When Are Analyst Recommendation Changes Influential?

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The existing literature measures the contribution of analyst recommendation changes using average stock-price reactions. With such an approach, recommendation changes can have a significant impact even if no recommendation has a visible stock-price impact. Instead, we call a recommendation change influential only if it affects the stock price of the affected firm visibly. We show that only 12% of recommendation changes are influential. Recommendation changes are more likely to be influential if they are from leader, star, previously influential analysts, issued away from consensus, accompanied by earnings forecasts, and issued on growth, small, high institutional ownership, or high forecast dispersion firms. (*JEL* G14, G20, G24)

Market observers at times attribute large stock-price changes to analyst recommendation changes. For instance, according to *The Wall Street Journal*, 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.[1] Though the finance literature finds that significant average abnormal returns are associated with recommendation

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[1] 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.

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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. Consequently, with the typical recommendation change, investors following a firm cannot 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 article, we investigate how frequently recommendation changes visibly impact stock prices, which we assess to be the case when a recommendation change has a significant stock-price impact, and we try to understand better when and why analyst recommendation changes have such an impact.

The existing literature that assesses the impact of recommendation changes does not make it possible to answer the questions we are interested in. 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 ability of analysts to visibly impact stock prices of individual firms. 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 that focuses on average abnormal returns does not make it possible to understand whether analysts can visibly move prices or how often they do so. Such an understanding is critical to assessing the role of analysts in generating information about firms and in influencing investors and management. In particular, it would be hard to argue that analysts influence investors and management systematically if they do not visibly move prices.

Our contribution is to identify recommendation changes that are impactful based on stock-level abnormal returns. We define a recommendation change as influential in returns if its associated abnormal return is in the same direction as the recommendation change and is statistically significant. An analyst might not affect the stock price, but she might lead investors to trade in response to her analysis. Therefore, we also use an alternative definition of an influential recommendation change based on turnover. With this definition, a recommendation change is influential if it leads to a statistically significant increase in turnover at the firm-level. These approaches ensure that the recommendation changes that we eventually label as influential are indeed those that are noticed by investors following the firm.

An important component of our contribution is that we conduct our main tests with 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. Not surprisingly, 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 about 12% of recommendation changes in our sample (that minimizes the impact of firm-specific news) are influential in returns and about 13% are influential in turnover. However, about one out of four analysts never had any influential recommendation change. Conditional on an analyst having an influential recommendation change, one in five of the analyst's recommendation changes are influential. This finding illustrates that influential recommendation changes come only from a subset of skilled analysts and that these influential recommendation changes are infrequent even for analysts within this subset.

Meredith Whitney's Citigroup downgrade on November 1, 2007, was associated with a drop in Citigroup's stock price of 6.9%. Yet, as a *Wall Street Journal* article recently reported, other analysts in the weeks before downgraded the stock with reports that had similar content.[2] 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. We consider a battery of analyst, recommendation, and firm variables. We find that recommendations away from the consensus and recommendations accompanied by any sort of earnings forecasts are more likely to be influential. Influential recommendations are also more likely to be from *Institutional Investor*–ranked analysts and analysts who have a history of being ahead of the herd in issuing recommendations. Analysts have hot hands in influential recommendations: An analyst who has had an influential recommendation in the past is more likely to have one in the future. 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.

When analyst recommendation changes are influential, they should lead to more analyst and investor activity in the stock as investors adjust their

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

holdings to the new information produced by analysts. We find this to be the case. Analyst activity increases after an influential analyst recommendation change compared to before. Forecast revisions by analysts following such a change are much larger than forecast revisions before such a change. Stock volatility and turnover are much larger in the three months following an influential analyst change than in the three months before. Finally, the firm's industry is also more likely to have a large return coinciding with the recommendation event—consistent with the analyst research containing an industry element affecting similar firms.

We are not the first to examine the differential impact of stock recommendation changes. For instance, Stickel (1995) finds 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) demonstrate 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. 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. 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. A key distinguishing feature of our approach from this literature is that we do not focus on average effects. Most authors find a significant effect of analyst recommendations on average for certain samples, and some authors find no significant effect. Our study is not about average effects, but rather about whether individual recommendations are influential. We could find evidence that some recommendations are influential even if the average recommendation in a sample has an insignificant stock-price reaction; alternatively, we could find that no recommendations are influential even if the stock-price reaction to analyst recommendations is significant on average.

A related paper, Altinkilic and Hansen (2009), reports evidence that the average recommendation revision does not produce an economically meaningful reaction after removing recommendations that piggyback on firm news, such as earnings announcements. They go on to conclude that analyst recommendations are therefore uninformative. Chen, Francis, and Schipper (2005) find that the average analyst recommendation or earnings forecast produces a price impact that does not differ from the average stock-price movement on non-recommendation days. Because these papers focus on average effects, they do not discuss or identify subsets of recommendations that are influential. Although our findings agree that the majority of recommendations are uninformative, we argue that analysts add value to financial markets by virtue of the fact that they can produce influential recommendations (e.g., as anecdotally illustrated in the Citigroup and Countrywide cases).[3] Since our threshold for an influential recommendation (ignoring the requirement of correct sign) corresponds to the 5% probability level, we expect 5% of recommendation changes to be significant by chance alone. We find that the percentage of influential recommendation changes is more than twice the percentage we would expect by chance alone. At the same time, our evidence shows that producing an influential recommendation change requires a combination of skills and circumstances that makes such recommendation changes infrequent.

Analysts also produce earnings forecast revisions. Prior work on the impact of earnings forecast revisions has focused on differentiating reaction magnitudes according to firm and analyst characteristics, for example, in Clement and Tse (2003) and Gleason and Lee (2003).[4] Therefore, we estimate the fraction of earnings forecast revisions that are influential. We find that roughly 5% of earnings forecast revisions are influential. Earnings forecast revisions accompanied by recommendations are twice as likely to be influential. Further, a recommendation change is more likely to be influential if it is accompanied by an earnings forecast. We conjecture that analyst research is more likely to be influential (according to our definition) when conveyed through a recommendation change, since it is a clear call to buy or sell a stock that can receive a great deal of attention in the press.

The rest of the study is organized as follows. Section 1 details the data and sample. Section 2 describes the average recommendation event abnormal return. Section 3 identifies which recommendations are influential and their characteristics and consequences. Section 4 investigates predictive variables for influential recommendations. Section 5 considers robustness tests, and Section 6 concludes.

1. Data and Sample

1.1 Recommendations data

The stock recommendations sample is from Thomson Financial's Institutional Brokers Estimate (I/B/E/S) U.S. Detail File, augmented with dates from the First Call Database. We build our sample starting from I/B/E/S ratings issued by individual analysts from 1993 to 2006, with ratings ranging from 1 (strong buy) to 5 (sell). Ratings are reversed (e.g., strong buy now denoted by 5) so that higher ratings correspond to more favorable recommendations. We focus on recommendation changes issued from 1994 onward since 1993

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[3] Our research design also has more power to identify informational effects of analysts since we investigate each recommendation change at the individual firm level. Average stock-price reactions disproportionately reflect recommendations at firms with greater analyst coverage. For instance, a firm with 30 analysts will typically have ten times more observations in a sample than a firm with three analysts. Yet the firm covered by 30 analysts would be one for which an individual recommendation is less likely to be informative.

[4] These papers are different from our approach in that they do not examine recommendations, rely on our method of identifying influential events, or examine volume reactions to the events.

observations are sparse (1993 data is used for prior ratings when available). Ljungqvist, Malloy, and Marston (2009) 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, fixed the alterations in the recommendation history file as of February 12, 2007. The dataset we use is dated March 15, 2007, and hence reflects these recent corrections by Thomson.

We focus 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 2010). The recommendation change (*recchg*) is computed as the current rating minus the prior rating by the same analyst. By construction, *recchg* ranges between -4 and $+4$. A rating is assumed to be outstanding according to the definition in Ljungqvist, Malloy, and Marston (2009). Specifically, a rating is outstanding if it has been confirmed by the analyst (in the I/B/E/S review date field) in the last twelve months and has not been stopped by the broker (in the I/B/E/S Stopped File). We exclude observations where there is no outstanding prior rating from the same analyst (i.e., analyst initiations or re-initiations are excluded). We remove analysts coded as anonymous by I/B/E/S since it is not possible to track their recommendation revisions. To ensure that our sample focuses on firms that are of sufficient interest to investors, we also remove observations for which fewer than three analysts have valid outstanding ratings.

We also deal with overall rating distribution changes due to the National Association of Securities Dealers (NASD) Rule 2711 in 2002. Many brokers reissued stock recommendations in response to the rule, with many of them changing to a three-point (buy, hold, sell) scale instead of a five-point (strong buy, buy, hold, underperform, sell) scale (Kadan, Madureira, Wang, and Zach 2009). As a result, 2002 contains the largest number of recommendations in I/B/E/S compared to any other sample year (Barber, Lehavy, McNichols, and Trueman 2006). We account for this structural break by using the I/B/E/S Stopped File to locate these rating distribution changes and adopt a three-point rating scale for the affected brokers.[5] These adjustments code 40% of I/B/E/S observations after September 2002 on three-point rating scales so that the *recchg* for these affected brokers would range between -2 and $+2$.

To ensure that our recommendation dates are reliable, we augment the I/B/E/S sample with real-time recommendation dates from First Call. A wrong date may result in us not capturing the true event date of the recommendation change and understating the influence of analysts. To insert First Call dates

[5] For 2002, we check for cases where a broker stopped all the recommendations in its coverage universe and resumed coverage in the subsequent days using only a three-point rating. We check one year post-resumption for the new distribution of ratings. When the new distribution contains only three distinct ratings [$\in$(1,3,5) or (2,3,4)], we assume this broker uses three-point ratings beginning with the resumption date. In the probit estimations, the rating change explanatory variable is based on three-point scales for the affected brokers. We verified that removing all three-point scale-based observations does not affect our results in Table 4.

into matched observations in I/B/E/S, we do the following. The broker names (bro_name) on First Call are matched by hand to the I/B/E/S translation file broker name (baname).[6] We then look seven days on either side of the I/B/E/S recommendation date to find a First Call observation that is matched on broker, firm, and recommendation level. When there are duplicate matches, the closest date observation is chosen (earlier date for ties). We found matches for 52% of the I/B/E/S observations (Ljungqvist, Malloy, and Marston 2009 also report a similar match rate of 46.8%). About 77% of these had recommendation dates unchanged, 21% had dates brought back by one day, and 2% had dates brought forward by one day. We use this First Call augmented sample from now on, although our results hold even when we use the I/B/E/S sample alone.

We adopt a two-day event window to incorporate the daily return reflecting the recommendation change.[7] To compute the two-day cumulative buy-and-hold abnormal return (CAR) for a recommendation change i, we define

$$CAR_i = \prod_{t=0}^{1}(1 + R_{it}) - \prod_{t=0}^{1}\left(1 + R_{it}^{DGTW}\right). \tag{1}$$

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).[8] Day 0 is either the First Call augmented recommendation date or the next trading day (for recommendations on non-trading days or recommendations between 4:30 PM and 11:59 PM on a trading day). We remove observations where the lagged price is less than one dollar on day 0 to prevent our results from being driven by low-priced stocks.

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6 First Call has the practice of sometimes recycling broker codes and backfilling the new broker name onto old recommendations. To mitigate this problem, we also rely on a file containing historical linkages between First Call broker codes and broker names in matching the broker names between First Call and I/B/E/S. This file is also used in Ljungqvist, Marston, and Wilhelm (2009), and we thank Alexander Ljungqvist for providing the data.

7 We find similar results with a three-day window from day −1 to +1. We also examine the average abnormal return around the event and find that days 0 and +1 account for almost all of the cumulative abnormal return in the −5 to +5 period. Hence, we believe that our recommendation dates are accurately aligned with contemporaneous stock-price reactions.

8 The results are similar when we use the sum of abnormal returns rather than buy-and-hold abnormal returns. The DGTW portfolios are computed as follows. Every July, firms are first sorted into quintiles based on their size (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.

1.2 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 (2009) go so far as to argue that once the impact of other corporate news is removed, analyst recommendation changes do not have a material impact. Malmendier and Shanthikumar (2007) and Loh (2010) 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 recommendations associated with earnings announcements falsely gives credit to the analyst recommendation for producing the earnings announcement price impact (see also Frankel, Kothari, and Weber 2006). To apply this screen, we obtain quarterly earnings announcement dates from Compustat.

Another type of firm-specific news release is earnings guidance issued by firms. Chen, Francis, and Schipper (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 (2008) contend that clustering in recommendation changes usually occurs because of firm-specific news. Therefore, we also identify days on which the I/B/E/S universe records multiple analysts issuing recommendations for the firm as potential firm-specific news events.

2. The Average CAR of Recommendation 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.

2.1 Descriptive statistics of recommendation changes

Our main sample contains 154,134 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. Figure 1 plots the transition probabilities in Panel A of Table 1. Looking at the bars in Figure 1, we see that there is a tendency for recommendations that are not holds to get revised into holds, while hold ratings themselves tend to get upgraded to buys.

Table 1
Descriptive statistics of recommendation changes

Panel A: Transition probabilities of recommendation changes

	Current Rec					
Prior Rec	1 Sell	2 Underperform	3 Hold	4 Buy	5 Strong Buy	Total
1 (Sell)	90	130	2,008	253	223	2,704
	3.3%	4.8%	74.3%	9.4%	8.2%	100%
2 (Underperform)	125	1,079	5,191	801	160	7,356
	1.7%	14.7%	70.6%	10.9%	2.2%	100%
3 (Hold)	2,139	5,554	7,661	24,098	12,195	51,647
	4.1%	10.8%	14.8%	46.7%	23.6%	100%
4 (Buy)	333	1,065	30,406	8,093	15,079	54,976
	0.6%	1.9%	55.3%	14.7%	27.4%	100%
5 (Strong Buy)	371	338	16,740	15,594	4,408	37,451
	1.0%	0.9%	44.7%	41.6%	11.8%	100%
Total	3,058	8,166	62,006	48,839	32,065	154,134

Panel B: Recommendation change categories

Rec Change	Frequency	Percentage
−4	371	0.2%
−3	671	0.4%
−2	19,944	12.9%
−1	51,679	33.5%
0	21,331	13.8%
+1	44,498	28.9%
+2	15,004	9.7%
+3	413	0.3%
+4	223	0.1%
Total	154,134	100%

The sample of recommendation (rec) changes are from I/B/E/S Detail U.S. File 1994 to 2006. Each rec change (or rating change) is an analyst's current rating minus his prior rating (prior ratings may be from 1993, but current ratings are from 1994 onward). Analyst initiations or ratings with no prior outstanding ratings are excluded. A rating is outstanding if it has been confirmed by the analyst (in the I/B/E/S review date field) in the last twelve months and has not been stopped by the broker (in the I/B/E/S Stopped File). Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between −4 and 4. Anonymous analysts and observations with less than three analysts with outstanding ratings are excluded. Panel A reports the transition probabilities of rec changes. For example, in column 1, when the prior rec is a sell, it has a 4.8% probability of transiting to an underperform rating. Panel B reports the frequencies of each rec change category.

Next, Panel B of Table 1 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 44,498 recommendations (28.9% of the sample), and the −1 group contains 51,679 recommendations (33.5%). Reiterations (rating change of 0) make up 13.8% of all recommendation changes.

2.2 Histogram of recommendation CAR

Figure 2 plots the histogram of two-day CARs of recommendation changes for one-point magnitude rating changes since these categories contain the largest

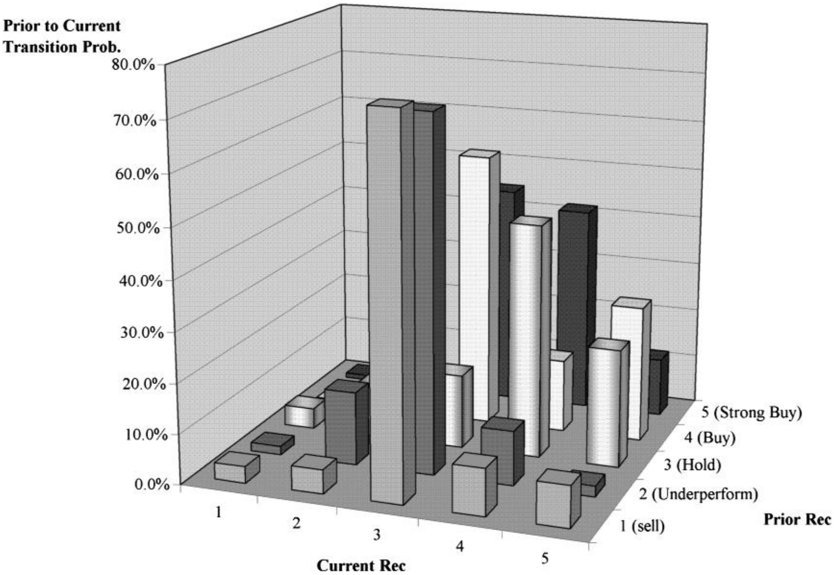


Figure 1
Transition probabilities of recommendation changes
The sample of recommendation (rec) changes is from I/B/E/S Detail U.S. File 1994 to 2006. Each rec change (or rating change) is an analyst's current rating minus his prior rating (prior ratings may be from 1993, but current ratings are from 1994 onward). Analyst initiations or ratings with no prior outstanding ratings are excluded. A rating is outstanding if it has been confirmed by the analyst (in the I/B/E/S review date field) in the last twelve months and has not been stopped by the broker (in the I/B/E/S Stopped File). Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between −4 and 4. Firms with less than three 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.

number of observations. The first chart shows the distribution of event CARs for one-point downgrades with the percentage of CARs that fall within 100 basis point bins. The histogram reveals two prominent trends. First, the zero bin (representing CARs of −0.5% to 0.5% and shaded black) accounts for more than 10% of all one-point downgrades. This forms initial evidence that a sizable number of recommendation changes may have little significant impact on stock prices. The distribution also does not appear to resemble a normal distribution, given that there are more left-tail observations than there are right-tail observations, implying negative skewness in the distribution. The second chart in Figure 2 shows the distribution of CARs for one-point upgrades. The chart here tells a similar story in that the zero bin contains a sizable number of observations and that tail observations may have a large influence so that the typical upgrade CAR may be very different from the mean upgrade CAR.

2.3 Impact of firm news events and influential observations on mean CAR

Table 2 shows the distribution statistics of recommendation change subsamples sequentially from −4 to +4. These descriptive statistics illustrate the

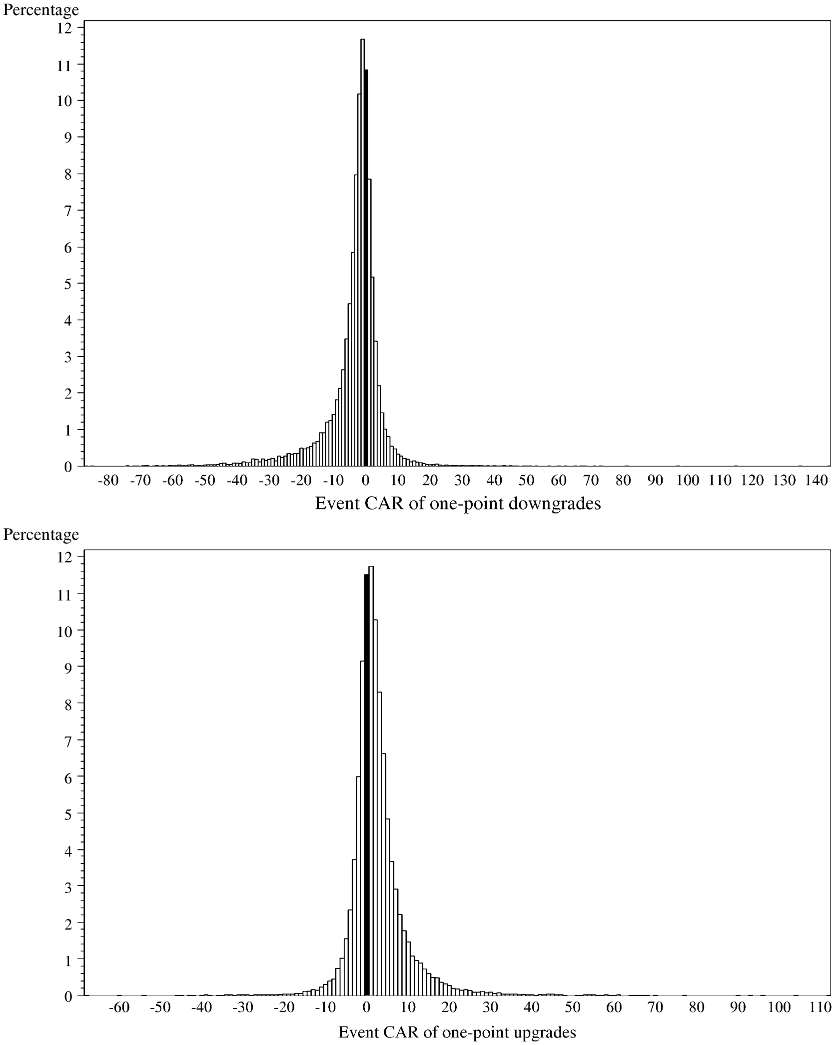


Figure 2
Histogram of CARs for one-point upgrades and downgrades
The sample of recommendation (rec) changes is from I/B/E/S Detail U.S. File 1994 to 2006. Each one-point rec change (or rating change) is an analyst's *c*urrent rating minus his prior rating. Analyst initiations or ratings with no prior outstanding ratings are excluded. The above shows the histogram of two-day [0,1] event CARs of one-point downgrades and one-point upgrades, respectively. CAR is the two-day buy-and-hold return around the rec less the corresponding return on a size-B/M-momentum matched DGTW characteristic portfolio. Each bin in the histogram is a CAR interval of 100 basis points (1%). The bin centered on a CAR of zero is shaded in black.

key point that the CAR distributions are not normal and that firm-specific news-contaminated recommendations and outliers have a strong impact on the means. For example, we illustrate with the fourth panel the rating change of −1. Sample 1 is the full set of −1 downgrades. The average CAR is a statistically significant −3.551%, based on standard errors clustered by calendar day. However, the median CAR is only −1.716%, and the modal CAR is just −0.5% (mid-point of 50 bps modal group). The Kolmogorov-Smirnov D statistic rejects the normality of the CAR distribution consistent with the observed skewness and kurtosis. Another interesting statistic (third column) is the percentage of positive-signed CARs. This shows that 30.2% of −1 rating changes actually had stock-price reactions of the wrong sign. Similar findings are in the other panels of Table 2.

We examine the impact of removing observations that are contaminated by contemporaneous firm-specific news releases. First, we exclude observations that fall in the three-day window around quarterly earnings announcement dates. This reduces the average CAR to −2.976% (see sample 2 in Table 2). Next, we also remove recommendations that fall in the three-day window around management earnings guidance days, and the average CAR drops dramatically to −1.913%. Finally, we remove days with multiple recommendations, and the average CAR now becomes −1.562%. Although this average is still statistically significant, we see that moving from sample 1 to sample 4 shaves the economic magnitude of the average CAR by more than half, from −3.551% to −1.562%. The median CAR also falls from −1.716% to −1.148%. This halving of the mean CAR is also evident in some other panels of the table and highlights that a large fraction of the average recommendation CAR could be attributed to contemporaneous firm news releases rather than to the recommendation itself, consistent with Chen, Francis, and Schipper (2005) and Altinkilic and Hansen (2009).

Finally, we consider the impact of removing outlier observations from this sample that is uncontaminated by firm news using two different approaches. The first approach trims 5% from both tails of the sample distribution, and we find that the average CAR reduces to −1.422% (see sample 5 row in Table 2). The second approach uses the least trimmed squares (LTS) method (e.g., Knez and Ready 1997) to identify outliers. Specifically, we estimate a regression using LTS with the CAR against a constant. We then compute the mean CAR by excluding the LTS-identified outliers. The average CAR is now −1.264%. These results show that the removal of outliers from both tails further tempers the magnitude of the typical recommendation absolute value average CAR.

3. Influential versus Non-influential Recommendation Changes

3.1 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. The first method classifies a recommendation change as influential if the CAR is in the correct direction *and* is statistically

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

Filtered Samples	Mean	Mode	% CAR +	Skew	Kurt	KS test	Percentiles 99%	75%	Median	25%	1%	# Obs
Recommendation Change = −4												
1) Full sample	−3.679***	−1.5	0.348	−2.29	10.56	0.261***	30.48	0.94	−1.258***	−4.01	−70.98	371
2) No earnings annc days	−3.135***	−1.5	0.348	−2.12	11.04	0.256***	30.48	0.89	−1.223***	−3.92	−55.11	319
3) No earnings annc or mgt forecasts days	−2.114***	−1.5	0.367	−2.30	15.31	0.255***	34.67	1.08	−1.063***	−3.44	−70.98	297
4) No earnings annc, mgt forecasts or multiple rec days	−1.278**	−1.5	0.360	−0.89	25.71	0.193***	14.84	0.94	−1.001***	−3.08	−36.10	242
5) Remove 5% from both tails of (4)	−1.025***	−1.5	0.344	−0.07	0.08	0.052	5.31	0.77	−1.001***	−2.82	−7.59	218
6) Remove LTS-identified outliers from (4)	−1.029***	−1.5	0.348	−0.08	0.69	0.057*	6.78	0.78	−1.001***	−2.86	−9.33	224
Recommendation Change = −3												
1) Full sample	−2.916***	−0.5	0.392	−1.43	7.68	0.203***	27.65	1.37	−0.840***	−4.55	−43.92	671
2) No earnings annc days	−2.234***	0	0.406	−1.56	10.26	0.209***	27.86	1.36	−0.680***	−3.75	−46.41	584
3) No earnings annc or mgt forecasts days	−1.158***	−0.5	0.422	−1.46	16.05	0.189***	27.86	1.53	−0.534***	−2.91	−41.78	538
4) No earnings annc, mgt forecasts or multiple rec days	−0.313	−0.5	0.427	0.16	10.38	0.163***	27.65	1.64	−0.401***	−2.46	−21.76	478
5) Remove 5% from both tails of (4)	−0.475***	−0.5	0.419	0.09	0.72	0.061***	8.35	1.30	−0.401***	−2.16	−8.01	432
6) Remove LTS-identified outliers from (4)	−0.569***	−0.5	0.414	−0.12	0.50	0.063***	6.81	1.27	−0.433***	−2.17	−8.95	430
Recommendation Change = −2												
1) Full sample	−4.007***	−0.5	0.315	−1.83	10.45	0.195***	16.40	0.61	−1.572***	−5.48	−46.46	19944
2) No earnings annc days	−3.372***	−0.5	0.331	−1.91	12.59	0.205***	16.69	0.71	−1.312***	−4.58	−45.94	16325
3) No earnings annc or mgt forecasts days	−1.941***	−0.5	0.353	−1.53	24.23	0.176***	16.93	0.86	−1.026***	−3.54	−33.81	14569
4) No earnings annc, mgt forecasts or multiple rec days	−1.432***	−0.5	0.356	0.00	30.74	0.139***	13.21	0.83	−0.934***	−3.20	−20.39	12599
5) Remove 5% from both tails of (4)	−1.277***	−0.5	0.341	−0.52	0.19	0.059***	4.49	0.61	−0.934***	−2.90	−9.00	11341
6) Remove LTS-identified outliers from (4)	−1.076***	−0.5	0.359	−0.18	0.50	0.050***	6.89	0.79	−0.851***	−2.85	−9.31	11733
Recommendation Change = −1												
1) Full sample	−3.551***	−0.5	0.302	−1.63	13.86	0.177***	14.30	0.51	−1.716***	−5.26	−39.37	51679
2) No earnings annc days	−2.976***	−0.5	0.315	−1.76	16.83	0.184***	13.73	0.59	−1.480***	−4.45	−37.67	41490
3) No earnings annc or mgt forecasts days	−1.913***	−0.5	0.332	−1.08	31.43	0.153***	13.55	0.72	−1.226***	−3.69	−26.84	37232
4) No earnings annc, mgt forecasts or multiple rec days	−1.562***	−0.5	0.337	0.38	41.12	0.121***	11.96	0.73	−1.148***	−3.44	−18.98	32564
5) Remove 5% from both tails of (4)	−1.422***	−0.5	0.318	−0.40	0.01	0.045***	4.49	0.50	−1.148***	−3.13	−8.94	29308
6) Remove LTS-identified outliers from (4)	−1.264***	−0.5	0.337	−0.14	0.47	0.042***	7.03	0.68	−1.074***	−3.14	−9.77	30646

(*continued*)

Table 2
Continued

Filtered Samples	Mean	Mode	% CAR +	Skew	Kurt	KS test	99%	75%	Median	25%	1%	# Obs
							Percentiles					
Recommendation Change = 0												
1) Full sample	−0.089**	0	0.490	0.24	42.71	0.134***	15.44	1.94	−0.065***	−1.97	−18.17	21331
2) No earnings annc days	−0.102**	−0.5	0.486	0.38	59.96	0.131***	13.84	1.81	−0.089***	−1.89	−16.78	18530
3) No earnings annc or mgt forecasts days	0.027	−0.5	0.488	1.64	78.47	0.117***	13.60	1.79	−0.074***	−1.83	−12.93	17877
4) No earnings annc, mgt forecasts or multiple rec days	0.070	−0.5	0.489	2.86	95.29	0.111***	12.99	1.78	−0.068***	−1.79	−12.16	16456
5) Remove 5% from both tails of (4)	0.002	−0.5	0.488	0.13	−0.11	0.024***	5.94	1.52	−0.068***	−1.57	−5.45	14812
6) Remove LTS-identified outliers from (4)	−0.046	−0.5	0.484	0.06	0.47	0.037***	7.40	1.61	−0.093***	−1.70	−7.24	15604
Recommendation Change = +1												
1) Full sample	2.503***	0.5	0.676	2.06	17.94	0.132***	25.68	4.47	1.498***	−0.67	−11.30	44498
2) No earnings annc days	2.074***	0.5	0.663	2.46	27.38	0.128***	22.00	3.90	1.298***	−0.73	−10.08	35436
3) No earnings annc or mgt forecasts days	2.050***	0.5	0.663	2.91	30.48	0.128***	21.06	3.82	1.274***	−0.72	−9.23	34125
4) No earnings annc, mgt forecasts or multiple rec days	1.914***	0.5	0.661	2.31	23.63	0.117***	19.50	3.70	1.228***	−0.72	−9.01	30772
5) Remove 5% from both tails of (4)	1.617***	0.5	0.679	0.57	−0.01	0.054***	9.57	3.39	1.228***	−0.51	−3.88	27696
6) Remove LTS-identified outliers from (4)	1.352***	0.5	0.652	0.21	0.36	0.041***	10.06	3.32	1.095***	−0.76	−6.97	29144
Recommendation Change = +2												
1) Full sample	2.303***	0.5	0.658	2.32	20.43	0.137***	25.62	4.14	1.231***	−0.72	−10.01	15004
2) No earnings annc days	1.919***	0.5	0.647	2.64	29.41	0.133***	22.27	3.63	1.068***	−0.77	−9.16	12187
3) No earnings annc or mgt forecasts days	1.885***	0.5	0.646	3.00	32.47	0.133***	20.56	3.56	1.042***	−0.77	−8.53	11773
4) No earnings annc, mgt forecasts or multiple rec days	1.745***	0.5	0.645	2.63	21.26	0.120***	18.78	3.41	0.991***	−0.76	−8.12	10685
5) Remove 5% from both tails of (4)	1.427***	0.5	0.661	0.65	0.10	0.070***	9.18	3.06	0.991***	−0.57	−3.63	9617
6) Remove LTS-identified outliers from (4)	1.149***	0.5	0.633	0.25	0.41	0.052***	9.54	2.97	0.844***	−0.80	−6.78	10121
Recommendation Change = +3												
1) Full sample	1.111***	0	0.554	1.70	13.67	0.124***	22.36	3.50	0.530**	−2.00	−20.00	413
2) No earnings annc days	1.050***	0	0.539	1.92	15.50	0.131***	27.81	3.50	0.450	−1.95	−20.00	362
3) No earnings annc or mgt forecasts days	1.216***	0	0.544	2.24	16.86	0.136***	27.81	3.59	0.461	−1.86	−13.88	355
4) No earnings annc, mgt forecasts or multiple rec days	1.110***	0	0.543	0.98	6.85	0.131***	22.36	3.41	0.458	−1.76	−13.88	322
5) Remove 5% from both tails of (4)	0.871***	0	0.548	0.59	0.20	0.082***	10.72	2.66	0.458	−1.46	−5.97	290
6) Remove LTS-identified outliers from (4)	0.752***	0	0.537	0.36	0.50	0.082***	11.51	2.73	0.439	−1.73	−8.65	307

(*continued*)

Table 2
Continued

Filtered Samples	Mean	Mode	% CAR +	Skew	Kurt	KS test	Percentiles 99%	75%	Median	25%	1%	# Obs
			Recommendation Change = +4									
1) Full sample	1.359***	−0.5	0.552	1.08	2.41	0.128***	17.18	2.93	0.673	−1.20	−7.88	223
2) No earnings annc days	1.247***	−0.5	0.565	1.17	3.16	0.138***	17.30	2.64	0.735*	−1.17	−9.06	191
3) No earnings annc or mgt forecasts days	1.168***	−0.5	0.565	1.14	3.39	0.136***	17.30	2.50	0.723*	−1.10	−9.06	186
4) No earnings annc, mgt forecasts or multiple rec days	1.088***	−0.5	0.551	1.23	3.85	0.143***	17.30	2.40	0.531	−1.20	−9.06	167
5) Remove 5% from both tails of (4)	0.848***	−0.5	0.556	0.75	0.57	0.069*	8.71	2.31	0.531	−1.08	−3.71	151
6) Remove LTS-identified outliers from (4)	0.543**	−0.5	0.532	0.27	0.61	0.060	8.42	2.23	0.248	−1.26	−6.85	156

The descriptive statistics of the abnormal returns to recommendation (rec) changes are reported. Recommendations are from I/B/E/S Detail U.S. File 1993–2006. Rec dates are from First Call for observations common between I/B/E/S and First Call. Each rec change is an analyst's current rating minus the analyst's prior rating. Analyst initiations are excluded. Ratings are coded as 1 (sell) to strong buy (5), and rating changes lie between −4 and 4. Observations with fewer than 3 analysts having outstanding ratings are excluded. Each panel reports summary statistics for the two-day (0,1) buy-and-hold event CAR (in percent) of a rec change group. 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 test is the Kolmogorov-Smirnov *D* statistic testing for the normality of the sample distribution where asterisks represent rejection of the null of normality. The samples are filtered according to the mentioned criteria. No earnings annc days refer to a filter sample excluding rec changes that occur in the three-day window around the firm's Compustat quarterly earnings announcement date. No mgt forecast days means we exclude 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 refers to excluding days where more than one analyst issues recs on the firm. Remove 5% from both tails of refers to the removal of the extreme 5% of outliers from the filtered sample. Least trimmed squares outliers (LTS) are identified by estimating a LTS regression of CAR against a constant. *, **, and *** represent that the null of zero (normality) is rejected at the 10%, 5%, and 1% level respectively, for the mean and the median (KS test). Statistical significance of the mean is based on standard errors clustered by calendar day.

significant using the market model. Specifically, we check if the CAR is in the same direction as the recommendation change and the absolute value CAR exceeds $1.96 \times \sqrt{2} \times \sigma_{\varepsilon}$. We multiply by $\sqrt{2}$ since the CAR is a two-day CAR. σ_{ε}, the idiosyncratic volatility, is the standard deviation of residuals from a daily time-series regression of past three-month (trading days -69 to -6) firm returns against market returns and the Fama-French factors SMB and HML. This measure roughly captures recommendation changes that observers would judge to be influential, namely those that are associated with noticeable abnormal returns that can be attributed to the recommendation changes.

The second approach classifies a recommendation change as influential when the increase in abnormal turnover (*abturn*) is statistically significant. With this measure, a recommendation change is influential because it leads investors to trade. Following Llorente, Michaely, Saar, and Wang (2002), $abturn = \log turnover - \overline{\log turnover}$, where $\overline{\log turnover}$ is the average of daily log *turnover* over the past three months, and $\log turnover = \log(turnover + 0.00000255)$.[9] Specifically, we check if the cumulative *abturn* is $> 1.96 \times \sqrt{2} \times \sigma_{abturn}$, where σ_{abturn} is the standard deviation of the stock's *abturn* in the past three months (days -69 to -6 from the recommendation date).

The first row of Table 3 reports the number of recommendation changes (reiterations, i.e., $recchg = 0$, are excluded here) that are categorized into each dimension of success. We see that 11.7% of all recommendation changes are defined as influential in returns and 12.8% are defined as influential in turnover. While the typical recommendation change is not influential, more than one recommendation out of ten is influential; 4.8% of recommendation changes are influential in both returns and turnover, 6.9% are influential in returns but not turnover, and 8.0% are influential in turnover but not returns.

3.2 Analyst characteristics of influential recommendation changes

We characterize influential recommendation changes by examining several analyst-, firm-, and recommendation-level characteristics. We start with analyst characteristics. We examine the relation between these variables and the likelihood of an influential recommendation in both a univariate and a probit setting.

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 more impact. We compute the *Forecast accuracy* quintile of an analyst by sorting analysts within a firm-year into quintiles using the last

[9] Daily turnover is from CRSP and defined as number of shares traded divided by the number of shares outstanding. Firms from NASDAQ have their shares traded divided by two to adjust for inter-dealer double counting.

Table 3
Comparing analyst and firm characteristics of influential versus non-influential recommendation changes

	Influential based on firm's abnormal returns				Influential based on firm's abnormal turnover			
			Difference				Difference	
Characteristics	Not Influ	Influential	Influ – Not	t−stat	Not Influ	Influential	Influ – Not	t−stat
Panel A: Analyst and recommendation characteristics								
Number of rec changes	77,537	10,292			76,595	11,234		
		11.7%				12.8%		
Forecast accuracy quintile	2.810	2.771	−0.039***	(−2.75)	2.810	2.776	−0.034**	(−2.45)
Away from consensus	0.358	0.416	0.058***	(9.84)	0.355	0.434	0.079***	(14.15)
Star analyst	0.159	0.205	0.046***	(9.53)	0.160	0.198	0.038***	(8.19)
Absolute analyst experience (# Qtrs)	28.45	29.64	1.192***	(4.63)	28.44	29.61	1.169***	(4.62)
Relative analyst experience	2.652	3.354	0.702***	(5.03)	2.671	3.162	0.491***	(3.52)
Concurrent earnings forecast	0.446	0.510	0.064***	(10.15)	0.448	0.492	0.044***	(7.16)
Influential before (any stock)	0.562	0.664	0.102***	(15.57)	0.562	0.656	0.094***	(14.45)
Influential before (same stock)	0.100	0.137	0.037***	(9.99)	0.100	0.132	0.032***	(8.96)
Panel B: Firm characteristics prior to recommendation								
B/M ratio	0.484	0.498	0.014***	(2.78)	0.485	0.485	−0.001	(−0.12)
Size ($m)	8971.7	7451.0	−1520.6***	(−5.49)	8810.9	8674.9	−136.03	(−0.47)
Institutional ownership	0.61	0.63	0.027***	(8.44)	0.61	0.64	0.029***	(9.69)
Dispersion ×100	14.167	15.119	0.952	(1.31)	14.267	14.368	0.101	(0.15)
Idiosyncratic volatility ×100	2.504	2.195	−0.310***	(−13.64)	2.501	2.240	−0.261***	(−11.28)
Total volatility ×100	2.876	2.556	−0.319***	(−11.79)	2.872	2.607	−0.265***	(−9.56)
Daily turnover ×100	0.655	0.603	−0.052***	(−7.42)	0.657	0.592	−0.065***	(−9.59)
Analyst activity (#EPS forecasts)	86.669	72.422	−14.247***	(−15.56)	86.156	77.112	−9.044***	(−9.93)

(*continued*)

Table 3
Continued

	Influential based on firm's abnormal returns				Influential based on firm's abnormal turnover			
			Difference				Difference	
Characteristics	Not Influ	Influential	Influ – Not	*t*-stat	Not Influ	Influential	Influ – Not	*t*-stat
Panel C: Change in firm environment around recommendation								
Leader-Follower Ratio (LFR) of rec	2.032	3.176	1.144***	(12.21)	1.955	3.619	1.664***	(16.57)
Δ Total volatility of daily ret ×100	−0.081	0.350	0.431***	(21.41)	−0.067	0.218	0.285***	(13.60)
Δ Idiosyncratic volatility ×100	−0.082	0.333	0.414***	(24.90)	−0.068	0.204	0.271***	(16.09)
Δ Dispersion ×100	0.876	0.375	−0.501	(−0.55)	0.834	0.691	−0.143	(−0.17)
Δ Daily turnover ×100	0.004	0.096	0.092***	(18.95)	−0.012	0.202	0.215***	(33.71)
Δ Analyst activity (# forecasts)	−0.359	4.978	5.337***	(9.65)	−0.151	3.111	3.263***	(5.61)
Δ in FY1 |Forecast Revision|×100	−0.010	0.011	0.021	(0.89)	−0.009	0.005	0.014	(0.62)
Δ in FY2 |Forecast Revision|×100	0.034	0.127	0.093***	(3.93)	0.032	0.139	0.107***	(4.38)
Δ in LTG |Forecast Revision|×100	0.040	0.121	0.081***	(3.16)	0.035	0.156	0.122***	(4.20)
Fraction with large industry vw return	0.042	0.123	0.080***	(18.45)	0.048	0.079	0.031***	(9.17)
Fraction with large industry ew return	0.067	0.123	0.056***	(12.12)	0.071	0.093	0.022***	(5.62)

Influential (Influ) recommendations (recs) are compared with non-influential recs. Influential definitions are based either on prior returns or on prior abnormal turnover. For example, for returns, a rec change is influential is its correct-signed [0,1] CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month *Idiosyncratic volatility* of daily returns. The sample is from I/B/E/S (1994–2006) with earnings annc. days, mgt. forecast days, and multiple-rec days removed (sample 4 in Table 2). Reiterations are excluded. Panel A reports the average analyst or rec characteristic. Forecast accuracy quintile is the quintile rank (lower rank = greater accuracy) of the analyst based on his last unrevised FY1 earnings forecast. A rec moves *Away from consensus* (dummy) 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* (dummy) are analysts who are ranked in *Institutional Investor*. *Analyst experience* is the no. of quarters since the analyst issued the first estimate or rec on I/B/E/S. *Concurrent earnings forecast* = 1 when the analyst issued any earnings forecast in the three-day window around the rec. *Influential before* indicates that the analyst was influential in the past. Panel B compares firm characteristics with variable definitions found in Section 3. Panel C compares the changes in the firm environment around the rec. *Leader-Follower Ratio* (*LFR*) is the gap sum of the prior two recs divided by the gap sum of the next two recs. A ratio>1 indicates a leader analyst whose recs are quickly followed by other brokers' recs. We also compute the Δ in *Total volatility* of daily returns from the prior three months to the three months after the rec (excluding ±5 days around the event). We also compute in the same manner other change variables. The reported values for *Total*, *Idiosyncratic volatility*, *Dispersion*, and *Turnover* are multiplied by 100 (e.g., 1.0 represents 1.0%). 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 forecast revisions are scaled by price (outlier revisions more than 100% of price are removed), and LTG forecasts are in percentages. Large Fama-French 49 industry returns = 1 when recommendations coincide with a large (>1.96 stdev than expected) abnormal return movement in the firm's industry value-weighted (vw) or equal-weighted (ew) returns over days [0,1]. 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.

unrevised FY1 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 (2006). Overlapping the 12-month period into the next fiscal year allows the accuracy rank to be applied during the months when the fiscal year's actual earnings are announced. Note that this 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) *Away from consensus*: Jegadeesh and Kim (2010) 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 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 1.1 for the definition of stale). This variable is defined based on three-point ratings to account for rating distribution differences between brokers.
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 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 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. Two measures of experience are computed. The first is *Absolute analyst experience*, which is the number of quarters that he appeared on I/B/E/S. The second is the *Relative analyst 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*: Kecskes, Michaely, and Womack (2009) report that stock recommendations accompanied by earnings 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.

6) *Influential before*: If an influential recommendation is related to analyst skill that is persistent, being influential in the past could be related to the current likelihood of being influential.

We compute the average of these analyst-specific variables for the different rating-change groups. Table 3 reports the averages for observations where these variables can be computed. The average analyst *Forecast accuracy* quintile of influential recommendation changes is 2.771, versus 2.810 for non-influential recommendations. The difference is statistically significant, but its economic importance is small; 41.6% of influential recommendation changes move away from the consensus, while only 35.8% of non-influential recommendation changes move away from the consensus—the difference is significant and sizable. Also, star analysts are responsible for 20.5% of influential recommendation changes and 15.9% of non-influential recommendations. Influential recommendations are also associated with higher *Absolute* and *Relative analyst experience*. A larger proportion of influential recommendation changes have concurrent earnings forecasts issued together with the recommendation change. Finally, being influential in the past for the same stock, as well as for any stock, appears to be positively related to the current recommendation becoming influential. Using the second definition of influential (based on increases in abnormal turnover) yields similar patterns of differences. Of the many variables we report, those associated with economically larger differences are *Away from consensus*, *Star analyst*, *Concurrent earnings forecast*, and *Influential before* variables.

Many of the variables we consider are correlated. To assess more precisely the relation between these variables and the probability that an analyst makes an influential recommendation, we estimate a probit model. This model allows us to estimate not only the incremental contribution of each variable, but also its economic significance. We cluster the standard errors in the probits by analyst as well as by firm (two-way clustering suggested by Thompson 2010). Although some of these variables have been examined in the literature assessing the determinants of the stock-price reaction to analyst recommendation changes, they have not been considered in a unified fashion, nor have they been examined in the context of identifying an influential recommendation change in the manner we defined.

The probit estimates in Table 4 show that a recommendation change is significantly more likely to be influential if it is by an analyst who has made an influential recommendation before. The marginal effect of *Influential before (any stock)* is 2.88%. Such an effect is large, since the unconditional probability of a recommendation change being significant is 11.70%. This means that when an analyst made at least one influential recommendation change in the past for any stock, the probability that the analyst's current recommendation change will be influential increases by 2.88%. In addition, if the analyst were influential before for the same stock, the probability of being influential goes up by another 1.21%. Other analyst variables that also have large economic effects are the variable *Rec away from consensus*, which has a marginal effect of 2.74%, *Star analyst* (3.84%), and *Concurrent earnings forecast* (2.22%).

Table 4
Predicting when a recommendation change will be influential

	Influential based on firm's abnormal returns		Influential based on firm's abnormal turnover	
Explantory Variable	Coefficient	Marg. Eff	Coefficient	Marg. Eff
Influential before (any stock)	0.154*** (8.35)	2.88%	0.130*** (7.17)	2.58%
Influential before (same stock)	0.065*** (2.93)	1.21%	0.052** (2.54)	1.03%
Rec level	0.045*** (4.01)	0.80%	0.008 (0.74)	0.16%
Absolute value of *recchg*	−0.017 (−1.00)	−0.16%	0.001 (0.03)	0.01%
Upgrade Dummy	0.080*** (4.01)	1.50%	−0.032 (−1.63)	−0.64%
Reg FD Dummy	0.206*** (8.82)	3.85%	0.219*** (9.24)	4.37%
Settlement Dummy	0.093*** (3.84)	1.73%	0.171*** (6.81)	3.42%
Past forecast accuracy quintile	−0.011* (−1.90)	−0.24%	−0.009 (−1.59)	−0.21%
Away from consensus	0.147*** (9.87)	2.74%	0.148*** (10.18)	2.96%
Star analyst	0.207*** (9.36)	3.87%	0.156*** (7.22)	3.11%
Absolute analyst experience	−0.001* (−1.96)	−0.41%	−0.001 (−1.61)	−0.31%
Relative analyst experience	0.001 (0.84)	0.14%	0.000 (0.36)	0.07%
Concurrent earnings forecast	0.119*** (7.87)	2.22%	0.110*** (7.71)	2.19%
Past Leader-Follower Ratio (LFR)	0.006*** (2.74)	0.36%	0.004** (1.98)	0.28%
Log(B/M)	−0.100*** (−9.66)	−1.51%	−0.061*** (−6.15)	−0.99%
Log(Size)	−0.082*** (−10.67)	−2.49%	0.017** (2.46)	0.53%
Price momentum	0.031** (2.38)	0.34%	0.042*** (3.40)	0.49%
Log(Institutional ownership)	0.049** (2.15)	0.38%	0.138*** (5.30)	1.15%
Log(Turnover)	0.042*** (2.82)	0.62%	−0.084*** (−5.36)	−1.32%
Log(Idiosyncratic volatility)	−0.351*** (−15.10)	−3.45%	−0.090*** (−4.04)	−0.95%
Dispersion	0.032*** (3.13)	0.38%	0.033*** (2.92)	0.42%

(*continued*)

Table 4
Continued

	Influential based on firm's abnormal returns		Influential based on firm's abnormal turnover	
Explantory Variable	Coefficient	Marg. Eff	Coefficient	Marg. Eff
Log(Analyst activity)	−0.138***	−2.17%	−0.148***	−2.48%
	(−11.49)		(−12.86)	
Pseudo R-sq	0.04745		0.03654	
# Observations	58384		58384	
Chi-Sq test	1485.68***		1323.57***	

The binary dependent variable is whether a recommendation (rec) is influential and the sample is sample 4 from Table 2 with reiterations excluded and firm and analyst characteristics required. Marginal effects are reported below the coefficient estimates. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability when the independent variable changes by one standard deviation (changes from 0 to 1). There are two definitions of influential. First, influential recs are those 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. The second uses an abnormal turnover greater than 1.96 standard deviations of that expected from the abnormal daily turnover in the stock's prior three-month history. The *Rec Level* is the rating level after the rec change (*recchg*) (1 = sell to 5 = strong buy). The absolute value of the *recchg*, *Upgrade* dummy, *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 (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* = 1 for ranked analysts in the most recent *Institutional Investor* polls. *Absolute analyst experience* is measured as the # of quarters in I/B/E/S. *Relative analyst experience* subtracts the average experience of other covering analysts. *Concurrent earnings forecast* = 1 when the same analyst issued any earnings forecast in the three-day window around the rec. *Leader-Follower Ratios* larger than one denote leader analysts. *Turnover*, *Idiosyncratic volatility*, and *Dispersion* are based on prior three-month averages. *Analyst activity* is total number forecasts issued by all analysts in the prior three months. *,**, and *** denote significance levels of 10%, 5%, and 1%, respectively, using standard errors clustered in two dimensions (by analyst and firm) with z statistics in parentheses.

Past *Forecast accuracy* and *Analyst experience* do not seem to provide much incremental predictability in identifying influential recommendations.

We also include the analyst's prior year *Leader-Follower Ratio* (*LFR*) as a predictive variable. Cooper, Day, and Lewis (2001) use this ratio to gauge the extent to which a forecast event leads other analysts to revise their estimates. A ratio larger than one denotes a leader analyst.[10] The coefficient on past *LFR* is statistically significant, although the marginal effect on predicting influential changes is modest at 0.36% (marginal effects of continuous variables are the change in the probability of making an influential recommendation when the explanatory variables change by one standard deviation). Altogether, we see that several analyst-specific variables are important in predicting influential recommendation changes. Our second definition of influential provides supportive evidence on the role of the variables discussed in this section. Because skill-related variables are strongly related to the influential likelihood,

[10] To compute this, 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. A ratio larger than one shows that other brokers issue new ratings quickly in response to the analyst's current recommendation.

we believe that it is analyst ability rather than chance that allows for the generation of influential recommendation changes.

3.3 Firm characteristics of influential recommendations

We consider how firm characteristics differ between the influential and non-influential subsamples of Panel B of Table 3. Certain firm characteristics could create conditions that make it more likely for analysts to make significant recommendation changes. For example, analysts may have more influence when the value of the firm depends more on growth options that are harder to value than assets-in-place. We see that influential recommendation changes tend to be issued on firms that have a lower B/M ratio and are therefore more likely to be growth firms. Also, the influential subsample is associated with smaller size, higher *Institutional ownership*, lower *Total volatility* and *Idiosyncratic volatility*, lower *Turnover*, and lower level of *Analyst activity* as proxied by the number of earnings forecasts during the prior three months. The results suggest that 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 it is not surprising that analysts are more likely to have a significant impact for high *Institutional ownership* firms. The second definition of influential recommendation changes yields similar results.

The probit estimation in Table 4 provides supplementary results. In the influential in returns column, the firms that are more likely to receive impactful recommendation changes are growth firms, small firms, high *Institutional ownership* firms, high prior *Turnover* firms, low *Idiosyncratic volatility* firms, higher earnings forecast *Dispersion* firms, and low prior *Analyst activity* (number of forecasts issued) firms. Some firm variables have large marginal effects on the probability of a recommendation change being influential. A one-standard-deviation change in size has a −2.49% impact on being influential. The effect for B/M is also high, at −1.51%. The impact of *Analyst activity* is −2.17%. These results are generally consistent with the idea that an analyst is able to contribute the most when the information environment surrounding the firm is uncertain (e.g., small size, low B/M, and high *Dispersion*). Similar results are obtained in the probit estimation using the influential in turnover definition.

3.4 Changes to firm characteristics in response to influential recommendations

Since an influential recommendation change by definition causes a significant stock-price or volume reaction, it must impact the way that investors view or value the firm. The *LFR* provides some insight from the perspective of other analysts (see Panel C of Table 3). If other analysts begin to issue recommendations quickly in response to the influential event, the *LFR* computed based on the influential recommendation would be large. Indeed, this is the case. The *LFR* of influential recommendations is 3.176, about 57% larger than the average *LFR* of 2.032 in the non-influential subsample. The difference is even starker in the influential in turnover definition, where the average *LFR* of influential recommendation changes is about 85% larger than the average *LFR* of the non-influential subsample. Analyst activity also increases by 4.978 forecasts three months after the event. This increase is about 7% of the original level of analyst activity (Panel B of Table 3 shows there are 72.422 forecasts in the three months prior to recommendation). Finally, average daily *Turnover* goes up by 0.096 from a benchmark of 0.603% prior to the recommendation—about a 15% increase. We also compare the change in average absolute magnitudes of monthly consensus earnings forecast revisions (scaled by price, with outlier observations larger than 100% of price removed) three months after the event to three months before. This change is higher for the influential subsamples compared to the non-influential subsample (e.g., for FY2 revisions, 0.127% is more than three times 0.034%).

Volatility also increases after an influential recommendation change. We compare volatility three months before and three months after the event, skipping the ten days around the event. The change in daily *Idiosyncratic volatility* of returns is 0.333% for influential recommendations, while it is slightly negative or close to zero for non-influential changes. Based on the average *Idiosyncratic volatility* of 2.195% (in Panel B of Table 3), a 0.333% increase represents a sizable increase of about 15% from the prior level.

Finally, we investigate whether influential recommendations have an impact on other firms in the same industry as the firm on which the recommendation is made. If the analyst's influential recommendation contains industry information, similar firms could also be impacted by the revision. For example, banking stocks were also negatively affected by Meredith Whitney's downgrade of Citigroup. Evidence of such positive spillover is also consistent with the theoretical work of Veldkamp (2006) on information markets that predict that agents have incentives to produce information with implications for a subset of assets. To allow a reasonable number of firms in the industry, we use the Fama and French (1997) 49 industry groups and show both value-weighted and equal-weighted industry returns. The industry's return is considered large when its two-day (0,1) market-adjusted return is in the same direction as the recommendation change and is greater than $1.96 \times \sqrt{2} \times \sigma_i$, where σ_i is the standard deviation of residuals from a time-series regression of the industry's daily returns against market returns for the past three months. We show that influential recommendations are associated with a larger fraction of large-impact industry returns. In Table 3, Panel C, about 12.3% of the influential recommendation changes are influential for the industry as well.

3.5 Post regulation probability of being influential

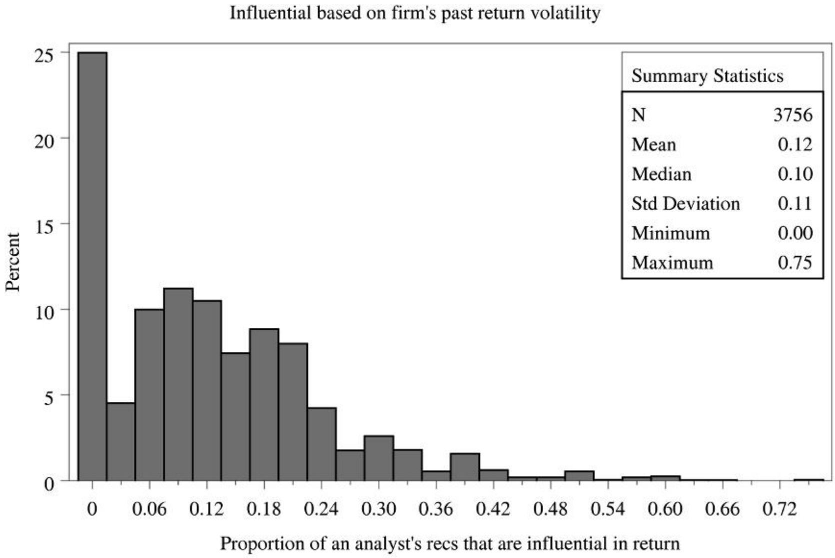
Our sample period straddles the pre- and post-regulation periods governing security analysis. Increased regulation can either stifle analysts' ability to produce impactful research (e.g., by limiting useful information channels) or increase the likelihood of influential recommendations (e.g., by mitigating conflicts of interest). Our probit estimations include indicator variables for Regulation Fair Disclosure (*Reg FD* = 1 from Sep 2002 onward) and the Global Analyst Settlement (*Settlement* = 1 from year 2003 onward). 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 of the main sources 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 coefficient for *Reg FD* is significantly positive, implying that influential recommendation changes are even more likely after *Reg FD* (the marginal effect is a large 3.58%).

For the period after the *Settlement*, Kadan, Madureira, Wang, and Zach (2009) find that the overall informativeness of recommendations was reduced (their sample goes up to 2004 only). Boni (2006) also finds similar evidence. Although the overall informativeness of recommendations decreased, Kadan, Madureira, Wang, and Zach (2009) also find that the falling number of optimistic recommendations could have caused optimistic recommendations to become more informative. Our probit estimations find some evidence that a recommendation change is more likely to be influential after the *Settlement* (marginal effect is 1.73%). When we add an interaction variable *upgrade* × *Settlement* to the estimations, we find that this interaction term is statistically insignificant for both definitions of influential. 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.[11] It is therefore possible that regulation scrutiny improved the overall quality of analyst recommendations.

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

Finally, we investigate whether influential recommendation changes are produced by only a subset of analysts. Our evidence so far points to the fact that influential recommendations are associated with certain analyst skills and firm environments that promote the utilization of such skills. If this were true, influential recommendation changes should emanate from only a subset of analysts

[11] One alternative explanation for why recommendations are more influential in the post-regulation period is that recommendation dating became more accurate later in the sample period and hence aligns better with contemporaneous stock price reactions. To test this, we drop the first three years (1994 to 1996) of the recommendations in the probits. Although the coefficients are attenuated, we still find marginal effects of about 1.14% to 2.75% for the *Reg FD* and *Settlement* variables.



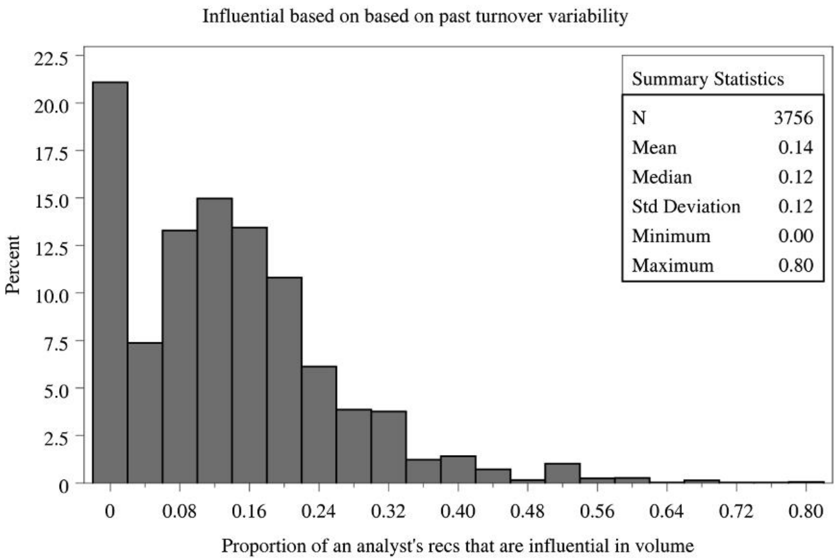


Figure 3
Histogram of proportion of an analyst's influential recommendation changes
We plot the histogram of the proportion of an analyst's recommendation (rec) changes that are influential. We focus on analysts who made at least five recs in the 1994 to 2006 period. The first chart uses the firm's past *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 abnormal turnover to determine if a rec change leads to an increase in abnormal turnover (1.96 standard deviations more).

that possess such skills. 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 returns definition of influential. Although the unconditional proportion of influential recommendation changes is 11.7% in the sample, 24.9% of all analysts never issue a single influential recommendation change in their recommendation histories (in our sample). For the turnover definition of influential, about 20.8% of analysts have never issued 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, consistent with the skill story. These distribution statistics tell a consistent story with our analyst characteristics analysis.

Table 5 shows that, if an analyst has ever been influential, about 22.1% of the analyst's recommendations are influential. This number is 23.5% for the turnover definition of influential. Table 5 also compares the characteristics of analysts who issue at least one influential recommendation change (*Ever influential*) in the sample versus the other (*Never influential*) 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. *Ever influential* analysts have better average analyst earnings forecast accuracy ranks. They are also more likely to have once been a *Star analyst* and have greater absolute and relative *Analyst experience* compared to *Never influential* analysts. The difference in the *Star analyst* proportion is especially large, with 25.3% stars for the Ever influential group versus 9.2% for the Never group. It is possible, however, that an analyst is more likely to be selected as a *Star analyst* because he or she has had influential recommendations. There is only mixed evidence that analysts in the *Ever influential* group issue more recommendations *Away from consensus* and issue *Concurrent earnings forecasts* with their recommendations.

4. Robustness Tests and Different Samples

4.1 Other definitions of influential

We also use other methods of classifying recommendation changes as influential and use different samples with generally similar results (results not reported here are in the online appendix of this article). We summarize those methods here.

First, we are sensitive to potential issues arising from the usage of an analyst's own prior recommendation in the computation of *recchg*. If the prior recommendation is stale, *recchg* could contain stale information and we could understate the fraction of influential recommendations. However, we are careful to use the review date in I/B/E/S and the stopped date so that we have confidence that the prior rating is still outstanding whenever we compute a *recchg* value.

Table 5
Analysts who had at least one influential recommendation change

	Influential based on firm's abnormal returns				Influential based on firm's abnormal turnover			
			Difference				Difference	
Characteristics	Never	Ever Influential	Ever–Never	*t*-stat	Never	Ever Influential	Ever–Never	*t*-stat
Number of Analysts	935	2,821			781	2,975		
		75.1%				79.2%		
% influential recs for typical analyst	0.0%	22.1%			0.0%	23.5%		
Forecast accuracy quntile	2.894	2.819	−0.076***	(−3.20)	2.907	2.819	−0.088***	(−3.38)
Away from consensus	0.357	0.367	0.010	(1.52)	0.348	0.369	0.021***	(2.88)
Was once a Star analyst	0.092	0.253	0.161***	(12.91)	0.101	0.243	0.142***	(10.60)
Absolute analyst experience (# Qtrs)	18.09	24.42	6.329***	(10.11)	18.71	23.93	5.218***	(7.57)
Relative analyst experience	−1.26	1.36	2.624***	(9.61)	−0.71	1.08	1.788***	(5.94)
Concurrent earnings forecast	0.477	0.462	−0.015*	(−1.66)	0.461	0.467	0.005	(0.55)

This table reports the average analyst or recommendation (rec) 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. Only analysts who had at least 5 recommendations (recs) in the 1994–2006 period are included. There are two definitions of influential. First, influential recs are those when a correct-signed [0,1] CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month *Idiosyncratic volatility* of daily returns. The second uses an abnormal turnover greater than 1.96 standard deviations of that expected from the abnormal daily turnover in the stock's prior three-month history. 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). I/B/E/S rec dates are replaced by those from First Call whenever available. Reiterations (rec change = 0) are also excluded. 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 rec moves *Away from 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 2010). *Star analysts* (dummy variable) are analysts who are ranked as All-Americans in the most recent annual *Institutional Investor* polls. *Absolute analyst experience* is measured as the # of quarters in I/B/E/S. *Relative analyst experience* subtracts the average experience of other covering analysts. *Concurrent earnings forecast* is a dummy indicating whether the analyst issued any type of earnings forecast in the three-day window around the rec. 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.

Table 6
Different definitions of influential

Method	Using alternative methods to define influential	Total	Non-Influential	Influential	Percentage
0	Recchg Original	87,829	77,537	10,292	11.7%
1	Recchg_Last	50,024	44,932	5,092	10.2%
2	Recchg_Consensus	96,282	86,942	9,340	9.7%
3	Influential based on raw returns	87,829	78,379	9,450	10.8%
4	Using rec-free days to compute prior volatilties	87,829	77,203	10,626	12.1%
5	Removing obs with large pre-event absolute return	76,638	68,100	8,538	11.1%

The fraction of influential recommendation changes (*recchg*) for different subsamples (methods) is reported. The definition of influential here is based on abnormal returns. The original *recchg* (method 0) variable is the analyst's current rec minus the analyst's own prior rec. A prior rec is outstanding only if it has a less-than-one-year-old review date and has not been stopped by the broker. A *recchg* is considered influential when the [0,1] CAR is the same sign as the *recchg* and the CAR is 1.96 standard deviations greater than expected based on the firm's prior three-month *Idiosyncratic volatility* of daily returns. Reiterations are excluded since the *recchg* is basically zero. Methods 1 and 2 amend the *recchg* definition: 1 is based on the current rec minus the last rec from any analysts (*recchg_last*), and 2 is based on the current rec minus the most recent consensus (*recchg_con*). Method 3 is method 0 except that a *recchg* is influential if the cumulative raw (not abnormal) return is influential. Method 4 amends method 0 by using only rec-free days to compute the prior return volatility of the firm. This removes days with recommendations from the prior three-month [−69, −6] period used to compute *Idiosyncratic volatility*. Method 5 uses method 0 except that it removes observations where the pre-event [−2, −1] contains an influential abnormal return in any direction.

Nevertheless, two alternative *recchg* variables are considered. The first is the recommendation change value computed as the current recommendation minus the last recommendation by any analyst (we denote this as *recchg_last*). This captures a revision in the time series of recommendations. The second is the current recommendation minus the most recent consensus recommendation (*recchg_con*). We estimate a multiple regression of CAR against the original *recchg*, *recchg_last*, and *recchg_con* variables and show that the two new recommendation-change variables do have incremental statistical power for the event CAR, although the original *recchg* variable has the largest economic significance (coefficients are 140, 8, and 19 basis points, respectively). These recommendation-change variables are based on three-point ratings (mapped from five-point rating scales), since it is not possible to form a consensus that mixes different rating scales. We then redo our analysis with the two alternative recommendation-change measures. We show that the influential (in returns) fraction for *recchg_last* and *recchg_con* is 10.2% and 9.7%, respectively. Table 6 reports these fractions. The influential fraction remains similar. In fact, the original *recchg* variable is the best avenue to locate influential recommendation changes. Re-estimating Tables 2 and 4 with these two new measures of *recchg* does not materially affect any of our other results.

We investigate whether coding a recommendation change as influential if it is influential in raw returns as opposed to abnormal returns makes a difference to our conclusions. The motivation for this analysis is that analyst recommendations could sometimes elicit market-wide responses (e.g., the Citigroup downgrade was accompanied by a drop in the S&P 500) and hence a method of identifying influential recommendations that nets out market returns may understate the influence of analysts. Using raw returns to define influential eliminates this problem. We show that the raw return-based measure of influential obtains a 10.8% fraction of influential observations, not higher but lower than our original 11.7%. Therefore, we are confident that our baseline approach to identify influential recommendations based on abnormal returns is not biased.

Fourth, one might argue that our approach is too conservative because the significance of the stock-price impact of recommendation changes does not depend on a benchmark, which itself might include influential recommendation changes. To evaluate this issue, we repeat our analysis by removing non-corporate event recommendation days from the computation of prior *Idiosyncratic volatility* of stock returns. This slightly increases the fraction of recommendation changes that are influential. The fraction is now 12.1%. This could be due to the fact that only a small fraction of recommendations are influential. Therefore, the typical estimate of *Idiosyncratic volatility* using all observations is not an overly high hurdle under our main influential definition.

Fifth, one potential concern is that influential recommendations have a large reaction because they piggyback on some firm-related event not captured by our screens. Because it is difficult to mount an exhaustive news wire search for corporate events in our large sample, we proxy for a contaminating event using the pre-recommendation stock returns. We impose this additional screen of removing recommendations if the absolute value of the day $[-2, -1]$ pre-event return is more than $1.96 \times \sqrt{2}$ standard deviations of the firm's prior *Idiosyncratic volatility* of returns. About 13% of observations are removed using this screen. However, none of our results are changed with this new sample. With this reduced sample, 11.1% of the recommendation changes are still classified as influential in returns.[12]

In sum, our results are robust to alternative definitions of recommendation changes, influential definitions, and different samples.[13]

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12 An additional concern is that there could be more important company-specific news events on or immediately before days that influential recommendations are made than on other days, so our identification of analyst recommendation changes as influential might be spurious. To investigate whether news events are more likely on days with influential recommendations, we select 100 influential and 100 non-influential observations randomly and use Factiva to search for corporate news in Dow Jones and Reuters newswires from day -2 to the recommendation date. We limit our search to corporate news relating to mergers and acquisitions, lawsuits, security issuance, dividend changes, debt rating news, and earnings guidance or announcements. We find 19 observations with such events in the influential sample and 25 in the non-influential sample. Hence, there is no evidence that the influential subsample contains more corporate news-motivated recommendation changes. Of the 44 observations, most do not elicit any large stock-price reaction. Our pre-event screen is hence especially useful for removing large reaction observations. The pre-event price screen removes 10 observations. The average absolute value of pre-event returns for these 10 is 17.9%. For the remaining 34 observations, the average absolute value of pre-event returns is only 1.9%. This provides evidence that most of the corporate events our screens miss do not exert a large impact on the stock price. We believe that using returns to identify pre-events is a better approach than searching for news articles because news articles may not always elicit discernible stock-price reactions.

13 One other test we do relates to addressing the concern that I/B/E/S provides only an incomplete record of the universe of stock recommendations (e.g., Ljungqvist, Malloy, and Marston 2009). We include broker-matched recommendations from First Call not found on I/B/E/S. We let these observations inherit an I/B/E/S analyst identifier if the closest prior and future (two-year window centered on the First Call observation) I/B/E/S recommendations have the same analyst identifier. With this combined sample, the percentage of influential recommendation changes remains similar, at 11.5%. Probit estimations also yield similar results.

4.2 Comparing influential fraction in earnings forecasts versus recommendation samples

Our article focuses on stock recommendations. However, analyst reports also contain another important output—revisions of earnings forecasts. Our prior is that stock recommendations are more likely to be influential. A recommendation is an explicit statement on whether an investor should buy or sell the stock, while an earnings forecast revision is not. Recommendations can receive a great deal of attention in the press, as evidenced by the examples at the start of this article; the same attention is rarely given to earnings forecast changes. Finally, a recommendation can encompass the joint impact of cash flow and discount rate news on the stock price, while standalone earnings forecasts contain only cash flow news. However, we now investigate whether the evidence is consistent with our prior.

We consider three forecast horizons: one-quarter-ahead, one-year-ahead, and long-term-growth (LTG) forecasts from I/B/E/S. We conduct a similar exercise in hand-matching broker names between I/B/E/S and First Call (FC) and utilize First Call dates whenever possible. For each forecast horizon, we classify earnings forecasts into upward and downward revisions based on three methods: *revision_own*, *revision_last*, and *revision_con*, in a manner akin to our three recommendation-change measures. We then remove firm news-contaminated observations using the sample 2 to 4 screens as in Table 2. The replication of Table 2 using earnings forecasts shows that revisions elicit statistically significant stock-price reactions, although their reaction magnitudes are smaller than those of recommendation changes (the online appendix contains these results).

We then report the influential fraction in Table 7. Interestingly, the fraction hovers around 5%. This is close to the percentage of influential observations that we would have expected by chance alone. However, whenever the earnings forecast revision is accompanied by a stock recommendation in the three-day window around the revision, the influential fraction goes up to about 10%, consistent with the results from our recommendation change sample. We also show evidence from the flip side—if the current recommendation change is accompanied by an earnings forecast in the three-day window, the influential fraction increases from 11.7% to 13.2%. This is in line with the findings of Kecskes, Michaely, and Womack (2009).

5. 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 when proper care is taken to account for

Table 7
Influential fraction of earnings forecasts with and without stock recommendations

Panel A: Forecast revisions sample

Forecast revision sample	Influential based on abnormal:	All forecast revisions			Revisions with recommendations		
		Not Influ	Influential	Percent	Not Influ	Influential	Percent
Annual	Returns	286,813	13,402	4.5%	18,094	2,023	10.1%
	Turnover	283,672	16,543	5.5%	17,676	2,441	12.1%
Quarterly	Returns	105,570	5,346	4.8%	6,268	799	11.3%
	Turnover	104,125	6,791	6.1%	6,081	986	14.0%
LTG forecasts	Returns	42,258	1,750	4.0%	3,119	310	9.0%
	Turnover	41,055	2,953	6.7%	2,930	499	14.6%

Panel B: Recommendation changes sample

Sample	Influential based on abnormal:	All recommendation changes			Rec changes with earnings forecasts		
		Not Influ	Influential	Percent	Not Influ	Influential	Percent
Rec Change	Returns	77,537	10,292	11.7%	34,608	5,253	13.2%
	Turnover	76,595	11,234	12.8%	34,331	5,530	13.9%

We examine what fraction of earnings forecasts revisions are influential (Influ) according to our definition. Earnings forecasts revisions based on yearly (FY1), quarterly (Q1), and long-term-growth (LTG) horizons are from the I/B/E/S Detail file from 1994 to 2006 where a revision is coded as an upward or downward revision based the current forecast minus the prior outstanding forecast by the same analyst. Dates from First Call are used as revision dates whenever available through hand-matching of broker name. The samples are then screened for contaminating events based on the sequence shown in Table 2. The final sample considered here is based on forecast revisions without contemporaneous earnings announcements, company guidance, and multiple same-horizon forecasts days. A revision is considered influential if its two-day event [0,1] return reaction is in the correct direction and 1.96 standard deviations more than expected based on the prior three-month daily *Idiosyncratic volatility* of stock returns. Abnormal turnover is also used as a benchmark for being influential. An earnings forecast is treated as accompanied by a recommendation when there is a recommendation issued by the same analyst in the three-day window around the earnings forecast revision date. Panel B, we list influential fractions based on the original recommendation-change sample in Table 4.

confounding news, the typical stock-price reaction is small enough that for an individual stock it would not be identifiable with a firm-level event study. When analyst recommendation changes have an identifiable impact at the firm level, we call them influential recommendation changes.

We show that some analyst recommendation changes lead to substantial changes in how a firm is assessed and valued by investors, leading to large returns and turnover relative to the history of the firm. 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 our criterion for influential recommendation changes ensures that the observations identified as influential can actually be noticed by investors following the firm. We find that about 12% of the recommendation changes are influential after eliminating recommendation changes associated with confounding firm news. Strikingly, a quarter of the analysts in our sample have no influential recommendation change in their recommendation histories. We find that influential recommendations are more likely to be from analysts with larger leader-follower ratios and more accurate earnings forecasts. Recommendations that go away from the consensus and are issued contemporaneously with earnings forecasts are also more likely to be influential. Having had an influential recommendation change before also improves the likelihood of having an impactful recommendation change, giving credit to the view that analyst skill is an important determinant of impactful research. Further, growth firms, small firms, high institutional ownership firms, and low analyst activity firms are more likely to be associated with influential recommendations.

Why is it that an analyst at times can make recommendations that are associated with a significant firm-level abnormal return or turnover? We conjecture that at times analysts can change how a corporation is viewed and that such "paradigm shifts" are responsible for the large impact of some of the recommendation changes. This perspective is related to Hong, Stein, and Yu (2007), who 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 move to reflect this paradigm shift. While our analysis does not amount to a test of their model, our evidence is consistent with an influential analyst recommendation change being able to precipitate such a paradigm shift. It is not surprising, therefore, that firms experiencing influential recommendation changes see their stock turnover increase, their volatility increase, and analysts make more and bigger earnings forecast changes. Further, industry returns are also impacted around the recommendation event.

Our evidence shows that focusing on the average stock-price reaction to changes in analyst recommendations leads to an incomplete assessment of the value of the information produced by analysts. The size of the average stock-price reaction to recommendation changes is small enough that investors would not notice how a recommendation affects a stock, if it does at all. This is because many analysts do not make influential recommendations and not all recommendations are influential. However, our evidence suggests that some analysts do make recommendation changes that change how a firm is assessed by investors.

Supplementary Data

Supplementary data are available online at http://www.sfsrfs.org/addenda/.

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