dates. No mgt forecast refer to excluding rec-changes that occur in the three-day window around the firm's management earnings guidance dates provided by First Call Guidelines. No multiple rec days refer to excluding days where more than one analyst issues recs on the firm. Least trimmed squares outliers (LTS) are identified by estimating a LTS regression of CAR against a constant.

Filtered Samples	Mean	Mode (50bps intervals)	% CAR +	Skew	Kurt	KS normal test	Percentiles							# Obs
							100%	99%	75%	Median	25%	1%	0%	
Recommendation Change = –4														
1) Full sample	-4.716***	-0.5	0.332	-1.101	7.708	0.214***	92.841	38.825	1.123	-1.844***	-6.673	-70.277	-79.662	572
	(0.000)									(0.000)				
2) No earnings annc days	-4.336***	-0.5	0.342	-1.229	8.348	0.233***	92.841	38.825	1.157	-1.525***	-5.634	-70.277	-79.662	491
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	-2.643***	-0.5	0.366	-1.178	12.703	0.229***	92.841	38.825	1.441	-1.181***	-4.644	-70.277	-79.662	451
	(0.001)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	-1.747***	-0.5	0.371	-2.285	17.953	0.197***	51.830	18.981	1.247	-0.991***	-3.760	-46.832	-79.662	377
	(0.001)									(0.000)				
5) Remove 5% from both tails of (4).	-1.157***	-0.5	0.358	0.096	0.684	0.066***	10.736	9.694	0.923	-0.991***	-3.327	-11.128	-11.570	341
	(0.000)									(0.000)				
6) Remove LTS-identified outliers from (4)	-1.253***	-0.5	0.355	-0.023	0.745	0.067***	10.736	9.694	0.898	-1.016***	-3.429	-11.570	-12.885	344
	(0.000)									(0.000)				
Recommendation Change = –3														
1) Full sample	-3.312***	-1	0.382	-0.840	5.993	0.182***	71.759	32.750	1.734	-1.231***	-5.773	-50.156	-73.070	858
	(0.000)									(0.000)				
2) No earnings annc days	-2.463***	-1	0.394	-0.840	7.482	0.191***	71.759	34.337	1.912	-1.047***	-5.011	-50.156	-73.070	748
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	-1.322***	-1	0.414	-0.783	10.530	0.187***	71.759	34.337	2.086	-0.802***	-4.104	-49.102	-73.070	701
	(0.006)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	-0.577	-1	0.415	0.056	11.002	0.169***	61.748	29.952	2.133	-0.718***	-3.672	-33.195	-63.861	629
	(0.146)									(0.000)				
5) Remove 5% from both tails of (4).	-0.646***	-1	0.406	0.268	1.052	0.061***	13.616	12.712	1.683	-0.718***	-3.136	-11.707	-13.755	567
	(0.001)									(0.000)				
6) Remove LTS-identified outliers from (4)	-0.842***	-1	0.397	-0.033	0.658	0.053***	11.647	10.406	1.446	-0.756***	-3.242	-11.707	-13.755	559
	(0.000)									(0.000)				

Table 2 (Cont'd)

Filtered Samples	Mean	Mode (50bps intervals)	% CAR +	Skew	Kurt	KS normal test	Percentiles 100%	99%	75%	Median	25%	1%	0%	# Obs
Recommendation Change = –2														
1) Full sample	-4.374***	-1	0.315	-0.993	9.265	0.171***	128.090	23.324	0.782	-2.003***	-6.841	-48.737	-82.120	27,075
	(0.000)									(0.000)				
2) No earnings annc days	-3.642***	-1	0.333	-0.938	11.110	0.185***	128.090	24.435	0.910	-1.622***	-5.572	-47.753	-82.120	22,475
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	-2.176***	-1	0.356	-0.394	18.096	0.170***	128.090	25.371	1.111	-1.282***	-4.352	-38.346	-82.120	20,368
	(0.000)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	-1.706***	-1	0.357	0.470	28.308	0.145***	128.090	19.672	1.052	-1.190***	-3.921	-27.228	-82.120	17,676
	(0.000)									(0.000)				
5) Remove 5% from both tails of (4).	-1.554***	-1	0.341	-0.496	0.280	0.055***	6.746	5.956	0.787	-1.190***	-3.527	-11.347	-12.557	15,910
	(0.000)									(0.000)				
6) Remove LTS-identified outliers from (4)	-1.301***	-1	0.358	-0.140	0.562	0.048***	10.736	8.926	0.974	-1.095***	-3.442	-11.523	-12.817	16,377
	(0.000)									(0.000)				
Recommendation Change = –1														
1) Full sample	-3.786***	-1	0.335	-1.149	10.108	0.159***	156.225	19.616	1.015	-1.775***	-6.267	-43.349	-86.701	57,290
	(0.000)									(0.000)				
2) No earnings annc days	-3.246***	-1	0.349	-1.269	11.816	0.170***	156.225	19.455	1.109	-1.481***	-5.318	-42.379	-86.701	47,724
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	-2.030***	-1	0.371	-0.767	19.422	0.150***	156.225	19.792	1.296	-1.168***	-4.301	-33.288	-86.701	43,643
	(0.000)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	-1.623***	-1	0.375	-0.151	25.088	0.127***	156.225	17.059	1.286	-1.074***	-3.933	-25.626	-86.701	38,515
	(0.000)									(0.000)				
5) Remove 5% from both tails of (4).	-1.420***	-1	0.361	-0.410	0.129	0.048***	7.099	6.350	0.987	-1.074***	-3.560	-11.239	-12.384	34,665
	(0.000)									(0.000)				
6) Remove LTS-identified outliers from (4)	-1.194***	-1	0.378	-0.127	0.513	0.045***	11.570	9.356	1.217	-0.977***	-3.534	-12.119	-13.384	36,058
	(0.000)									(0.000)				
Recommendation Change = 0														
1) Full sample	-0.076**	0	0.494	0.360	37.133	0.127***	196.327	18.864	2.299	-0.041**	-2.300	-21.156	-76.972	42,805
	(0.044)									(0.023)				
2) No earnings annc days	-0.075**	0	0.492	0.543	46.935	0.123***	196.327	17.401	2.170	-0.065***	-2.197	-18.744	-70.902	38,038
	(0.041)									(0.001)				
3) No earnings annc or mgt forecasts days	0.074**	0	0.495	1.451	57.905	0.114***	196.327	17.094	2.165	-0.034*	-2.120	-15.643	-70.902	37,015
	(0.035)									(0.055)				
4) No earnings annc or mgt forecasts or mutiple rec days	0.112***	0	0.495	2.156	70.290	0.111***	196.327	16.426	2.138	-0.034*	-2.083	-14.362	-69.226	33,861
	(0.001)									(0.053)				
5) Remove 5% from both tails of (4).	0.033	0	0.494	0.108	-0.143	0.021***	7.633	6.955	1.847	-0.034**	-1.821	-6.455	-7.048	30,475
	(0.122)									(0.041)				
6) Remove LTS-identified outliers from (4)	-0.016	0	0.491	0.040	0.457	0.034***	10.048	8.706	1.937	-0.062***	-1.970	-8.636	-10.145	32,062
	(0.521)									(0.001)				

Table 2 (Cont'd)

Filtered Samples	Mean	Mode (50bps intervals)	% CAR +	Skew	Kurt	KS normal test	Percentiles							# Obs
							100%	99%	75%	Median	25%	1%	0%	
Recommendation Change = +1														
1) Full sample	2.687***	0.5	0.652	2.203	23.696	0.127***	154.432	30.831	5.275	1.530***	-1.095	-16.019	-71.010	47,006
	(0.000)									(0.000)				
2) No earnings annc days	2.211***	0.5	0.638	2.511	31.949	0.130***	154.432	27.576	4.540	1.273***	-1.160	-15.013	-71.010	38,708
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	2.216***	0.5	0.638	2.877	36.071	0.131***	154.432	27.220	4.441	1.254***	-1.129	-13.266	-71.010	37,460
	(0.000)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	2.049***	0.5	0.636	2.436	27.115	0.123***	148.831	24.569	4.236	1.201***	-1.121	-12.357	-54.099	33,963
	(0.000)									(0.000)				
5) Remove 5% from both tails of (4).	1.689***	0.5	0.651	0.571	0.114	0.059***	12.705	11.702	3.811	1.201***	-0.858	-5.397	-5.981	30,567
	(0.000)									(0.000)				
6) Remove LTS-identified outliers from (4)	1.368***	0.5	0.627	0.198	0.460	0.048***	13.472	12.263	3.744	1.056***	-1.148	-9.157	-11.637	32,070
	(0.000)									(0.000)				
Recommendation Change = +2														
1) Full sample	2.783***	0.5	0.668	2.839	36.939	0.131***	171.386	30.421	5.198	1.694***	-0.889	-15.435	-69.245	20,397
	(0.000)									(0.000)				
2) No earnings annc days	2.330***	0	0.653	2.982	40.107	0.136***	154.432	27.869	4.520	1.405***	-0.959	-14.474	-69.245	16,740
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	2.320***	0	0.653	3.330	45.270	0.138***	154.432	27.126	4.390	1.377***	-0.943	-12.755	-69.245	16,191
	(0.000)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	2.111***	0	0.649	3.456	47.704	0.130***	152.010	23.884	4.133	1.291***	-0.945	-11.440	-49.089	14,682
	(0.000)									(0.000)				
5) Remove 5% from both tails of (4).	1.739***	0	0.666	0.571	0.055	0.053***	12.050	11.058	3.758	1.291***	-0.701	-4.719	-5.191	13,214
	(0.000)									(0.000)				
6) Remove LTS-identified outliers from (4)	1.445***	0	0.641	0.228	0.377	0.040***	12.681	11.636	3.685	1.134***	-0.963	-7.960	-10.684	13,837
	(0.000)									(0.000)				
Recommendation Change = +3														
1) Full sample	1.267***	-1	0.542	1.046	7.426	0.125***	54.906	27.236	4.252	0.522*	-2.530	-22.427	-32.143	518
	(0.001)									(0.059)				
2) No earnings annc days	1.182***	-1	0.536	1.217	8.506	0.131***	54.906	30.059	3.905	0.353	-2.519	-22.427	-32.143	463
	(0.004)									(0.137)				
3) No earnings annc or mgt forecasts days	1.341***	-1	0.537	1.396	9.180	0.137***	54.906	30.059	3.900	0.362	-2.404	-19.794	-32.143	456
	(0.001)									(0.122)				
4) No earnings annc or mgt forecasts or mutiple rec days	1.057***	-1	0.525	0.693	4.033	0.126***	35.642	24.354	3.396	0.263	-2.425	-18.793	-26.115	415
	(0.003)									(0.326)				
5) Remove 5% from both tails of (4).	0.844***	-1	0.528	0.599	0.342	0.085***	13.035	12.570	3.005	0.263	-2.222	-7.967	-8.885	375
	(0.000)									(0.302)				
6) Remove LTS-identified outliers from (4)	0.583**	-1	0.515	0.303	0.500	0.078***	13.555	12.998	2.963	0.097	-2.357	-11.648	-12.969	388
	(0.021)									(0.577)				

Table 2 (Cont'd)

Filtered Samples	Mean	Mode (50bps intervals)	% CAR +	Skew	Kurt	KS normal test	Percentiles							# Obs
							100%	99%	75%	Median	25%	1%	0%	
Recommendation Change = +4														
1) Full sample	1.919***	-1	0.613	1.080	9.072	0.124***	46.785	26.140	4.651	1.113***	-1.319	-14.121	-30.655	333
	(0.000)									(0.000)				
2) No earnings annc days	1.649***	1	0.606	1.254	12.579	0.130***	46.785	26.140	4.204	1.082***	-1.302	-13.232	-30.655	287
	(0.000)									(0.000)				
3) No earnings annc or mgt forecasts days	1.906***	1	0.612	2.340	13.865	0.125***	46.785	26.140	4.341	1.084***	-1.260	-11.439	-12.303	276
	(0.000)									(0.000)				
4) No earnings annc or mgt forecasts or mutiple rec days	1.678***	-1	0.602	2.764	19.026	0.128***	46.785	17.965	3.574	0.996***	-1.247	-10.383	-12.303	241
	(0.000)									(0.002)				
5) Remove 5% from both tails of (4).	1.354***	-1	0.613	0.555	-0.310	0.090***	9.997	8.878	3.062	0.996***	-1.101	-4.248	-4.625	217
	(0.000)									(0.001)				
6) Remove LTS-identified outliers from (4)	1.119***	-1	0.593	0.233	0.137	0.068**	10.451	9.380	3.049	0.932***	-1.247	-7.516	-9.700	226
	(0.000)									(0.006)				

Table 3
Removing influential tail to make recommendation event CAR insignificant

This table reports the average recommendation (rec) change event CAR (in percent) when x% of the influential tail of sample 4 of Table 2 is removed. Sample 4 is the rec change sample where we remove recs falling in the three-day window associated with earnings announcements and management forecasts, and firm-days with recs from multiple analysts. When the average CAR becomes insignificant, subsequent rows below are intentional left blank. The sample of rec changes are from I/B/E/S Detail U.S. File. Each rec change is an analyst's current rating minus his prior rating. Recs with no prior ratings (i.e., initiations) are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between -4 and 4. The mean three-day event buy-and-hold CAR are reported with *, **, and *** indicating statistical significance (based on standard errors clustered by calendar day) at the 10%, 5%, or 1% levels respectively. CAR is daily buy-and-hold raw return less the buy-and-hold return on a size-B/M-momentum matched portfolio.

x% of influential tail removed	Mean event CAR of recommendation change category							
	-4	-3	-2	-1	1	2	3	4
0%	-1.747***	-0.577	-1.706***	-1.623***	2.049***	2.111***	1.057***	1.678***
1%	-1.261***		-1.332***	-1.275***	1.700***	1.760***	0.766**	1.383***
2%	-0.796**		-1.111***	-1.063***	1.498***	1.568***	0.553*	1.251***
3%	-0.447		-0.936***	-0.894***	1.332***	1.413***	0.360	1.094***
4%			-0.786***	-0.749***	1.189***	1.278***		0.998***
5%			-0.655***	-0.619***	1.061***	1.157***		0.865***
6%			-0.535***	-0.501***	0.943***	1.047***		0.787***
7%			-0.425***	-0.392***	0.833***	0.945***		0.716***
8%			-0.322***	-0.290***	0.730***	0.850***		0.611***
9%			-0.224***	-0.194***	0.632***	0.759***		0.545**
10%			-0.131***	-0.102***	0.539***	0.673***		0.450**
11%					0.451***	0.590***		0.389*
12%					0.365***	0.511***		0.331
13%					0.283***	0.435***		
14%					0.204***	0.361***		
15%					0.126***	0.289***		
16%					0.051*	0.219***		
17%					-0.022	0.151***		
18%						0.084**		
19%						0.018		
Beginning #obs	377	629	17676	38515	33963	14682	415	241

Table 4
Comparing analyst and firm characteristics of influential versus non-influential recommendation changes

Influential recommendations (recs) are compared with non-influential recs. There are two definitions of influential. First, influential recs are those are when a correct-signed CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month idiosyncratic volatility of daily returns. Second, influential recs are defined as those whose normalized CARs are more than 1.96 standard deviations better than the mean prior 12-month normalized CAR of the similar rating change category. A normalized CAR is simply the CAR scaled by the firm's prior idiosyncratic volatility. The sample is from I/B/E/S with earnings announcement days, management forecast days, and multiple-rec days removed (sample 4 in Table 2). Reiterations (rec change=0) are also excluded. Panel A reports the average analyst or rec characteristic by subsamples. Forecast accuracy quintile is the quintile rank (lower rank=greater accuracy) of the analyst based on his last unrevised FY1 earnings forecast for that fiscal year according to Loh and Mian (2006)). A rec moves away from the consensus (dummy variable) when the absolute deviation of the new rec from the consensus is larger than the absolute deviation of the prior rec from the consensus (as in Jegadeesh and Kim (2006)). Star analysts (dummy variable) are analysts who are ranked as All-Americans in the most recent annual *Institutional Investor* polls. Analyst experience in quarters is the number of quarters since the analyst issued his first earnings forecasts or stock rec on I/B/E/S. Concurrent earnings forecast is a dummy indicating whether the analyst issued any type of earnings forecast in the three-day window around the rec (as in Michaely and Womack (2006)). Panel B compares firm characteristics prior to the rec issue. B/M ratio is measured as in Fama and French (2006), size is the prior month CRSP market cap, institutional ownership is the percent of the firm owned by 13f institutions reported in the most recent quarter-end. Turnover is based on the last three-month average daily percentage of shares traded divided by total shares outstanding. Idiosyncratic volatility is the standard deviation of the residuals from a time-series regression of past three-months' daily returns against the Fama-French three factors and total volatility is the standard deviation of prior three-month daily returns. Dispersion is the standard deviation of the I/B/E/S reported mean FY1 forecast divided by the absolute value of the mean forecast. # of forecasts is the number of forecasts (all horizons) issued by all analysts for the firm in the last three months. Panel C compares the changes in the firm environment around the rec. Leader-follower ratio is the gap sum of the prior two recs divided by the gap sum of the next two recs. Ratios larger than one indicate a leader analyst whose recs are quickly followed by other brokers' rec issuances. We also compute the Δ in volatility of daily returns from the prior 3 months to the 3 months after the rec (excluding the three-day event window). We also computed in the same manner, Δ idiosyncratic volatility of daily returns, and Δ average daily turnover. Δ Dispersion is the change one month before to one month after the rec, where dispersion is the standard deviation of the I/B/E/S reported mean FY1 forecast divided by the absolute value of the mean forecast. The reported values for total, idiosyncratic volatility, dispersion, and turnover are multiplied by 100 (e.g. 1.0 represents 1.0%). Δ in # of EPS forecasts is the # of EPS (all horizons) forecasts issued by all analysts for the firm three months after the rec minus three months before. Δ |Forecast Revision| is computed for the FY1 and FY2 and long-term growth (LTG) consensus analyst forecast revisions from three months before to three months after the rec. FY1 and FY2 consensus forecasts revisions are scaled by price and LTG forecasts are in percent. Asterisks in the difference columns indicate statistical significance using standard errors clustered by calendar day where *,**, and *** represent significance levels of 10%, 5%, and 1% respectively.

Characteristics	Influential based on firm's idio-volatility				Based on distribution of past rec CARs			
	Not Influ	Influential	Difference		Not Influ	Influential	Difference	
			Influ – Not	t-stat			Influ – Not	t-stat
Panel A: Analyst and recommendation characteristics								
Number of recommendations	98,575	10,972			106,026	3,521		
		10.0%				3.2%		
Forecast accuracy quntile (1= most accurate)	2.801	2.770	-0.032**	(-2.13)	2.800	2.755	-0.045*	(-1.80)
Away from consensus	0.525	0.579	0.054***	(9.48)	0.528	0.603	0.075***	(8.33)
Star analyst	0.184	0.214	0.030***	(4.93)	0.186	0.226	0.040***	(4.59)
# Qtrs analyst in I/B/E/S	28.593	29.107	0.514**	(2.10)	28.658	28.238	-0.420	(-1.13)
Relative firm-specific experience in qtrs	0.337	0.548	0.211**	(2.45)	0.361	0.291	-0.069	(-0.55)
Concurrent earnings forecast	0.453	0.540	0.087***	(12.27)	0.459	0.564	0.105***	(10.61)
Panel B: Firm characteristics prior to recommendation								
B/M ratio	0.490	0.498	0.008	(1.31)	0.491	0.503	0.012	(1.40)
Size ($m)	8757.98	6743.43	-2014.6***	(-7.77)	8683.78	4714.72	-3969.1***	(-11.21)
Institutional ownership	0.599	0.616	0.017***	(5.37)	0.601	0.584	-0.016***	(-3.75)
Dispersion ×100	14.205	15.211	1.006	(1.06)	14.281	15.061	0.780	(0.55)
Idiosyncratic volatility ×100	2.647	2.387	-0.260***	(-10.66)	2.627	2.451	-0.176***	(-5.72)
Total volatility ×100	2.916	2.642	-0.274***	(-9.79)	2.895	2.682	-0.213***	(-6.25)
Daily turnover	0.642	0.591	-0.050***	(-7.27)	0.640	0.536	-0.105***	(-11.06)
# of EPS forecasts	80.221	64.813	-15.408***	(-17.52)	79.575	51.649	-27.926***	(-26.66)
Panel C: Change in firm environment around recommendation								
Leader-follower ratio of rec	2.032	3.143	1.111***	(11.63)	2.079	4.074	1.995***	(9.36)
Δ Volatility of daily ret ×100 (-3mth,+3mth)	-0.119	0.333	0.452***	(23.37)	-0.093	0.520	0.614***	(21.62)
Δ Idiosyncratic volatility ×100 (-3mth,+3mth)	-0.111	0.340	0.451***	(26.71)	-0.086	0.527	0.613***	(23.04)
Δ Dispersion ×100 (- 1mth,+1mth)	1.074	0.637	-0.437	(-0.41)	0.958	3.192	2.234	(0.96)
Δ Daily turnover ×100 (-3mth,+3mth)	-0.006	0.085	0.092***	(23.55)	-0.002	0.130	0.131***	(19.43)
Δ in # of EPS forecasts (-3mth,+3mth)	-1.036	4.828	5.864***	(10.38)	-0.649	5.589	6.238***	(8.51)
Δ in FY1 |Forecast Revision|×100 (-3mth,+3mth)	0.141	0.926	0.785*	(1.65)	0.192	1.069	0.877	(0.85)
Δ in FY2 |Forecast Revision|×100(-3mth,+3mth)	0.075	1.088	1.012***	(2.58)	0.131	1.559	1.428*	(1.82)
Δ in LTG |Forecast Revision|×100 (-3mth,+3mth)	-0.010	0.004	0.014	(0.58)	-0.010	0.038	0.048	(1.33)

Table 5
Analysts who had at least one influential recommendation change

Analysts who had at least 5 recommendations (recs) in the 1994-2006 period are compared according to whether their recs have ever been influential. There are two definitions of influential. First, influential recs are those are when a correct-signed CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month idiosyncratic volatility of daily returns. Second, influential recs are defined as those whose normalized CARs are more than 1.96 standard deviations better than the mean prior 12-month normalized CAR of the similar rating change category. A normalized CAR is simply the CAR scaled by the firm's prior idiosyncratic volatility. The sample is from I/B/E/S with earnings announcement days, management forecast days, and multiple-recommendation days removed (sample 4 in Table 2). Reiterations (rec change=0) are also excluded. Panel A reports the average analyst or recommendation characteristic by analysts who were ever influential versus those who were never influential. The percentage of analyst recs that are influential is the average proportion of an individual analyst's recs that are influential conditional on the analyst ever being influential in the whole sample. Forecast accuracy quintile is the quintile rank of the analyst based on his last unrevised FY1 earnings forecast for that fiscal year according to Loh and Mian (2006)). A recommendation moves away from the consensus (dummy variable) when the absolute deviation of the new recommendation from the consensus is larger than the absolute deviation of the prior recommendation from the consensus (as in Jegadeesh and Kim (2006)). Star analysts (dummy variable) are analysts who are ranked as All-Americans in the most recent annual *Institutional Investor* polls. Analyst experience in quarters is the number of quarters since the analyst issued his first earnings forecasts or stock recommendation on I/B/E/S. Concurrent earnings forecast is a dummy indicating whether the analyst issued any type of earnings forecast in the three-day window around the recommendation (as in Michaely and Womack (2006)). Asterisks in the difference columns indicate statistical significance using standard errors clustered by calendar day where *,**, and *** represent significance levels of 10%, 5%, and 1% respectively.

Characteristics	Influential based on firm's idio-volatility				Based on distribution of past rec CARs			
	Never	Ever Influential	Difference		Never	Ever Influential	Difference	
			Ever–Never	t-stat			Ever–Never	t-stat
Number of Analysts	1,010	3,055 75.2%			2,320	1,745 42.9%		
% of analyst's recs that are influential	0.0%	18.9%			0.0%	10.9%		
Forecast accuracy quntile	2.913	2.809	-0.103***	(-4.50)	2.856	2.807	-0.049***	(-2.91)
Away from consensus	0.525	0.536	0.011**	(2.02)	0.530	0.537	0.008**	(1.97)
Was once a Star analyst	0.104	0.240	0.136***	(11.05)	0.151	0.280	0.129***	(9.90)
# Qtrs analyst in I/B/E/S	16.869	23.729	6.860***	(11.86)	19.081	25.939	6.859***	(12.60)
Relative firm-specific experience in qtrs	-2.464	-0.781	1.683***	(11.23)	-2.062	-0.053	2.009***	(15.46)
Concurrent earnings forecast	0.481	0.471	-0.009	(-1.06)	0.477	0.469	-0.008	(-1.15)

Table 6
Probit predicting when a recommendation change will be influential

The dependent variable is whether a recommendation (rec) is influential. There are two definitions of influential. First, influential recs are those are when a correct-signed CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month idiosyncratic volatility of daily returns. Second, influential recs are defined as those whose normalized CARs are more than 1.96 standard deviations better than the mean normalized CAR of the similar rating change category for the entire sample period. A normalized CAR is simply the CAR scaled by the firm's prior idiosyncratic volatility. The explanatory variables are as follows. The Rec Level is the rating level after the rec change (1=sell to 5=strong buy). The absolute value of the rec change, upgrade dummy, and reg FD dummy (=1 after Aug 2000) and Settlement dummy (=1 in 2003 and after) are also included. Past forecast accuracy quintile is the average quintile rank of the analyst based on his last unrevised FY1 earnings forecast for all the firms he covers in the previous fiscal year. Smaller ranks denote greater accuracy. Away from consensus=1 when the absolute deviation of the new rec from the consensus is larger than the absolute deviation of the prior rec from the consensus. Star analysts rank is the All-Americans rank in the most recent annual *Institutional Investor* polls. We reverse ranks so that high numbers correspond to superior ranks, i.e., top rank=4, second=3, third=2, runner-up=4. Absolute analyst experience based on the # of quarters since the first earnings forecasts or stock rec on I/B/E/S. Relative firm-specific experience is based on the analyst's firm-specific experience less the average experience of other analysts covering the stock. Concurrent earnings forecast=1 when the same analyst issued any type of earnings forecast in the three-day window around the rec. Leader-follower ratio (LFR) is computed as follows. The gaps between the current rec and the previous two recs from other brokers are computed and summed. The same is done for the next two recs. The LFR is the gap sum of the prior two recs divided by the gap sum of the next two recs. The past ratio is the average of the analyst's LFRs from the prior 12 months. B/M is the book-to-market ratio and size is the end-June market cap, and momentum is the holding period return in the prior 12 calendar months skipping a month, and institutional ownership is the percent of the firm owned by 13f institutions reported in the most recent quarter-end. Turnover is based on the last three-month average daily percentage of shares traded divided by total shares outstanding. Idiosyncratic volatility is the standard deviation of the residuals from a time-series regression of past three-months' daily returns against the Fama-French three factors. Dispersion is the standard deviation of the I/B/E/S reported mean FY1 forecast divided by the absolute value of the mean forecast. # of forecasts is the number of forecasts (all horizons) issued by all analysts for the firm in the last three months. *,**, and *** represent significance levels of 10%, 5%, and 1% respectively, using standard errors clustered by analyst, with associated *z* statistics in parentheses.

Table 6 (Cont'd)

Explantory Variable	Influential based on firm's prior idio. volatility		Influential based on distribution of past CARs	
	Coefficient	Marg. Eff	Coefficient	Marg. Eff
Rec level	-0.029***	-0.005***	-0.024	-0.001
	(-2.60)	(-2.60)	(-1.50)	(-1.50)
Absolute value of rec change	0.042***	0.007***	-0.014	-0.001
	(2.70)	(2.70)	(-0.61)	(-0.61)
Upgrade Dummy	0.137***	0.023***	0.143***	0.008***
	(6.47)	(6.45)	(4.52)	(4.45)
Reg FD Dummy	0.112***	0.018***	0.165***	0.009***
	(4.47)	(4.47)	(4.66)	(4.61)
Settlement Dummy	0.091***	0.015***	-0.010	-0.000
	(3.46)	(3.37)	(-0.25)	(-0.25)
Past forecast accuracy quintile	-0.013**	-0.002**	0.000	0.000
	(-2.19)	(-2.19)	(0.01)	(0.01)
Rec away from consensus	0.130***	0.021***	0.138***	0.007***
	(8.64)	(8.63)	(6.19)	(6.16)
Star analyst rank (rank: 0 to 4, 4 =top)	0.055***	0.009***	0.043***	0.002***
	(6.74)	(6.75)	(3.35)	(3.33)
# Qtrs analyst in I/B/E/S	-0.000	-0.000	-0.001	-0.000
	(-0.42)	(-0.42)	(-1.19)	(-1.19)
Analyst's relative experience	0.003**	0.000**	0.003*	0.000*
	(2.28)	(2.28)	(1.84)	(1.84)
Concurrent earnings forecast	0.193***	0.032***	0.226***	0.012***
	(12.76)	(12.72)	(9.85)	(9.96)
Past Leader-Follower Ratio	0.008***	0.001***	0.009***	0.000***
	(3.77)	(3.77)	(3.18)	(3.18)
Log(B/M)	-0.092***	-0.015***	-0.106***	-0.006***
	(-9.23)	(-9.24)	(-7.23)	(-7.24)
Log(Size)	-0.076***	-0.013***	-0.117***	-0.006***
	(-9.89)	(-9.99)	(-10.32)	(-10.70)
Price momentum	-0.040**	-0.007**	-0.070***	-0.004***
	(-2.51)	(-2.51)	(-2.61)	(-2.61)
Log(Institutional ownership)	0.064***	0.010***	0.045	0.002
	(2.74)	(2.75)	(1.32)	(1.32)
Log(Turnover)	0.067***	0.011***	0.097***	0.005***
	(4.57)	(4.58)	(4.59)	(4.58)
Log(Idiosyncratic volatility)	-0.312***	-0.051***	-0.353***	-0.018***
	(-13.79)	(-13.94)	(-10.12)	(-10.35)
Dispersion	0.019**	0.003**	0.013	0.001
	(2.28)	(2.27)	(1.41)	(1.42)
Log(# of forecasts)	-0.135***	-0.022***	-0.180***	-0.009***
	(-11.80)	(-11.71)	(-11.17)	(-11.03)
Pseudo R-sq	0.03719		0.05550	
# Observations	62572		62572	
Chi-Sq test	1138.93***		686.39***	

Figure 1
Transition probabilities of recommendation changes

The sample of recommendation (rec) changes are from I/B/E/S Detail U.S. File 1993 to 2006. Each rec change (or rating change) is an analyst's current rating minus his prior rating. Analyst initiations are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between -4 and 4. Firms with less than 3 analysts making up the consensus are excluded. The chart plots the transition probabilities of rec changes—the probability that a prior rec transits to any of the five rating categories.

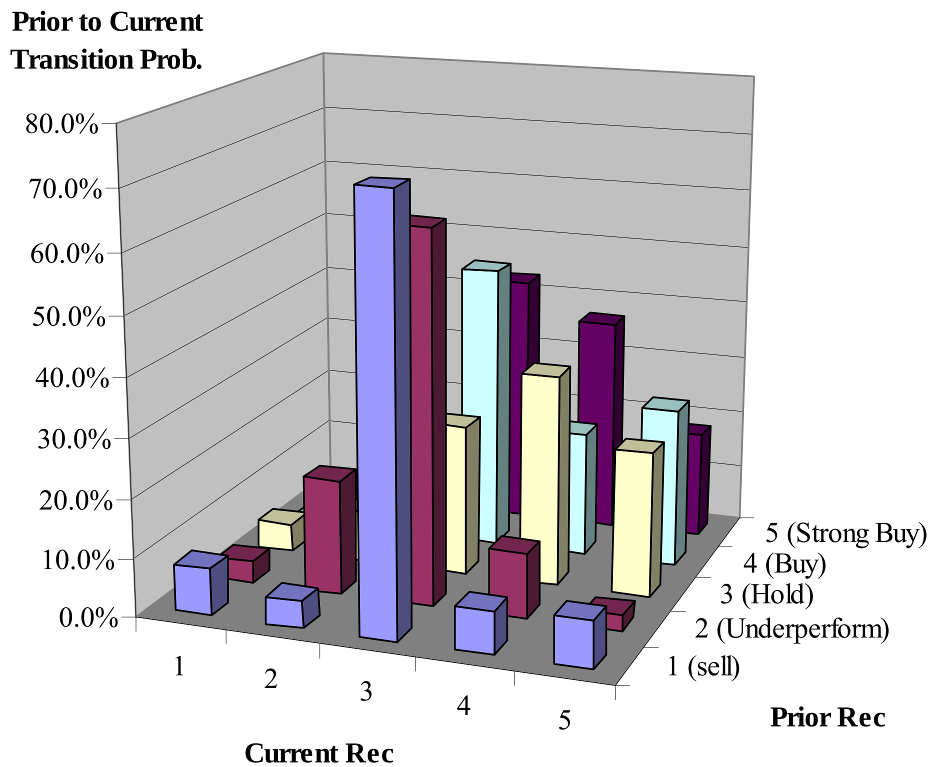

Figure 2

CAR of upgrades and downgrades

The sample of recommendation (rec) changes are from I/B/E/S Detail U.S. File 1993 to 2006. Each rec change (or rating change) is an analyst's current rating minus his prior rating. Analyst initiations are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between -4 and 4. Firms with less than 3 analysts making up the consensus are excluded. The charts plots the histogram of three-day event CARs of one-point upgrades, two-point upgrades, two-point downgrades, and one-point downgrades respectively. CAR is the three-day buy-and-hold return around the rec less the corresponding return on a size-B/M-momentum matched DGTW characteristic portfolio.

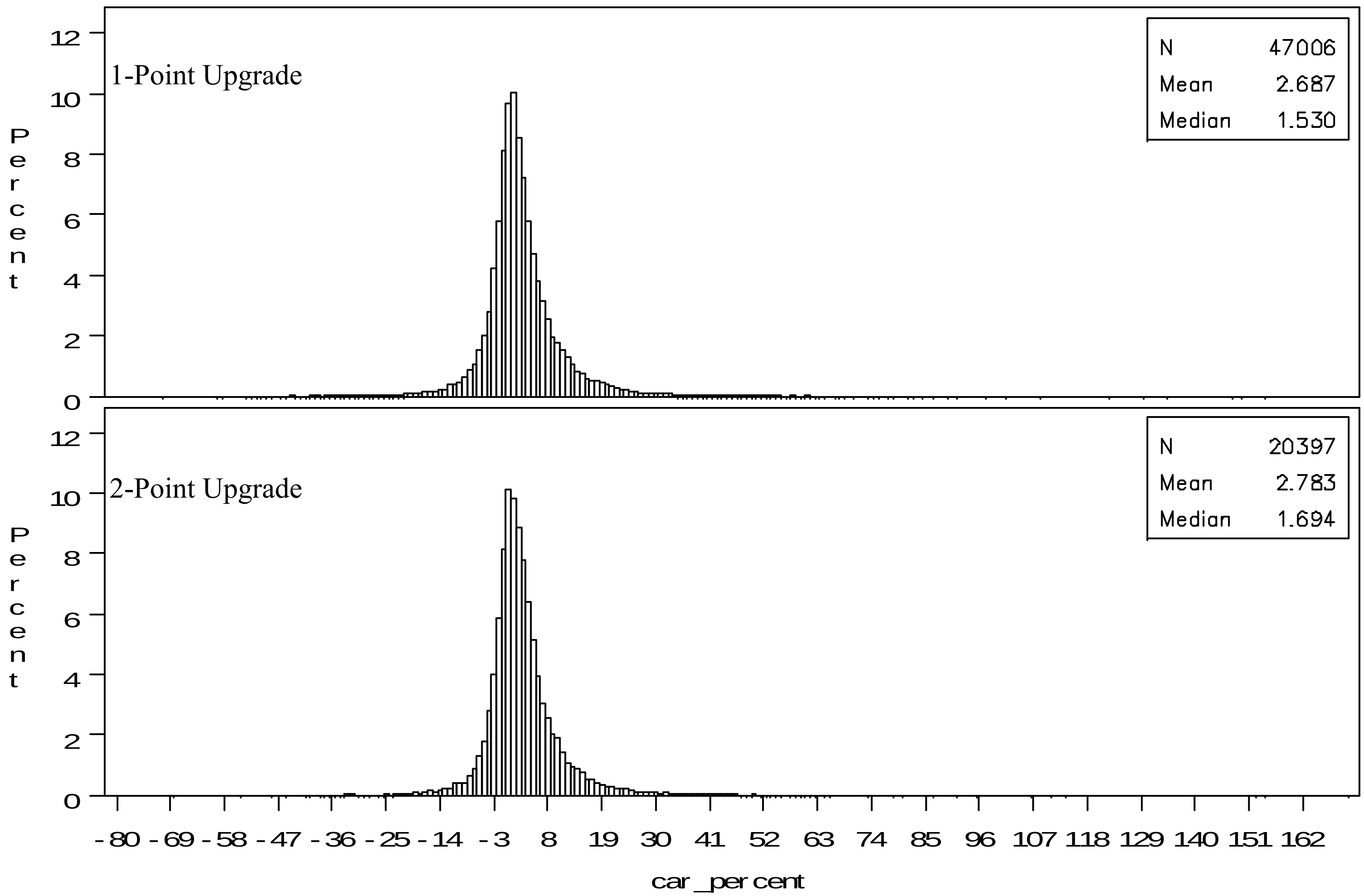

Figure 2 (Cont'd)

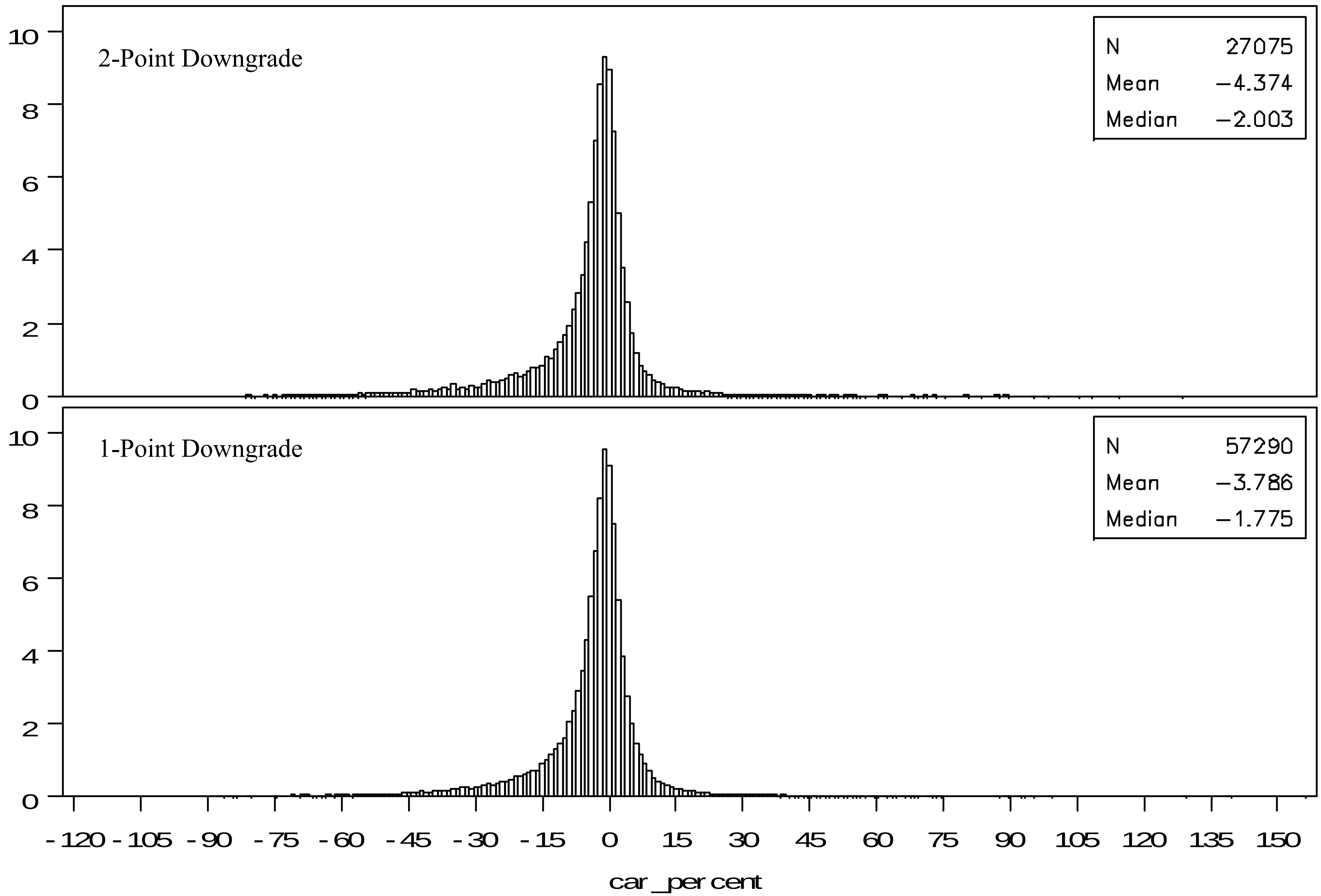

Figure 3
Histogram of proportion of an analyst's influential recommendation changes

We plot the histogram of the proportion of an analyst's recommendation (rec) changes that are influential. We focus on analysts who made at least five recs in the 1994 to 2006 period. The first definition of influential uses the firm's past idiosyncratic volatility of daily returns to determine if a rec change is influential (1.96 standard deviations away). The second uses the history of prior same magnitude rec change CARs to determine if a change is influential (1.96 standard deviations away).