What Drives the Value of Analysts' Recommendations:

Earnings Estimates or Discount Rate Estimates?

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Abstract

When an analyst changes his recommendation of a stock, his valuation differs from the market's valuation based on differences in earnings estimates and/or discount rate estimates. We argue that earnings-based recommendation changes are characterized by hard information, greater verifiability, and shorter forecast horizons compared to discount rate-based recommendation changes. Therefore, earnings-based recommendation changes are less subject to analysts' cognitive and incentive biases and thus they are more informative than discount rate-based recommendation changes. Consistent with this argument, we find that investors differentiate between earnings-based and discount rate-based recommendation changes. Both the initial market reaction to and the drift after recommendation changes are twice as big for earnings-based versus discount rate-based recommendation changes. Trading on earnings-based recommendation changes earns risk-adjusted returns of over three percent per month.

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1. Introduction

When an analyst changes his recommendation of a stock, he indicates to the market that his valuation differs from the market's valuation. Within the framework of the standard discounted cash flow model of valuation, the difference in valuation between the analyst and the market must come from differences in estimates of cash flows, discount rates, and/or growth rates. This is the case even though analysts typically use multiples valuation models rather than discounted cash flow valuation models (e.g., Asquith, Mikhail, and Au (2005)).[1] In this paper, we study the extent to which cash flow estimates, discount rate estimates, and growth rate estimates drive the informativeness of analysts' recommendations.

We focus explicitly on changes in analysts' earnings estimates and implicitly on changes in analysts' discount rate estimates and long-term earnings growth rate estimates ("implicitly" because changes in analysts' discount rate estimates and growth rates estimates are rarely reported).[2] We refer to the former as "earnings-based recommendation changes" and to the latter as "discount rate-based recommendation changes".[3]

Why should earnings-based recommendation changes be more informative than discount rate-based and growth rate-based recommendation changes? As we argue below, compared to discount rate-based recommendation changes, earnings-based recommendations changes are characterized by hard information, greater verifiability, and shorter forecast horizons. Consequently, they are less subject to analysts' cognitive biases (e.g., McNichols and O'Brien

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[1] Analysts virtually always use multiples valuation in their reports. However, it is easy to show that multiples valuation models are implicitly based on cash flow estimates and discount rate estimates (e.g., Damodaran (2006) and Grinblatt and Titman (2001)).

[2] Brav and Lehavy (2003) study of recommendations and price targets (from which they infer discount rates) and Brav, Lehavy, and Michaely (2005) study of analysts' expected returns are notable exceptions. Even in these cases, the data (from First Call) cover only a few years and are no longer produced.

[3] We study recommendation changes rather than recommendation levels because market efficiency implies that price changes are primarily caused by new information rather than by information already known by the market. The empirical evidence suggests that recommendation changes contain more information than recommendation levels (e.g., Jegadeesh, Kim, Krische, and Lee (2004) and Barber, Lehavy, and Trueman (2008)).

(1997)) and incentive biases (e.g., Lin and McNichols (1998), Michaely and Womack (1999), and Malmendier and Shanthikumar (2007)).

First, earning-based recommendation changes are based on hard information whereas discount rate-based recommendation changes are based on soft information. Analysts virtually always a produce a projected income statement for their earnings estimates for the next fiscal year or two. They also explain in detail the main items in their projected income statement in order to justify their earnings estimates. Such explanations may even refer to comprehensive long-term industry analyses produced by the analyst. By contrast, analysts rarely change their discount rate estimates and growth rate estimates let alone justify them with detailed explanations.

Second, investors can and do verify the accuracy of short-term earnings estimates ex post, namely, when the firm announces its earnings each quarter. Indeed, earnings estimate accuracy is one of the evaluation criteria of the annual Institutional Investor ranking of analysts. The ex post verification of analysts' earnings estimates incentivizes analysts to produce more accurate earnings estimates. By contrast, discount rates are difficult to estimate accurately both ex ante and ex post (e.g., Fama and French (1997)). This is also the case for growth rates (e.g., Chan, Karceski, and Lakonishok (2003)).

Third, the behavioral literature finds that the longer is the forecast horizon, the more optimistic are economic agents' forecasts (e.g., Ganzach and Krantz (1991) and Amir and Ganzach (1998)). This implies that analysts' short-term earnings estimates are more accurate than their discount rate estimates or long-term earnings growth rate estimates. Indeed, Brav, Lehavy, and Michaely (2005) find that analysts' expected returns are optimistic on average. Chan, Karceski, and Lakonishok (2003) find that this is also the case for analysts' growth rate estimates.

Our arguments above suggest that growth rate-based recommendation changes are conceptually similar to discount rate-based recommendation changes in that both are characterized by soft information, less verifiability, and longer forecast horizons. We therefore predict that earnings-based recommendation changes should be more informative than discount rate-based recommendation changes. For example, upgrades with earnings estimates increased should have a more positive total market reaction (initial market reaction and drift) than upgrades with no earnings estimates change, and downgrades with earnings estimates decreased should have a more negative total market reaction than downgrades with no earnings estimates change.

We test this prediction using data from I/B/E/S between 1994 and 2007. We also examine a random sample of 150 analyst reports, and we find that the I/B/E/S data are consistent with the analyst reports. Roughly one-third of our recommendation changes are based on changes in analysts' earnings estimates in the same direction. Analysts only change their growth rate estimates for roughly five percent of recommendation changes. Moreover, analysts virtually never explicitly change their discount rate estimates. However, in their reports, analyst usually imply that their recommendation changes without earnings estimate changes are based on discount rate changes by stating explicitly that they believe that the stock is mispriced.

We find that the initial market reaction is bigger for earnings-based recommendation changes than for discount rate-based recommendation changes. The average two-day initial market reaction to earnings-based upgrades is roughly 66 percent bigger than the initial market reaction to discount rate-based upgrades (3.55% versus 2.13%). Similarly, the initial market reaction to earnings-based downgrades is roughly 200 percent bigger than the initial market reaction to discount rate-based downgrades (-5.11% versus -1.72%).

Previous studies on recommendations document that returns continue to drift during the months after the recommendation change in the same direction as the initial market reaction (e.g., Stickel (1995), Womack (1996), and Barber, Lehavy, McNichols, and Trueman (2001)). Therefore, we examine the drift after recommendation changes, and we find evidence of continuation of the initial market reaction. The average 21-day drift after earnings-based upgrades (where the drift is measured as returns in excess of returns on benchmark portfolios matched on size, book-to-market, and momentum) is roughly 180% bigger than the drift after discount rate-based upgrades (1.83% versus 0.65%). Similarly, the drift after earnings-based downgrades is roughly 55 percent bigger than the drift after discount rate-based downgrades (-1.24% versus -0.79%). Overall, our results suggest that earnings-based recommendation changes have both a bigger initial market reaction and drift than discount rate-based recommendation changes.

In addition to the absolute earnings estimate changes that we examined before, we examine recommendation changes with relative earnings estimate changes, which we define as changes in analysts' earnings relative to the consensus. We would expect the total market reaction to a relative earnings change to be bigger if the analyst provides new information to the market. For example, upgrades with earnings increased should have a bigger total market reaction if the analyst's earnings are above rather than below the market consensus.

We find that the average initial market reaction to upgrades with earnings increased to above versus below the consensus is 3.70% versus 3.30% (compared to 2.13% for no earnings change) and that the difference is statistically significant. The 21-day drift after upgrades with earnings increased to above versus below the consensus is 2.24% versus 1.16% (compared to 0.65% for no earnings change). For downgrades, the average initial market reaction if earnings decrease to below versus above the consensus is -5.62% versus -3.33% (compared to -1.72% for no earnings change). The drift after downgrades with earnings decreased to below versus above the consensus is -1.31% versus -1.03% (compared to -0.79% for no earnings change).

An alternative interpretation of our results is that the total market reaction to earnings-based recommendation changes is bigger because the analyst sends two explicit signals (recommendations and earnings) rather just one explicit signal with discount rate-based recommendation changes (just recommendations). The double signal interpretation suggests that the number of signals matters rather than their characteristics. This implies that the total market reaction should be similar for recommendation changes with growth rate changes and recommendation changes with earnings changes because, in both cases, the analyst sends two signals rather than one. We find that the total market reaction is bigger for earnings-based recommendation changes than for growth rate-based recommendation changes. In fact, the total market reaction is similar for growth rate-based recommendation changes and discount rate-based recommendation changes. These results are consistent with growth rate-based recommendation changes being characterized by soft information, less verifiability, and longer forecast horizons like discount rate-based recommendation changes.

We extend our analysis to explain the total market reaction with firm characteristics and recommendation change characteristics. We account for multiple recommendation changes on the same day, the prestige of the broker making the recommendation, contemporaneous earnings announcements, recommendation changes, earnings changes, and returns during the week before the recommendation change, market efficiency (as proxied by market capitalization, turnover, institutional ownership, and analyst coverage), book-to-market, and momentum. We also test whether our results are driven by the post-earnings announcement drift after earnings surprises during the quarter before the recommendation change, by star analysts, particular analysts, or by the level of the previous recommendation. We find that the differences between earnings-based and discount rate-based recommendation changes are roughly the same as in our univariate results.

Our results for the post-recommendation drift naturally suggest a potentially profitable trading strategy. In particular, we test whether an investor can earn excess returns by implementing two trading strategies, namely, (1) buying all upgrades and selling all downgrades and (2) buying upgrades with earnings increased and selling downgrades with earnings decreased. We find that the 21-day holding-period four-factor alphas from these strategies are 2.01% and 3.37%, respectively. These alphas are very economically and statistically significant, and the trading profits from these strategies persist throughout our sample period.

The rest of this paper is organized as follows. Section 2 presents the data and sample. Section 3 presents the main results. Section 4 presents robustness tests of the main results. Section 5 presents the trading strategy results. Section 6 concludes.

2. Data and Sample

We select our sample from the universe of all publicly traded U.S. firms that are listed on CRSP between 1994 and 2007. To be included in our sample, a firm must be publicly traded for at least one year at the time of the recommendation change (because we measure event-time returns excess of benchmark portfolios that require at least one year of data). Data on recommendations, earnings estimates, and long-term earnings growth rates issued between 1994 and 2007 are taken from I/B/E/S. For all observations in our sample, we must know the identity of the analyst, the recommendation must not be issued by an analyst employed by Lehman Brothers (because I/B/E/S does not have earnings estimates data for Lehman Brothers), the recommendation must not be an initiation or a reiteration (it must be a recommendation change), the recommendation change must not be the result of a rating scale change associated with the Global Settlement, the firm must be covered by at least two analysts, and the earnings estimate change associated with the recommendation change must be classifiable as an earnings increase, no change, or decrease. This leaves 123,250 recommendation changes (firm-date observations) comprising 7,040 unique firms and 3,517 unique trading dates. The Appendix describes the details.

We create recommendation change categories by collapsing our firm-date-analyst observations to firm-date observations. Our guiding principle here is that our categories of interest should only include recommendation changes that unambiguously belong there. Thus, for example, we classify a firm-date observation as an upgrade only if all analysts who change their recommendation that day upgrade the stock (none downgrade). If there are conflicting recommendations for a stock on a given day, we drop the observation (2,321 firm-date observations). We further split recommendation change categories based on earnings estimate changes concurrent with recommendation changes. We define an "earnings estimate increase" as an increase in either or both of the fiscal year one and fiscal year two estimates. We define an "earnings estimate decrease" analogously. We thus have six recommendation change categories consisting of three categories for upgrades, i.e., with earnings increased, with no earnings change, and with earnings decreased, and the same three categories for downgrades. The Appendix describes the details.

We define increases, no changes, and decreases in growth rate estimates based on growth rate estimates concurrent with recommendation changes. Since previous growth rate estimates are not always available, we can only measure growth rate changes for roughly 62 percent of our sample (76,714 out of 123,250 observations). Moreover, only roughly five percent of the recommendation changes in our sample (6,638 out of 123,250 observations) are accompanied by a growth rate estimate change.

We compute the number of analysts covering a stock and consensus estimates by counting the number of earnings estimates and computing the mean earnings estimate of all brokers with earnings estimates issued within the previous year for the next fiscal year. The Appendix describes the details. We classify a broker as "prestigious" from November of the current year to October of the following year if the broker is one of the top fifteen brokers in the Institutional Investor magazine issue of October of the current year. The Appendix provides our list of prestigious brokers. We classify an analyst as a "star" from November of the current year to October of the following year if the analyst is one of the top ranked analysts in the Institutional Investor magazine issue of October of the current year.

Stock trading data are from CRSP. We obtain factor returns from Ken French's website. Since we implement trading strategies conditional upon recommendation changes, we must ensure that the recommendation changes are known at the time we trade. Since the recommendation may be issued after the close of event day 0, we (conservatively) assume that a recommendation made on a given trading day is known by the open of the following trading day. Therefore, to compute event-time returns, we measure event day 0 returns from the closing price of event day -1 to the open price of event day +1, and we measure event day +1 returns from the open price of event day +1 to the close of event day +1. For recommendations issued after the close of event day 0, investors can trade as late as the open of event day +1. We follow Daniel, Grinblatt, Titman, and Wermers (1997) and measure event-time returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. We refer to these as "excess returns". Accounting data, including quarterly earnings announcement dates, are from Compustat, and institutional ownership data are from Thomson's 13f filings data.

Turning now to our sample, we examine the characteristics of recommendations changes in different recommendation change categories. We consider the distribution of recommendation changes among categories, the percent of recommendation changes in each category around earnings announcements, and the mean market capitalization, book-to-market, turnover, institutional ownership, and analyst coverage of recommendation changes in each category (all are measured in percentiles except for analyst coverage, which is measured in number of analysts).

[Insert Table 1 about here]

Table 1 presents the results. Just over one-half of recommendation changes are not accompanied by earnings estimate changes. About one-third of upgrades have earnings estimates increase and the same fraction of downgrades have earnings estimates decrease. Roughly one-tenth of upgrades have earnings estimates decrease and the same fraction of downgrades have earnings estimates increase.

About one-quarter of both upgrades and downgrades are issued around earnings announcements. Analysts are more likely to issue recommendation changes with earnings estimate changes around earnings announcements. Only roughly 15 percent of recommendation changes with no earnings change are issued around earnings announcements whereas roughly one-third of recommendation changes with earnings estimate changes are issued around earnings announcements.

Our sample firms are typically big firms, growth firms, liquid firms, firms with high institutional ownership, and firms with high analyst coverage. However, there is very little variation in these firm characteristics across recommendation change categories. In other words, we do not find that earning-based recommendation changes and discount rate-based recommendations changes differ on average by size, valuation, liquidity, institutional ownership, and analyst coverage.

We also redo our results in Table 1 for growth rate changes. Like in Table 1 for recommendation changes and earnings changes, we find (in Table 3) that growth rate changes do not differ on average by firm characteristics. We also find that the proportion of observations that are around earnings announcements (roughly 25 percent) does not differ for growth rate increases, no changes, and decreases.

To better understand our data, we examine a random sample of 150 analyst reports. For each of our recommendation categories, we randomly sample twenty-five observations for which we extract the corresponding analyst reports from Investext. We begin by verifying our classification of recommendation changes and earnings changes based on I/B/E/S data.

We find that our recommendation change categories based on I/B/E/S data are generally consistent with the analyst reports. Insofar as the I/B/E/S data are different from the reports and the report are correct, our recommendation change categories based on I/B/E/S data are noisy, thus the results of this paper underestimate the difference in the informativeness of earnings-based versus discount rate-based recommendation changes.

Several stylized facts emerge from the reports about why analysts disagree with the market and thus change their recommendation. Analysts virtually always justify their disagreement using multiples valuation (typically based on comparable firms' multiples but also based on the firm's historical multiples) with their earnings estimates (typically net income, but also operating income and sales) as the denominator (consistent with Asquith, Mikhail, and Au (2005)).

Moreover, analysts issue explicit discount rate estimates for only 12 percent of our observations (compared to 12.8 percent of Asquith, Mikhail, and Au (2005)'s observations). They also issue explicit growth rate estimates for 50 percent of our observations compared to 62 percent our I/B/E/S data observations. However, they only change their growth rate estimates in three percent of their reports compared to five percent of our I/B/E/S data observations. Overall, the I/B/E/S data appear to be consistent with the corresponding analyst reports.

3. Main Results

3.1. Univariate Analysis of the Total Market Reaction to Recommendation Changes

We predict that earnings-based recommendations changes should be more informative than discount rate-based recommendation changes. Specifically, upgrades with earnings increased should have a more positive total market reaction than upgrades with no earnings change. Downgrades with earnings decreased should have a more negative total market reaction than downgrades with no earnings change.

We test our prediction by examining the total market reaction to recommendation changes in the different categories (upgrades with earning increased, upgrades with no earnings change, upgrades with earnings decreased, etc.).[4] We follow Daniel, Grinblatt, Titman, and Wermers (1997) and measure event-time returns in excess of returns on benchmark portfolios matched on size, book-to-market, and momentum during the two-day ([-1,0]) event window around the recommendation change. We measure event day 0 returns from the closing price of

[4] Both earnings estimates and discount rate estimates have an idiosyncratic and systematic component (the latter is usually interpreted as an industry-wide component by analysts). For example, for the discount rate, a risk factor (a systematic component) may change or a factor loading (an idiosyncratic component) may change. Whether such changes are idiosyncratic or systematic does not affect the design or interpretation of our tests.

event day -1 to the open price of event day +1, and we measure event day +1 returns from the open price of event day +1 to the close of event day +1. There is one observation for each firm-date.

[Insert Table 2 about here]

Table 2 presents the results. Earnings-based recommendations have a significantly bigger initial market reaction than discount rate-based recommendation changes. Specifically, the average initial market reaction to upgrades with earnings increased is 3.55% compared to 2.13% for upgrades with no earnings change (discount rate-based upgrades) and 1.11% for upgrades with earnings decreased. These patterns are similar for downgrades. The initial market reaction to downgrades with earnings decreased is -5.11% compared to -1.72% for downgrades with no earnings change (discount rate-based downgrades) and -0.35% for downgrades with earnings increased.

Previous studies on recommendations document that returns continue to drift during the months after the recommendation change in the same direction as the initial market reaction. Therefore, we examine the drift after recommendation changes. A priori, it is not clear whether the drift after earnings-based recommendation changes should be bigger or smaller than after discount rate-based recommendation changes. On the one hand, many corporate events are characterized by underreaction to news and thus the drift could continue in the same direction as the initial market reaction (e.g., earnings announcements (Bernard and Thomas (1989, 1990)), seasoned equity offerings (Loughran and Ritter (1995)), and repurchases (Ikenberry, Lakonishok, and Vermaelen (1995))). On the other hand, since earnings-based recommendations appear to be more informative as evidenced by their bigger initial market reaction, the drift could be smaller and perhaps even in the opposite direction to the initial market reaction. Therefore, the direction of the drift is an empirical question. To examine the drift, we compute excess returns during various event windows after the recommendation change ([+1,+5], [+1,+10], [+1,+15], [+1,+21], [+1,+42], and [+1,+63]).

Table 2 presents the results. Earnings-based recommendations changes are more informative as measured by the drift than discount rate-based recommendation changes. For example, the average 21-day drift after upgrades with earnings increased is 1.83% compared to 0.65% for upgrades with no earnings change (discount rate-based upgrades) and 0.36% for upgrades with earnings decreased. These patterns are similar for downgrades. The 21-day drift after downgrades with earnings decreased is -1.24% compared to -0.79% for downgrades with no earnings change (discount rate-based downgrades) and 0.23% (not statistically significant) for downgrades with earnings increased. The market appears to underreact more to earnings-based recommendation changes than to discount rate-based recommendation changes.[5]

[Insert Figure 1 about here]

The patterns that we find during the month after the recommendation change are similar over shorter and longer horizons. Figure 1 presents the drift during the one, two, and three weeks and one, two, and three months after the recommendation change. The drift is greater for earnings-based recommendation changes than for discount rate-based recommendation changes over horizons of at least three months. Much of the magnitude of the drift is within the first month after the recommendation change, but the drift continues in the same direction for months thereafter.

We argue that recommendation changes with no earnings change are driven by discount rate changes. However, an analyst may upgrade a stock without changing his earnings to reiterate

[5] We examine the impact of the forecast horizon associated with earnings estimates on our results. We redo Table 2 by the quarter of the fiscal year in which a recommendation change takes place (i.e., by the number of quarters until the first fiscal year end, and we find that our results are the same.

that his previous earnings was and remains above the consensus. Similarly, an analyst may downgrade a stock without changing his earnings to reiterate that his previous earnings was and remains below the consensus. This implies that, if some recommendation changes with no earnings are driven by earnings changes, our recommendation change categories are noisier than the true categories, so the true difference in the total market reaction to earnings-based versus discount rate-based recommendation changes is bigger than the difference we report.

To estimate the importance of this earnings reiteration effect on our results, we test whether recommendation changes with no earnings change are driven by earnings changes by testing whether the total market reaction is the same if the previous estimate is above the consensus versus below the consensus. If the total market reaction is the same, then such recommendation changes are not driven by earnings. Consequently, we redo Table 2 for recommendation changes with no earnings change split into two sub-categories based on whether previous earnings are above versus below the consensus. We find that the total market reaction is the same across both sub-categories (results not tabulated), which is consistent with recommendation changes with no earnings change being predominantly driven by discount rate changes.

3.2. The Role of Growth Rate Estimate Changes

Growth rate-based recommendation changes are conceptually similar to discount rate-based recommendation changes in that both are characterized by soft information, less verifiability, and longer forecast horizons. Moreover, in the analyst reports that we examine, we find that only three percent of recommendation changes are accompanied by growth rate estimate changes. Nevertheless, our sample includes several thousand recommendation changes with growth rate changes. We now directly examine the total market reaction associated with these growth rate changes.

[Insert Table 3 about here]

Table 3 presents the results for the sub-sample of recommendation changes for which we can measure growth rate changes (62 percent of our I/B/E/S sample). Within this sub-sample, growth rates increase or decrease for roughly nine percent of the observations (or for roughly five percent of the observation of our full sample). For recommendation changes with no earnings change, growth rates change for roughly five percent of the observations. For recommendation changes with earnings changes, growth rates change for 12-15 percent of the observations. We find similar figures in the random sample of 150 analyst reports that we examine.

We split each recommendation change category into three sub-categories, namely, growth rate increases, no changes, and decreases. We find that for recommendation changes with no earnings change, the total market reaction is the same whether growth rates are increased, no changed, or decreased. The pairwise differences in the initial market reaction and the drift associated with growth rate increases, no changes, and decreases are not statistically significant (except for downgrades with no earnings changes for growth rate increases versus no changes). These results suggest that recommendation changes with no earnings change are likely driven by discount rate changes and not by growth rate changes.

Moreover, we find that for recommendation changes with earnings changes, the total market reaction is the same whether growth rates are increased, no changed, or decreased. The pairwise differences in the initial market reaction and the drift associated with growth rate increases, no changes, and decreases are not statistically significant with the main exception of downgrades with earnings decreased. These results suggest that while earnings-based recommendation changes are more informative than discount rate-based recommendation changes, recommendation changes associated with growth rate changes have no incremental information content.

Our results shed light on whether recommendation changes with earnings changes can be interpreted as a "double signal". According to this interpretation, there is a bigger total market reaction to recommendation changes with earnings changes versus no earnings changes because the market receives two signals versus one, namely, a recommendation change plus an earnings change versus only a recommendation change. By the same argument, recommendation changes with growth rate changes should also be interpreted by the market as a double signal versus no growth rate changes.

While we find that recommendation changes with earnings changes are associated with a significantly different total market reaction from recommendation changes with no earnings change, we find the total market reaction to recommendation changes does not differ depending on growth rate changes. This suggests that it is not the quantity of signals alone that matters. This is also consistent with our argument that earnings-based recommendation changes are conceptually different from growth rate-based recommendation changes because the former compared to the latter are characterized by hard information, greater verifiability, and shorter forecast horizons.

3.3. Multivariate Analysis of the Total Market Reaction to Recommendation Changes

Our univariate results may be explained by the characteristics of the recommendation changes or the characteristics of the firms being recommended. We explicitly account for these factors using multiple regression analysis. We begin with the firm characteristics in Table 1 (size, valuation, liquidity, institutional ownership, and analyst coverage). Many of these characteristics are proxies for the speed at which information is impounded into prices (we refer to them collectively as market efficiency proxies), so they may explain cross-sectional differences in the total market reaction. In general, stocks that are more liquid, have greater ownership by sophisticated investors, and are covered by more analysts contain more information. Thus recommendation changes should have a smaller impact on the prices of such firms since such recommendations contain less new information. Moreover, the new information they do contain should be impounded into prices faster so the drift should be smaller.

Several recommendation change characteristics may also explain the total market reaction. In particular, multiple recommendation changes by several analysts on the same day may be more informative than a single recommendation change by one analyst. Recommendation changes by analysts who work for prestigious brokers may also be more informative because analysts who work for prestigious brokers may have a better reputation than their peers for issuing more informative recommendations (see Fang and Yasuda (2009)).

Recommendations changes occurring around earnings announcements are more likely to be classified as earnings-based recommendations (see Table 1). However, the information content of such recommendation changes may be attributable to the news released by the firm rather than to the analyst who changes his recommendation and earnings estimate in response to this news. Similarly, if the initial market reaction is not complete and returns drift after recommendation changes, then the return drift from previous recommendation changes may leak into the current recommendation change. The same reasoning applies to earnings estimate changes. Thus we also account for recommendation changes and earnings estimate changes (during the previous week).

We run regressions of excess returns (measured as returns in excess of returns on benchmark portfolios matched on size, book-to-market, and momentum) on dummies for our recommendation change categories and control variables. We do not include a dummy for recommendation changes with no earnings change. We capture multiple recommendation changes, recommendation changes by prestigious brokers (defined in the Appendix), and earnings announcements using dummies. We capture previous recommendation changes using the number of upgrades minus the number of downgrades during the week ending two days before the recommendation day. We account for any remaining recent news using the raw return during the week ending two days before the recommendation day. We measure previous earnings estimate changes using the dollar change in the consensus earnings estimate during the week ending two days before the recommendation day divided by the closing price per share two days before the recommendation day. We also proxy for the extent to which information is impounded into prices across stocks ("market efficiency"). Ideally, we would control directly for market capitalization, turnover, institutional ownership, and analyst coverage. However, these variables are highly correlated so it is impractical to include them directly in our regressions. Principal components analysis allows us to reduce the dimensionality of our data, in our case, to the first principal component of these four variables, a linear combination of these variables, and we include this market efficiency proxy in our regressions.[6] Finally, we control for market-to-book and momentum,

[Insert Table 4 about here]

Table 4 presents the results. The difference in the initial market reaction to discount rate-based and earnings-based recommendation changes is economically and statistically significant after accounting for firm characteristics and recommendation change characteristics. For

[6] Our results are the same if we include each of our market efficiency proxies individually in our regressions.

example, compared to the initial market reaction for upgrades with no earnings change, the initial market reaction is 1.31 percentage points higher when earnings increase compared to 1.42 percentage points in the univariate analysis (Table 2). For upgrades with earnings decreased, the initial market reaction is 1.35 percentage points lower compared to 1.02 percentage points in the univariate analysis.

Our control variables have the expected effect on the initial market reaction to recommendation changes. The initial market reaction is significantly bigger (more positive for upgrades and more negative for downgrades) on days with multiple recommendation changes, when the recommendation change is issued by a prestigious broker, when the recommendation change occurs around an earnings announcement, for firms with higher returns during the previous week, for firms that are priced more efficiently, for firms with lower valuations, and for firms with greater momentum during the previous year.

The magnitude of the drift in the multivariate analysis (Table 4) is very similar to the magnitude of the drift in the univariate analysis (Table 2). For example, the average 21-day excess return for upgrades with earnings increased is 1.18 percentage points higher than for upgrades with no earnings change in the univariate analysis and 1.08 percentage points higher in the multivariate analysis. Our control variables generally have relatively little effect on the drift.

Overall, comparing the univariate and multivariate analyses, the initial market reaction and the drift are generally similar in magnitude, so our results are robust to accounting for firm characteristics and recommendation change characteristics.

3.4. Relative Earnings Estimate Changes

Thus far, we have examined the informativeness of recommendation changes with absolute earnings changes. However, we would expect the total market reaction to a relative earnings change to be bigger if the analyst provides new information to the market. Therefore, we examine recommendation changes with relative earnings changes defined as changes in analyst's earnings relative to the consensus.[7] For example, upgrades with earnings increased should have bigger total market reaction if the analyst's earnings are above rather than below the consensus. Specifically, we redo our results for Table 4 but we split earnings changes based on whether the analyst's earnings are above or below the consensus.

[Insert Table 5 about here]

Table 5 presents the results. The difference in the initial market reaction and the drift for upgrades with earnings increased to above versus below the consensus is economically and statistically significant (except for the drift for downgrades with earnings decreased). For example, compared upgrades with no earnings change, the incremental initial market reaction is 1.52 versus 1.00 percentage points higher when earnings increase to above versus below the consensus, respectively. In the univariate analysis (not tabulated), the corresponding figures are 1.57 and 1.17 percentage points, respectively. For downgrades, the incremental initial market reaction is 1.42 versus 3.30 percentage points higher when earnings decrease to above versus below the consensus, respectively. In the univariate analysis (not tabulated), the corresponding figures are 1.61 and 3.90 percentage points, respectively.

The patterns are similar for the drift. For example, compared to upgrades with no earnings change, the incremental drift 1.49 versus 0.47 percentage points higher when earnings increase to above versus below the consensus, respectively. For downgrades, the incremental drift is 0.31 versus 0.54 percentage points lower when earnings decrease to above versus below

[7] Gleason and Lee (2003) study earnings estimate changes and find that earnings estimate change with new information are associated with a bigger market reaction.

the consensus, respectively. These results are very similar to our results in the univariate analysis (not tabulated).

[Insert Figure 2 about here]

The patterns that we find during the month after the recommendation change are similar over shorter and longer horizons. Figure 2 presents the drift during the one, two, and three weeks and one, two, and three months after the recommendation change. The drift is greater for upgrades with earnings increased to above versus below the consensus over horizons of at least three months. The same is true for downgrades with earnings decreased to above versus below the consensus. Not surprisingly, much of the magnitude of the drift is within the first month after the recommendation change, but the drift continues in the same direction for months thereafter.

4. Robustness Tests

We perform numerous robustness tests of our results. Specifically, we redo our results in Table 5 controlling for contemporaneous earnings announcements, earnings surprises during the previous quarter, star analysts, particular analysts, the level of the previous recommendation, unclassifiable earnings changes, structural changes in the equity research industry, and clustering of observations. Table 6 and Table 7 present the results. Each regression corresponds to a different robustness test. For expositional simplicity, we only present results for recommendation changes with earnings increased or decreased to above or below the consensus (four dummies). If applicable, we also present results for new control variables that we use in Table 6 and Table 7 but not in Table 5. We discuss the details of each robustness test below.

[Insert Table 6 about here]

[Insert Table 7 about here]

First, we test whether our results are driven by recommendation changes that are contemporaneous with earnings announcements. While in our previous results we have already controlled for earnings announcements during the week ending on the recommendation day, we now exclude them altogether and redo our results in Table 5 without controlling for earnings announcements. The results in Table 6 and Table 7 are the same as in Table 5 except for the initial market reaction (in some cases, the coefficient estimates are smaller by roughly 50 basis points).

Second, we test whether our results are driven by the earnings surprise during the quarter before the recommendation change day. Perhaps analysts increase their earnings estimates after positive earnings surprises and decrease their earnings estimates after negative earnings surprises. If this is the case, then both the initial market reaction and the drift are actually caused by the earnings surprise before the recommendation change and not by the earnings change that accompanies the recommendation change. Moreover, the drift that we document is actually the post-earnings announcement drift. To test this explanation, we redo our results in Table 5 controlling for whether the earnings surprise at the earnings announcement during the previous quarter was positive and without controlling for earnings announcements. We measure earnings surprises as returns in excess of returns on benchmark portfolios matched on size, book-to-market, and momentum during the three days centered on the quarterly earnings announcement date in the previous quarter. To avoid overlaps between the two days during which we measure the initial market reaction to recommendation changes and the three days during which we measure the earnings surprise, we exclude earnings announcements that are contemporaneous with recommendation changes. The results in Table 6 and Table 7 are the same as in Table 5 except for the initial market reaction (in some cases, the coefficient estimates are smaller by roughly 50 basis points). Positive earnings surprises at the earnings announcement during the previous quarter are associated with a slightly lower initial market reaction and a slightly higher drift for both upgrades and downgrades.

Third, we test whether our results are driven by star analysts (e.g., Emery and Li (2009)). Perhaps star analyst's recommendation changes have a bigger total market reaction and star analysts issue disproportionately more earnings-based recommendation changes than discount rate-based recommendation changes. If this is this case, then the total market reaction to earnings-based versus discount rate-based recommendation changes is actually caused by star analysts. To test this explanation, we redo our results in Table 5 controlling for whether the analyst issuing the recommendation change is a star analyst according to Institutional Investor magazine. We do not control for star analysts in Table 5 because we do not have data on star analysts during the last fourteen months of our sample.[8] The results in Table 6 and Table 7 are the same as in Table 5. Moreover, star analysts do not seem to be associated with the total market reaction except for the initial market reaction to upgrades, which is 21.9 basis points higher for star analysts.

Fourth, we test whether our results are driven by particular analysts. Perhaps the explanation for star analysts is actually for particular analysts regardless of whether they are starts. To test this explanation, we redo our results in Table 5 with analyst fixed effects. We drop firm-date pairs with more than one analyst. The results in Table 6 and Table 7 are the same as in Table 5.

[8] In results that we do not tabulate, we find that the star analysts issue 11% of the recommendation changes in our sample. For our recommendation change categories, the proportion of star analysts is always within 1.5 percentage points of 11%. In other words, star analysts do not issue disproportionately more earnings-based recommendation changes than discount rate-based recommendation changes.

Fifth, we test whether our results change if we account for the level of the previous recommendation by the analyst (see Loh and Stulz (2009)). While it is not clear that the total market reaction to earnings-based versus discount rate-based recommendation changes should depend on the level of previous recommendation, the marginal effect of an upgrade may be smaller if the level of the previous recommendation is higher and bigger if the level of the previous recommendation is lower. To test this explanation, we redo our results in Table 5 controlling for the level of the previous recommendation by the analyst. We use the mean previous recommendation level for firm-date pairs with more than one analyst. The results in Table 6 and Table 7 are the same as in Table 5. A higher level of the previous recommendation is associated with a lower total market reaction except for the drift after upgrades in which case it is associated with a slightly higher drift.

Sixth, we test whether our results change if include in our sample recommendation changes with unclassifiable earnings changes (we cannot classify earnings changes because, for example, there is no previous earnings estimate). We do so by controlling for such recommendation changes with a dummy. The results in Table 6 and Table 7 are the same as in Table 5. The total market reaction is roughly the same for recommendation changes with unclassifiable earnings changes and recommendation changes with no earnings change (not tabulated). Recommendation changes with unclassifiable earnings changes are associated with a slightly higher total market reaction except for the initial market reaction to downgrades, which is 53.7 basis points lower.

Seventh, we test whether our results persist before and after two major structural changes in the equity research industry, namely, Regulation Fair Disclosure and Global Settlement. The literature suggests that the informativeness of recommendation changes has decreased after

Regulation Fair Disclosure in October 2000 (see Gintschel and Markov (2004)) and after the Global Settlement in April 2003 (see Kadan, Madureira, Wang, and Zach (2009)). Perhaps the relative informativeness of earnings-based versus discount rate-based recommendation changes has been eroded by these structural changes. To test this, we split our sample into three sub-periods, namely, January 1994 to September 2000, October 2000 to March 2003, and April 2003 to December 2007. We redo our results in Table 5 for each sub-period and we test whether our results obtain in each sub-period. Our results (not tabulated) still consistently show that earnings-based recommendation changes are associated with a bigger total market reaction than discount rate-based recommendation changes.

Finally, we examine how our results are affected by clustering of firms on the same dates within recommendation change categories. To remove such clustering, we collapse observations to the date level by computing mean excess returns (measured as returns in excess of returns on benchmark portfolios matched on size, book-to-market, and momentum) across firms in a given recommendation change category for a given date. We then redo our results in Table 2. The results (not tabulated) show that the corresponding excess returns in the two tables are roughly the same, clustering of firms on the same dates within recommendation change categories does not change our results.

5. Trading Strategy

Our results for the post-recommendation drift naturally suggest a potentially profitable trading strategy. An investor may be able to earn excess returns by buying the upgrades with the highest investment value and selling the downgrades with the lowest investment value. In particular, the investor could buy upgrades with earnings increased and sell downgrades with earnings decreased. We compare this strategy to a strategy of buy all upgrades and selling all downgrades.

Our objective is to form portfolios for two trading strategies based on the recommendation change categories for our sample of recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates. In the first strategy (the "unconditional strategy" for simplicity of reference), we buy all upgrades and sell all downgrades. In the second strategy (the " conditional strategy"), we buy all upgrades with earnings increased and sell all downgrades with earnings decreased. Broadly speaking, we form long minus short portfolios each day based on signals from the previous day for each trading day between 1994 and 2007, and we use these portfolios to compute summary statistics (e.g., mean raw return, four-factor alpha, etc.).

We begin with a portfolio holding period that is one of the holding periods we have examined thus far, i.e., 1, 5, 10, 15, 21, 42, and 63 trading days. Let the portfolio holding period be S. Let t denote the trading day in during the period from 1994 to 2007, t = 1, 2, …, 3,525. We begin on the first trading day in 1994 for which we have a trading signal (e.g., any upgrade) from the previous day (t = 0). We form a portfolio (be it long, short, or long minus short) at the open of the first day of the holding period and hold portfolios until the last day of the first holding period (t = S) at which point we close out the portfolio. At the open of the following day (t = S+1), we once again form portfolios based on signals from the previous day (t = S) and hold them until the last day of the second holding period (t = 2S) and so on (while t ≤ 3,525/S). None of these daily portfolio returns are overlapping regardless of whether S = 1 or S > 1.

If we have N signals on which to trade (e.g., more than one firm is upgraded), we invest 1/N of the portfolio in each firm on the first day of the holding period. The return on the portfolio on the first holding period day (t = 1, S+1, 2S+1, …) is $(1/N)\sum_{i=1}^{N} R_t^i$ where R_t^i is the return on stock i that day. The return on the portfolio on every other day is simply $\left(V_t / V_{t-1}\right) - 1$ where V_t is the value of portfolio on day t. We stress that on the first day in the portfolio holding period, the return is the open-to-close return, and on all other days in the portfolio holding period, the return is the standard close-to-close return. Thus for the first day in the portfolio holding period, even if the recommendation change comes after the close of the previous day, we trade on it at the open of the first day in the holding period.

In doing so, we create a single time-series of daily returns from a portfolio created from trading on some signal (e.g., buy all upgrades) every day and holding the same portfolio for S days before trading and holding again. For any portfolio formation date, we only form portfolios when we have at least one stock in the long portfolio and at least one stock in the short portfolio. We construct our long minus short portfolios as zero-investment portfolios.

From this single time-series of daily portfolio returns, we compute the mean and standard deviation of the raw daily returns. We also compute the mean risk-adjusted return by regressing the daily portfolio returns, R_t, on the daily returns of the standard four asset pricing factors (market risk premium, size, book-to-market, and momentum). The regression equation is $R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_t$ for t = 1, 2, … , 3,525. We thus compute a four-factor alpha, a standard error, and a t-statistic. We compute daily returns to allow comparability across portfolio holding periods, but we also compute holding period returns.

Were we to stop here, we would be discarding trading signal from all $\left(S-1\right)/S$ days that are not portfolio formation days. To avoid discarding these signals, we repeat the preceding computations for each of the first S trading days in 1994 (t = 1, 2, … , S). We thus have S means and standard deviations of raw daily returns and four-factor alphas and their t-statistics. For example, for the 21-day holding period, we repeat this procedure 21 times, first, starting on day t=1, second, starting on day t=2, and so on, until day t=21. For expositional simplicity, rather than reporting all S of these four summary statistics for all S (S $\in$ {1, 5, 10, 15, 21, 42, 63}), we report the means of each of these four summary statistics for all S.

[Insert Table 8 about here]

[Insert Table 9 about here]

Table 8 and Table 9 present the raw returns results for the unconditional and conditional strategies, respectively.[9] Portfolios are formed almost every trading day during 1994-2007 (3,525 trading days) for the unconditional compared to 95 percent of days for the conditional strategy. There is a mean of roughly 35 firms in each portfolio (firms long plus firms short) for the unconditional strategy and roughly 12 firms for the conditional strategy. This is consistent with the results in Table 1 that show that roughly 32 percent of upgrades have earnings increased and roughly 36 percent of downgrades have earnings decreased. The difference in the number of daily returns and the number of firms arises because there are fewer conditional signals (all upgrades and all downgrades) than conditional signals (upgrades with earnings increased and downgrades with earnings decreased) upon which we can trade.

Several patterns emerge when we examine across various holding periods the raw returns of the unconditional and conditional strategies. First, mean raw daily returns are almost always positive for the long portfolios for both strategies and negative for the short portfolios of both strategies. Second, raw returns for long minus short portfolios are always positive for both strategies. Third, the magnitudes of the mean raw daily returns for all three portfolios (long, short, and long minus short) are all decreasing over time but the decrease is much greater for the short

[9] If, in Table 8, we also include recommendation changes with unclassifiable earnings changes, our results are the same. Moreover, if we exclude firms with a stock price of less than five dollars and firms with market capitalization below the twentieth percentile of the market capitalization of NYSE firms, our results are also the same. Therefore, our results are not driven by illiquid stocks.

portfolios for both strategies. Thus the profitability of the long minus short portfolios does not appear to be result of short sales constraints. Fourth, the magnitude of the raw returns for the conditional strategy is roughly two-thirds bigger than the magnitude of raw returns for the unconditional strategy.

To give two examples of the magnitudes of raw returns, ten-day holding period raw returns for the long, short, and long minus short portfolios are 1.07%, -0.56%, and 1.63%, respectively for the unconditional strategy and 1.69%, -0.98%, and 2.68% for the conditional strategy. For the 21-day holding period, the corresponding figures are 1.74%, -0.49%, and 2.22% for the unconditional strategy and 2.81%, -1.04%, and 3.83% for the conditional strategy. On an annual basis, for the ten-day holding period, the long minus short portfolio strategy translates into an annual return of 41.1% and 67.5% for the unconditional and conditional strategies, respectively. For the 21-day holding period, the corresponding figures are 26.7% and 45.9%.

Table 8 and Table 9 also present the risk-adjusted returns results for the unconditional and conditional strategies, respectively. Simply put, the only difference for the long and short portfolios between the raw returns and the four-factor alphas is that the daily four-factor alphas are one to four basis points lower than the daily raw returns. For the long minus short portfolios, the raw returns and four-factor alphas are very similar, so for neither strategy is profitability substantially decreased by the four standard asset pricing factors. Moreover, for both strategies, the four-factor alphas are very similar to the corresponding figures in Table 2.[10] Furthermore, the four-factor alphas are still driven mainly by the positive drift of the upgrades rather than the negative drift of the downgrades but the difference is not as pronounced for the four-factor alphas as it is for the raw returns. Finally, we assess the significance of the four-factor alphas by

[10] To compare excess returns and four-factor alphas, the excess return should (and does) roughly equal the four-factor alpha times the length of the portfolio holding period.

averaging the corresponding t-statistics and reporting how many are statistically significant (e.g., for the 21-day holding period, we average 21 t-statistics). For all holding periods of 21 days or less, for all long minus short portfolios, all t-statistics are statistically significant.

In summary, three main results emerge from Table 8 and Table 9. First, the unconditional and conditional strategies are both significantly profitable and likely to be greater than transactions costs incurred by institutional investors. Second, each strategy is similarly profitable whether profitability is measured using raw returns or risk-adjusted returns. Third, the conditional strategy is roughly two-thirds more profitable than the unconditional strategy for all holding periods for up to three months after the recommendation change.

Another important consideration is how the profitability of our trading strategies varies over time during our sample period of 1994-2007. To this end, we examine the time-series variation in the drift during our sample period. We implement the same trading strategies as in Table 8 and Table 9 for a portfolio formation interval and a portfolio holding period length of ten days. However, rather than computing a single mean of the raw daily returns during our sample period, we compute the mean each month.

[Insert Figure 3 about here]

Figure 3 present the results. First, while the drift is more profitable for the conditional strategy than for the unconditional strategy, it is also somewhat more risky. The unconditional strategy earns negative returns during only 11 out of 168 months during our sample period whereas the conditional strategy earns negative returns during 15 months. The months with the most negative returns are concentrated after the technology boom (during 2001-2002). Second, the profitability of the drift for both strategies is similar at the end of our sample period compared to the beginning. We can clearly conclude that our results have not disappeared in recent years.

Finally, we also examine a trading strategy based on recommendation changes with relative earnings estimate changes. Table 5 shows that upgrades with earnings increased to above the consensus and downgrades with earnings decreased to below the consensus have a bigger total market reaction than upgrades with earnings increased and downgrades with earnings decreased, respectively. Thus we implement a trading strategy consisting of buying upgrades with earnings increased above the consensus and selling downgrades with earnings decreased to below the consensus. We find that the results are similar but of greater magnitude than the results in Table 9. Mean returns are roughly ten percent bigger but the standard deviation of returns is also roughly ten percent bigger. For example, for the 21-day holding period, raw returns for the long minus short portfolio are 4.29% compared to 3.83% in Table 9. In summary, a trading strategy based on recommendation changes with relative earnings estimate changes is somewhat more profitable but also more risky.

6. Conclusion

When an analyst changes his recommendation of a stock, he indicates to the market that his valuation differs from the market's valuation. Within the framework of the standard discounted cash flow model of valuation, the difference in valuation between the analyst and the market must come from differences in estimates of cash flows, discount rates, and/or growth rates. In this paper, we study the extent to which cash flow estimates, discount rate estimates, and growth rate estimates drive the informativeness of analysts' recommendations as measured by the initial market reaction to recommendation changes and the post-recommendation drift.

Why should earnings-based recommendation changes be more informative than discount rate-based and growth rate-based recommendation changes? We argue that earnings-based recommendations changes are more informative because such recommendations are characterized by hard information, greater verifiability, and shorter forecast horizons. Consequently, they are less subject to analysts' cognitive and incentive biases.

We predict that earnings-based recommendation changes should be more informative than discount rate-based recommendation changes. We find evidence consistent with this prediction. Both the initial market reaction and the drift are significantly bigger for earnings-based recommendation changes than discount rate-based recommendation changes. The economically and statistically significant drift suggests that the full information content of both earnings-based and discount rate-based recommendation changes is not immediately impounded into prices.

In addition to the absolute earnings estimate changes that we examined before, we examine recommendation changes with relative earnings estimate changes, which we define as changes in analysts' earnings relative to the consensus. We find that the total market reaction to a relative earnings change is bigger if the analyst provides new information to the market. We also perform numerous robustness tests of our results. We find that our results are robust to controlling for firm characteristics, recommendation change characteristics, contemporaneous earnings announcements, earnings surprises during the previous quarter, star analysts, particular analysts, the level of previous recommendation, and unclassifiable earnings changes.

We also examine growth rate changes, and we find that the total market reaction is bigger for earnings-based recommendation changes than for growth rate-based recommendation changes. Moreover, the total market reaction is similar for growth rate-based recommendation changes and discount rate-based recommendation changes. These results are consistent with growth rate-based recommendation changes being characterized by soft information, less verifiability, and longer forecast horizons like discount rate-based recommendation changes. However, they are inconsistent with the double signal interpretation of our results, which predicts that the total market total market reaction should be similar for earnings-based recommendation changes and growth rate-based recommendation changes because, in both cases, the analyst sends two explicit signals rather than one.

Our results for the post-recommendation drift naturally suggest a potentially profitable trading strategy. In particular, we test whether an investor can earn excess returns by implementing two trading strategies, namely, (1) buying all upgrades and selling all downgrades and (2) buying upgrades with earnings increased and selling downgrades with earnings decreased. We find that the alphas from these strategies are very economically and statistically significant, and the trading profits from these strategies persist throughout our sample period.

Finally, a recent body of the asset pricing literature suggests that cash flow information, rather than discount rate information, is the main determinant of changes in asset prices (e.g., Cohen, Polk, and Vuolteenaho (2003a), Chen and Zhao (2008), Campbell, Polk, and Vuolteenaho (2009), and Cohen, Polk, and Vuolteenaho (2003b)). Cohen, Polk, and Vuolteenaho (2003a) further suggest that changes in cash flows typically explain roughly 75 percent of the variation in prices and returns. Within the context of the literature on equity research analysts, we provide evidence that even over short horizons (days and weeks rather than years) changes in cash flows explains substantially more of returns than do changes in discount rates.

Appendix

A.1. Sample construction

We construct our sample as follows. We obtain investment recommendations data and earnings estimates data from I/B/E/S. We select our sample starting with all I/B/E/S recommendations from November 1993 to December 2007 (478,261 firm-date-analyst triples). We keep only observations for which we know the identity of the analyst (leaves 465,418 firm-date-analyst triples). We keep only observation that we can match to CRSP using CUSIP-date pairs (leaves 451,290 firm-date-analyst triples). We drop recommendations made by analysts employed by Lehman Brothers because this broker cannot be found among I/B/E/S earnings estimates (leaves 438,707 firm-date-analyst triples). We drop recommendations without a previous recommendation, i.e., where recommendation changes are undefined (leaves 281,431 firm-date-analyst triples), as well as reiterations (leaves 218,466 firm-date-analyst triples).[12] We drop recommendations associated with the Global Settlement (leaves 213,034 firm-date-analyst triples).[13]

We collapse firm-date-analyst triples to firm-date pairs (leaves 197,852 firm-date pairs) as explained below. In the process, we also create recommendation change categories at the firm-date level. We drop observations for which there is more than one recommendation and at least one recommendation is an upgrade and at least one is a downgrade, i.e., there are conflicting

[12] To be conservative, we do not exclude what may be stale previous recommendations (clearly, our recommendations themselves are not stale). Roughly 75% and 95% of our observations have a previous recommendation within one year and two years before the recommendation, respectively. If we only retain observations with previous recommendations within on year before the recommendation, our results are the same.

[13] On April 23, 2003, the SEC, NASD, NYSE, and ten of the biggest U.S. investment banks reached the Global Settlement, an enforcement agreement that sought to address conflicts of interest in the investment banking industry. Many brokers changed their rating system, typically in anticipation of the Global Settlement and from a five-point scale to a three-point scale. Consequently, around the time of the Global Settlement, I/B/E/S recommendations include recommendations that reflect changes in rating systems but otherwise contain no information. Such recommendations appear as recommendations made on a given day for many or all of the stocks covered by a given broker.

recommendations (leaves 195,260 firm-date pairs). We keep observations for publicly traded U.S. operating firms between 1994 and 2007, where publicly traded U.S. operating firms are defined as firms with CRSP share codes of 10 or 11 (leaves 174,586 firm-date pairs). We drop firms that are not publicly traded for at least one year at the time of the recommendation change because we measure event-time returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles, (leaves 164,219 firm-date pairs). We drop firms with only one analyst covering them because we study not only absolute recommendation changes but also relative recommendation changes and relative recommendation changes are not defined for firms covered by only one analyst (leaves 160,907 firm-date pairs). Finally, we drop recommendation changes with earnings estimate changes that are not classifiable as an earnings increase, no change, or decrease[14] (leaves 123,250 firm-date pairs). The sample comprises 7,040 unique firms and 3,517 unique trading dates (compared to 3,525 unique trading dates between 1994 and 2007).

A.2. Construction of recommendation change categories

We construct our recommendation change categories as follows. This construction is a result of collapsing firm-date-analyst triples to firm-date pairs. Most firm-date-analyst triples (97 percent) have just one analyst, so for most firm-date pairs, the following applies to a single analyst. By construction, all analysts for a given firm-date pair have the same recommendation change.

We first define earnings changes at the firm-date-analyst level. We match recommendations and earnings estimates using unique firm-date-analyst identifiers in I/B/E/S. We consider a recommendation change to have an earnings estimate change if we find a match

[14] Roughly 85 percent of these dropped recommendation changes are not associated with a previous earnings estimate.

by firm-date-analyst triples in both the recommendations and earnings estimates databases.[15] We define earnings estimate change for a given firm-date-analyst triple for a given fiscal year end date as the earnings estimate on the day of the recommendation change minus the most recent earnings estimate. We do so for both the first and second fiscal year end after the date of recommendation change ("FY1" and "FY2", respectively). Next, for each firm-date pair, we count the number of recommendation changes, the number of earnings estimates increases, and the number of earnings estimates decreases. We define an "earnings estimate increase" as a strict (>0) increase in the FY1 earnings estimate and a weak increase in the FY2 earnings estimate (≥0) or vice versa. If only one of the FY1 and FY2 earnings estimate changes is non-missing, we define "earnings estimate increase" based on the non-missing earnings estimate change. We define an "earnings estimate decrease" analogously. We define "no earnings estimate change" as an absence of both current FY1 and FY2 earnings estimates on the day of the recommendation change but a presence of previous earnings estimates for both FY1 and FY2.

We then define earnings changes at the firm-date level. We define an "earnings estimate increase" as all analysts making a recommendation change increasing their earnings estimates. We define an "earnings estimate decrease" analogously. We define "no earnings estimate change" as all analysts making a recommendation change not changing their earnings estimate or at least one analyst increasing his earnings estimate and at least one decreasing his earnings estimate.

Next, we define earnings estimate changes relative to the earnings estimates consensus at the firm-date-analyst level. We only do so for FY1 earnings estimates because we cannot compute the consensus for FY2 earnings estimates because of insufficient FY2 earnings

[15] If we extend the window for potential matches to the fifteen calendar days centered on the recommendation date, we capture only an inconsequential number of additional matches. Not surprisingly, if we extend the window, our results are the same.

estimates data. We define an "earnings estimate increased to above the consensus" as a strict increase in the FY1 earnings estimate for which the earnings estimate is above the consensus. We define an "earnings estimate increased to below the consensus" as a strict increase in the FY1 earnings estimate for which the earnings estimate is below the consensus. We define an "earnings estimate decreased to above the consensus" and an "earnings estimate decreased to below the consensus" analogously. At the firm-date level, we then define earnings estimate increased/decreased to above/below the consensus based on whether all analysts making a recommendation change also change their earnings estimates relative to the consensus in the same way.

We construct our long-term earnings growth rate estimate changes similarly to our short-term earnings estimate changes with two exceptions. First, there is exactly none or one growth rate estimate for each firm-date-analyst triples rather than earnings estimates for fiscal years one and two after the recommendation change. Therefore, defining growth rate estimate increases, no changes, and decreases is straightforward. Second, many firms do not have a single previous growth rate estimate during the five years before the recommendation change. Therefore, for these firms, the growth rate estimate change is undefined.

We match recommendations and long-term earnings growth rate estimates using unique firm-date-analyst identifiers in I/B/E/S. We consider a recommendation change to have a growth rate estimate change if we find a match by firm-date-analyst triples in both the recommendations and growth rate estimates databases.[16] We define growth rate estimate change for a given firm-date-analyst triple for a given fiscal year end date as the growth rate estimate on the day of the recommendation change minus the most recent growth rate estimate.

[16] If we extend the window for potential matches to the fifteen calendar days centered on the recommendation date, we capture only an inconsequential number of additional matches. Not surprisingly, if we extend the window, our results are the same.

We then define growth rate changes at the firm-date level. We define a "growth rate estimate increase" as all analysts making a recommendation change increasing their growth rate estimates. We define a "growth rate estimate decrease" analogously. We define "no growth rate estimate change" as all analysts making a recommendation change not changing their growth rate estimate or at least one analyst increasing his growth rate estimate and at least one decreasing his growth rate estimate.

A.3. Computation of analyst coverage and consensus estimates

We compute analyst coverage and the consensus estimate for each firm as follows. We begin with the I/B/E/S earnings estimates detail file, and, each calendar day during our sample period, which we call the "summary date" (e.g., June 30, 1994), we keep all estimates issued during the year ending on the summary date (e.g., July 1, 1993 to June 30, 1994). We further keep only estimates for the first fiscal year end date during the year after the summary date (e.g., December 31, 1994). If there is more than one estimate per broker, we keep the estimate closest to but before the summary date. We use the resulting estimates to compute analyst coverage (the number of estimates) and the consensus earnings estimate (the mean estimate).

A.4. List of prestigious brokers

The top fifteen brokers from Institutional Investor magazine are as follows (applicable periods are in parentheses): Banc of America Securities (November 1999 to October 2008), Bear, Stearns & Co. (November 1993 through October 2008), Citi/Salomon/Smith Barney (November 1993 to October 2008), Credit Suisse/First Boston (November 1993 to October 2008), Deutsche Bank Securities/Deutsche Banc Alex Brown/Deutsche Morgan Grenfell (November 1996 to October 2008), Donaldson, Lufkin & Jenrette (November 1993 to October 2001), Goldman Sachs (November 1993 to October 2008), J. P. Morgan (November 1998 to October 2008), Kidder Peabody (November 1993 to October 1995), Lehman Brothers (November 1993 to October 2008), Morgan Stanley/Morgan Stanley Dean Witter (November 1993 to October 2008), Merrill Lynch (November 1993 to October 2008), Prudential Equity Group/Bache (November 1993 to October 2007), Sanford C. Bernstein (November 1993 to October 2008), and Schroder/Wertheim/Schroder Wertheim/Wertheim Schroder (November 1993 to October 2000), and UBS/Paine Webber (November 1993 to October 2008).

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Table 1
Descriptive Statistics

This table presents descriptive statistics. The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates consisting of 7,040 firms and 3,517 trading dates. A recommendation change is around an earnings announcement if there is an earnings announcement during the week ending on the recommendation day. Market capitalization, book-to-market, turnover, and institutional ownership are measured in percentiles.

			Means				
Recommendation change category	Percent of upgrades or downgrades	Percent around earnings announce-ments	Market cap. (percent-tiles)	B/M (percent-tiles)	Turnover (percent-tiles)	Inst. ownership (percent-tiles)	Analyst coverage (number of analysts)
All upgrades (56,341 observations)	100.0	24.6	81.0	40.2	70.7	75.2	15.5
Upgrades with earnings increased	32.5	37.1	81.0	39.2	70.9	75.2	15.4
Upgrades with no earnings change	53.5	16.0	81.6	39.9	70.7	75.5	15.7
Upgrades with earnings decreased	14.0	28.3	78.7	43.7	70.7	74.4	14.8
All downgrades (66,909 observations)	100.0	22.9	78.7	40.7	70.8	74.1	14.6
Downgrades with earnings increased	10.3	36.0	81.1	35.5	71.1	75.3	15.2
Downgrades with no earnings change	53.6	15.0	80.1	39.5	70.4	74.4	15.0
Downgrades with earnings decreased	36.1	30.9	75.9	44.1	71.3	73.3	13.8
Standard deviations			18.2	25.7	21.9	18.9	9.6

Table 2
Stock Returns by Recommendation Change Category in Event-Time

This table presents mean excess returns by recommendation change category in event-time. Returns are presented during various event windows relative to the recommendation day. The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Recommendation change category	Mean excess returns							
	[-22,-2]	[-1,0]	[+1,+5]	[+1,+10]	[+1,+15]	[+1,+21]	[+1,+42]	[+1,+63]
All upgrades	-0.23***	2.45***	0.43***	0.67***	0.85***	0.99***	1.16***	1.36***
Upgrades with earnings increased	2.16***	3.55***	0.77***	1.15***	1.46***	1.83***	2.07***	2.48***
Upgrades with no earnings change	-1.02***	2.13***	0.33***	0.51***	0.65***	0.65***	0.78***	0.93***
Upgrades with earnings decreased	-2.72***	1.11***	0.04	0.15	0.18	0.36***	0.52***	0.40*
All downgrades	-0.31***	-2.81***	-0.53***	-0.67***	-0.76***	-0.85***	-1.09***	-1.21***
Downgrades with earnings increased	4.00***	-0.35***	0.10	0.13	0.20	0.23	0.09	0.43
Downgrades with no earnings change	1.43***	-1.72***	-0.45***	-0.59***	-0.69***	-0.79***	-1.03***	-1.20***
Downgrades with earnings decreased	-4.13***	-5.11***	-0.83***	-1.02***	-1.15***	-1.24***	-1.52***	-1.69***

Table 3
Stock Returns by Recommendation Change Category and Earnings Growth Rate Change Category in Event-Time

This table presents mean excess returns by recommendation change category and earnings growth rate change category in event-time. Returns are presented during the [-1,0] and [+1,+21] event windows relative to the recommendation day. The sample comprises recommendation changes with between 1994 and 2007 corresponding to 76,714 firm-dates. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Obs.	Excess returns during [-1,0]			Excess returns during [+1,+21]		
Upgrades with earnings increased and							
growth rate increased (A)	1,102	3.91	(A)-(B)	0.10	1.61	(A)-(B)	-0.22
no growth rate change (B)	9,868	3.81	(B)-(C)	-0.17	1.83	(B)-(C)	-0.14
and growth rate decreased (C)	456	3.98	(A)-(C)	-0.07	1.97	(A)-(C)	-0.36
Upgrades with no earnings change and							
growth rate increased (A)	516	2.21	(A)-(B)	-0.02	0.50	(A)-(B)	-0.26
no growth rate change (B)	17,705	2.23	(B)-(C)	0.57*	0.76	(B)-(C)	0.41
and growth rate decreased (C)	336	1.66	(A)-(C)	0.55	0.35	(A)-(C)	0.15
Upgrades with earnings decreased and							
growth rate increased (A)	263	1.18	(A)-(B)	0.02	0.87	(A)-(B)	0.35
no growth rate change (B)	4,076	1.16	(B)-(C)	-0.08	0.52	(B)-(C)	1.56**
and growth rate decreased (C)	308	1.24	(A)-(C)	-0.06	-1.04	(A)-(C)	1.91*
Downgrades with earnings increased and							
growth rate increased (A)	228	-0.50	(A)-(B)	-0.25	0.24	(A)-(B)	-0.10
no growth rate change (B)	3,489	-0.25	(B)-(C)	0.01	0.34	(B)-(C)	1.24**
and growth rate decreased (C)	259	-0.26	(A)-(C)	-0.24	-0.90	(A)-(C)	1.14
Downgrades with no earnings change and							
growth rate increased (A)	298	-0.51	(A)-(B)	1.26***	-1.51	(A)-(B)	-0.86
no growth rate change (B)	21,318	-1.77	(B)-(C)	0.44	-0.65	(B)-(C)	-0.06
and growth rate decreased (C)	564	-2.21	(A)-(C)	1.70***	-0.59	(A)-(C)	-0.92
Downgrades with earnings decreased and							
growth rate increased (A)	315	-3.22	(A)-(B)	2.28***	0.34	(A)-(B)	1.56**
no growth rate change (B)	13,406	-5.50	(B)-(C)	1.75***	-1.22	(B)-(C)	-0.76**
and growth rate decreased (C)	1,993	-7.25	(A)-(C)	4.03***	-0.46	(A)-(C)	0.80

Table 4
Stock Returns for Recommendation Changes and Earnings Changes
Controlling for Firm and Recommendation Characteristics in Event-Time

This table presents regressions of excess returns on recommendation change category dummies and control variables in event-time. Returns are presented during various event windows relative to the recommendation day. The sample comprises upgrades between 1994 and 2007 corresponding to 123,250 firm-dates. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. There is no dummy for recommendation changes with no earnings change. The recommendation change by a prestigious broker dummy equals one if all recommendation changes on a given firm-date are made by analysts at prestigious brokers. Brokers are classified as prestigious if they are among the top fifteen brokers in equity research analysis according to Institutional Investor magazine. The earnings announcement dummy equals one if there is a quarterly earnings announcement during the week ending on the recommendation day. Percent change in the consensus earnings estimate during the previous week is the dollar change in the consensus earnings estimate during the week ending two days before the recommendation day divided by the closing price per share two days before the recommendation day. Percent raw return during the previous week is the raw return during the week ending two days before the recommendation day. The market efficiency proxy is the first principal component of market capitalization, turnover, institutional ownership, and analyst coverage. Market capitalization, turnover, institutional ownership, book-to-market, and momentum are measured in percentiles. Momentum is measured during the first eleven months of the year ending the month before the recommendation day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Below each coefficient estimate is its corresponding robust t-statistic in parentheses.

	Excess returns for upgrades during		Excess returns for downgrades during	
	[-1,0]	[+1,+21]	[-1,0]	[+1,+21]
Earnings increased dummy	1.312***	1.083***	1.480***	0.889***
	(20.623)	(9.792)	(14.884)	(5.428)
Earnings decreased dummy	-1.348***	-0.403**	-2.853***	-0.488***
	(-14.263)	(-2.568)	(-33.026)	(-4.134)
Multiple recommendation changes on the same day dummy	4.190***	0.956***	-7.246***	-0.334
	(14.869)	(2.868)	(-21.887)	(-1.157)
Recommendation change by a prestigious broker dummy	0.829***	0.011	-0.839***	0.018
	(13.642)	(0.108)	(-10.399)	(0.164)
Earnings announcement dummy	0.890***	0.441***	-1.106***	0.480***
	(11.400)	(3.724)	(-11.653)	(3.904)
Number of upgrades minus number of downgrades during the previous week dummy	-0.143	0.434*	-0.293*	-0.037
	(-0.946)	(1.875)	(-1.826)	(-0.134)
Percent change in the consensus earnings estimate during the previous week	-0.529	0.068	-0.710***	0.334
	(-1.548)	(0.149)	(-2.978)	(0.822)
Percent raw return during the previous week	-0.036***	-0.007	0.031***	-0.015*
	(-7.089)	(-0.807)	(5.496)	(-1.868)
Market efficiency proxy	-0.543***	-0.334***	0.423***	0.255***
	(-21.649)	(-8.275)	(14.032)	(6.630)
Book-to-market	-0.511***	-0.271	2.559***	-0.582**
	(-3.920)	(-1.235)	(16.217)	(-2.499)
Momentum	-2.568***	0.045	0.938***	-0.071
	(-18.802)	(0.196)	(5.832)	(-0.299)
Constant	3.290***	0.675***	-2.691***	-0.557***
	(29.187)	(3.441)	(-19.876)	(-2.751)
Observations	55,520	55,520	65,690	65,690
Adjusted R^2	0.049	0.004	0.070	0.002

Table 5
Stock Returns for Relative Recommendation Changes and Relative Earnings Changes Controlling for Firm and Recommendation Characteristics in Event-Time

This table presents the same regressions as Table 4 except that earnings estimate changes are broken out by the location of the analyst's earnings compared to the consensus.

	Excess returns for upgrades during		Excess returns for downgrades during	
	[-1,0]	[+1,+21]	[-1,0]	[+1,+21]
Earnings increased to above the consensus dummy	1.522***	1.491***	1.825***	1.089***
	(20.570)	(11.456)	(16.124)	(5.571)
Earnings increased to below the consensus dummy	0.996***	0.469***	0.912***	0.550**
	(11.182)	(3.114)	(5.686)	(2.119)
Earnings decreased to above the consensus dummy	-0.857***	-0.045	-1.424***	-0.310*
	(-6.101)	(-0.175)	(-12.020)	(-1.712)
Earnings decreased to below the consensus dummy	-1.571***	-0.566***	-3.300***	-0.544***
	(-13.515)	(-3.083)	(-34.004)	(-4.158)
Multiple recommendation changes on the same day dummy	4.181***	0.937***	-7.147***	-0.322
	(14.844)	(2.818)	(-21.618)	(-1.116)
Recommendation change by a prestigious broker dummy	0.837***	0.024	-0.840***	0.019
	(13.777)	(0.228)	(-10.430)	(0.171)
Earnings announcement dummy	0.862***	0.379***	-1.081***	0.475***
	(10.999)	(3.179)	(-11.386)	(3.852)
Number of upgrades minus number of downgrades during the previous week dummy	-0.146	0.432*	-0.279*	-0.035
	(-0.963)	(1.868)	(-1.739)	(-0.128)
Percent change in the consensus earnings estimate during the previous week	-0.583*	-0.004	-0.793***	0.320
	(-1.699)	(-0.008)	(-3.320)	(0.785)
Percent raw return during the previous week	-0.037***	-0.008	0.029***	-0.016*
	(-7.165)	(-0.884)	(5.223)	(-1.894)
Market efficiency proxy	-0.543***	-0.334***	0.410***	0.253***
	(-21.686)	(-8.293)	(13.580)	(6.586)
Book-to-market	-0.508***	-0.264	2.544***	-0.584**
	(-3.894)	(-1.205)	(16.147)	(-2.510)
Momentum	-2.641***	-0.073	0.785***	-0.103
	(-19.292)	(-0.315)	(4.865)	(-0.433)
Constant	3.329***	0.741***	-2.610***	-0.538***
	(29.541)	(3.770)	(-19.254)	(-2.656)
Observations	55,520	55,520	65,690	65,690
Adjusted R^2	0.050	0.005	0.072	0.002

Table 6
Robustness Tests for Recommendation Upgrades

This table presents the same regressions as Table 5 but for recommendation upgrades only. Compared to Table 5, each column changes the sample and/or control variables as follows. In column (1), recommendation changes with earnings announcements during the previous week are excluded and the earnings announcement dummy is excluded. In column (2), the same regression is run as in column (1) but there is a dummy for whether the earnings surprise at the earnings announcement during the previous quarter was positive. In column (3), there is a dummy for whether the analyst issuing the recommendation change is a star analyst according to Institutional Investor magazine. In column (4), recommendation changes with more than one analyst per firm-date pair are dropped and analyst fixed effects are included. In column (5), there is a control for the level of the previous recommendation by the analyst. In column (6), there is a dummy for recommendation changes with unclassifiable earnings changes. Only selected regression results are tabulated.

Panel A: Initial Market Reaction						
	Excess returns during [-1,0]					
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings increased to above the consensus	0.926*** (11.751)	0.919*** (11.446)	1.468*** (18.775)	1.328*** (15.154)	1.536*** (20.750)	1.498*** (20.358)
Earnings increased to below the consensus	0.833*** (8.783)	0.847*** (8.784)	1.033*** (10.684)	0.781*** (7.915)	1.034*** (11.579)	0.968*** (10.863)
Earnings decreased to above the consensus	-0.707*** (-5.095)	-0.741*** (-5.180)	-0.874*** (-5.747)	-0.638*** (-4.088)	-0.867*** (-6.175)	-0.860*** (-6.113)
Earnings decreased to below the consensus	-1.141*** (-9.011)	-1.125*** (-8.729)	-1.471*** (-11.960)	-1.498*** (-11.703)	-1.568*** (-13.511)	-1.590*** (-13.750)
Positive earnings surprise dummy		-0.329*** (-5.210)				
Star analyst dummy			0.219** (2.146)			
Level of the previous recommendation					-0.355*** (-8.922)	
Unclassifiable earnings change dummy						0.123* (1.739)
Control variables in Table 5 (not tabulated)	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Drift						
	Excess returns during [+1,+21]					
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings increased to above the consensus	1.567*** (9.787)	1.528*** (9.185)	1.498*** (10.770)	1.461*** (9.479)	1.504*** (11.555)	1.511*** (11.703)
Earnings increased to below the consensus	0.555*** (3.230)	0.548*** (3.112)	0.485*** (2.965)	0.504*** (2.878)	0.505*** (3.349)	0.472*** (3.134)
Earnings decreased to above the consensus	-0.051 (-0.180)	-0.007 (-0.024)	0.023 (0.082)	0.156 (0.537)	-0.055 (-0.213)	-0.050 (-0.194)
Earnings decreased to below the consensus	-0.496** (-2.303)	-0.556** (-2.502)	-0.500** (-2.538)	-0.528** (-2.522)	-0.564*** (-3.069)	-0.571*** (-3.122)
Positive earnings surprise dummy		0.228* (1.918)				
Star analyst dummy			0.131 (0.785)			
Level of the previous recommendation					-0.341*** (-4.913)	
Unclassifiable earnings change dummy						0.266** (2.164)
Control variables in Table 5 (not tabulated)	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Robustness Tests for Recommendation Downgrades

This table presents the same regressions as Table 6 but for recommendation downgrades only.

Panel A: Initial Market Reaction						
	Excess returns during [-1,0]					
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings increased to above the consensus	1.191*** (9.474)	1.086*** (8.633)	1.808*** (15.061)	1.710*** (12.780)	1.820*** (16.084)	1.742*** (15.340)
Earnings increased to below the consensus	0.509*** (2.717)	0.428** (2.360)	0.952*** (5.894)	0.974*** (5.268)	0.929*** (5.800)	0.860*** (5.352)
Earnings decreased to above the consensus	-1.471*** (-11.359)	-1.482*** (-11.195)	-1.387*** (-11.141)	-1.334*** (-9.887)	-1.418*** (-11.965)	-1.391*** (-11.787)
Earnings decreased to below the consensus	-3.344*** (-30.263)	-3.326*** (-29.533)	-3.315*** (-32.385)	-2.848*** (-23.569)	-3.293*** (-33.902)	-3.153*** (-33.447)
Positive earnings surprise dummy		-0.060 (-0.768)				
Star analyst dummy			-0.067 (-0.562)			
Level of the previous recommendation					-0.273*** (-5.147)	
Unclassifiable earnings change dummy						-0.537*** (-6.108)
Control variables in Table 5 (not tabulated)	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Drift						
	Excess returns during [+1,+21]					
	(1)	(2)	(3)	(4)	(5)	(6)
Earnings increased to above the consensus	1.110*** (4.591)	1.141*** (4.791)	1.177*** (5.653)	0.990*** (4.579)	1.091*** (5.582)	1.141*** (5.855)
Earnings increased to below the consensus	0.705** (2.462)	0.733** (2.494)	0.536* (1.930)	0.499* (1.690)	0.542** (2.089)	0.571** (2.201)
Earnings decreased to above the consensus	-0.124 (-0.598)	-0.195 (-0.925)	-0.312 (-1.582)	-0.420** (-2.022)	-0.312* (-1.728)	-0.300* (-1.663)
Earnings decreased to below the consensus	-0.594*** (-3.881)	-0.662*** (-4.211)	-0.520*** (-3.752)	-0.631*** (-4.130)	-0.547*** (-4.179)	-0.527*** (-4.116)
Positive earnings surprise dummy		0.203* (1.719)				
Star analyst dummy			-0.219 (-1.205)			
Level of the previous recommendation					0.123* (1.652)	
Unclassifiable earnings change dummy						0.213* (1.684)
Control variables in Table 5 (not tabulated)	Yes	Yes	Yes	Yes	Yes	Yes

Table 8
Summary of Daily Returns for Calendar-Time Portfolios Formed Using All Upgrades and All Downgrades

This table presents daily returns statistics for portfolios formed based on recommendation changes in calendar-time. The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates consisting of 56,341 upgrades and 66,909 downgrades. Calendar-time returns are computed as follows. The portfolio formation interval equals the portfolio holding period length. Based on recommendation changes on the day before the portfolio formation date, all upgrades are bought ("long") and all downgrades are sold ("short"). Two time-series of daily portfolio returns are computed, one for longs and one for shorts. The risk-free rate is subtracted from both the long and short portfolios. A time-series of daily portfolio returns for a long minus short portfolio is also computed as the difference between the returns of the long and short portfolios. The number of daily returns is the number of trading days with return during the 3,525 trading days between 1994 and 2007. The number of daily returns, the mean number of firms, and the mean and standard deviation of the raw daily returns are computed using these three time-series. Four-factor regressions are also run to compute alphas and their t-statistics. The holding period raw return equals the mean of the raw daily returns multiplied by the length of the portfolio holding period. The holding period four-factor alpha is the four-factor alpha from daily returns multiplied by the length of the portfolio holding period. Return statistics are computed for as many sets of three portfolios as there are days in the portfolio formation interval and the means of the return statistics (means and standard deviations of raw returns and four-factor alphas and their t-statistics) are tabulated. The percent of t-statistics that are statistically significant at the five percent level are also tabulated. t-statistics are computed using robust standard errors.

Portfolio formation interval = length of portfolio holding period (days)	Portfolio type	Means of the following statistics								
		Number of daily returns	Mean number of firms	Mean of raw daily returns (%)	Holding period raw return (%)	Standard deviation of raw daily returns (%)	Four-factor alpha from daily returns (%)	Holding period four-factor alpha (%)	t-statistic of four-factor alpha (%)	Four-factor alphas significant at 5% level
1	Long	3,508	16.1	0.178	0.178	1.357	0.154	0.154	8.24	100%
	Short	3,515	19.0	-0.317	-0.317	1.346	-0.331	-0.331	-18.01	100%
	Long-short	3,506	35.1	0.493	0.493	1.348	0.483	0.483	21.19	100%
5	Long	3,508	16.1	0.122	0.611	1.421	0.093	0.465	5.62	100%
	Short	3,515	19.0	-0.099	-0.497	1.481	-0.121	-0.604	-6.89	100%
	Long-short	3,506	35.1	0.223	1.117	1.338	0.215	1.076	9.50	100%
10	Long	3,505	16.1	0.107	1.070	1.438	0.076	0.764	4.73	100%
	Short	3,512	19.0	-0.056	-0.556	1.476	-0.077	-0.770	-4.58	100%
	Long-short	3,503	35.1	0.163	1.629	1.312	0.154	1.536	6.92	100%
15	Long	3,500	16.1	0.094	1.412	1.440	0.063	0.950	3.92	100%
	Short	3,507	19.0	-0.038	-0.566	1.466	-0.059	-0.878	-3.57	100%
	Long-short	3,498	35.1	0.132	1.977	1.303	0.122	1.827	5.53	100%
21	Long	3,494	16.1	0.083	1.744	1.436	0.052	1.097	3.24	95%
	Short	3,501	19.0	-0.023	-0.492	1.460	-0.044	-0.923	-2.72	81%
	Long-short	3,492	35.1	0.106	2.224	1.293	0.095	2.005	4.36	100%
42	Long	3,473	16.0	0.063	2.647	1.434	0.031	1.301	1.93	50%
	Short	3,480	19.0	-0.003	-0.112	1.451	-0.025	-1.034	-1.53	38%
	Long-short	3,471	35.0	0.065	2.741	1.282	0.055	2.317	2.53	71%
63	Long	3,452	16.0	0.058	3.653	1.427	0.024	1.519	1.53	33%
	Short	3,459	19.0	0.006	0.396	1.437	-0.018	-1.145	-1.15	19%
	Long-short	3,450	35.0	0.051	3.236	1.271	0.042	2.644	1.96	48%

Table 9
Summary of Daily Returns for Calendar-Time Portfolios Formed Using Upgrades With Earnings Increased and Downgrades With Earnings Decreased

This table presents the same daily returns statistics as Table 8 with one exception. The sample comprises recommendation changes corresponding to 42,457 firm-dates consisting of 18,308 upgrades with earnings increased, which are bought, and 24,149 downgrades with earnings decreased, which are sold.

Portfolio formation interval = length of portfolio holding period (days)	Portfolio type	Means of the following statistics								
		Number of daily returns	Mean number of firms	Mean of raw daily returns (%)	Holding period raw return (%)	Standard deviation of raw daily returns (%)	Four-factor alpha from daily returns (%)	Holding period four-factor alpha (%)	t-statistic of four-factor alpha (%)	Four-factor alphas significant at 5% level
1	Long	3,369	5.4	0.280	0.280	1.877	0.249	0.249	8.34	100%
	Short	3,473	7.0	-0.460	-0.460	1.952	-0.471	-0.471	-15.55	100%
	Long-short	3,334	12.4	0.741	0.741	2.393	0.720	0.720	17.38	100%
5	Long	3,369	5.4	0.201	1.004	1.893	0.165	0.823	5.74	100%
	Short	3,473	7.0	-0.170	-0.849	1.991	-0.185	-0.925	-6.50	100%
	Long-short	3,334	12.4	0.370	1.848	2.295	0.349	1.746	8.80	100%
10	Long	3,366	5.4	0.169	1.687	1.912	0.131	1.314	4.61	100%
	Short	3,470	7.0	-0.098	-0.984	1.994	-0.114	-1.143	-4.07	100%
	Long-short	3,331	12.4	0.268	2.677	2.279	0.247	2.469	6.27	100%
15	Long	3,361	5.4	0.149	2.240	1.937	0.111	1.670	3.87	100%
	Short	3,465	6.9	-0.068	-1.013	1.985	-0.083	-1.242	-2.99	87%
	Long-short	3,326	12.4	0.215	3.226	2.294	0.193	2.902	4.87	100%
21	Long	3,355	5.4	0.134	2.806	1.937	0.095	1.996	3.35	95%
	Short	3,459	6.9	-0.050	-1.044	1.972	-0.065	-1.375	-2.38	71%
	Long-short	3,320	12.4	0.182	3.825	2.285	0.160	3.366	4.08	100%
42	Long	3,335	5.4	0.090	3.790	1.956	0.052	2.198	1.83	43%
	Short	3,439	6.9	-0.017	-0.714	1.972	-0.034	-1.426	-1.26	29%
	Long-short	3,301	12.4	0.109	4.593	2.301	0.088	3.708	2.23	60%
63	Long	3,314	5.4	0.081	5.106	1.954	0.041	2.570	1.48	25%
	Short	3,418	6.9	-0.006	-0.409	1.959	-0.026	-1.662	-0.98	14%
	Long-short	3,280	12.3	0.088	5.572	2.290	0.069	4.335	1.78	40%

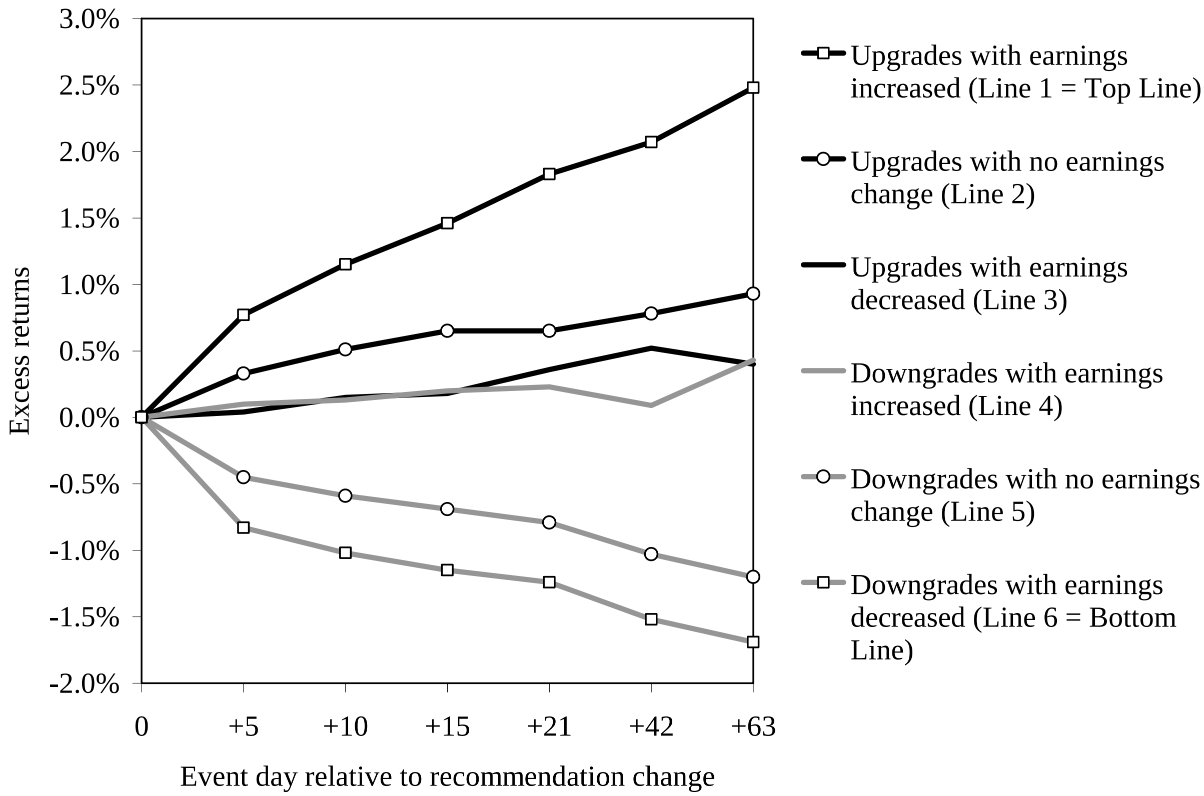


Figure 1. Stock returns by recommendation upgrades and downgrades and earnings estimate increases, no changes, and decreases in event-time. The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles.

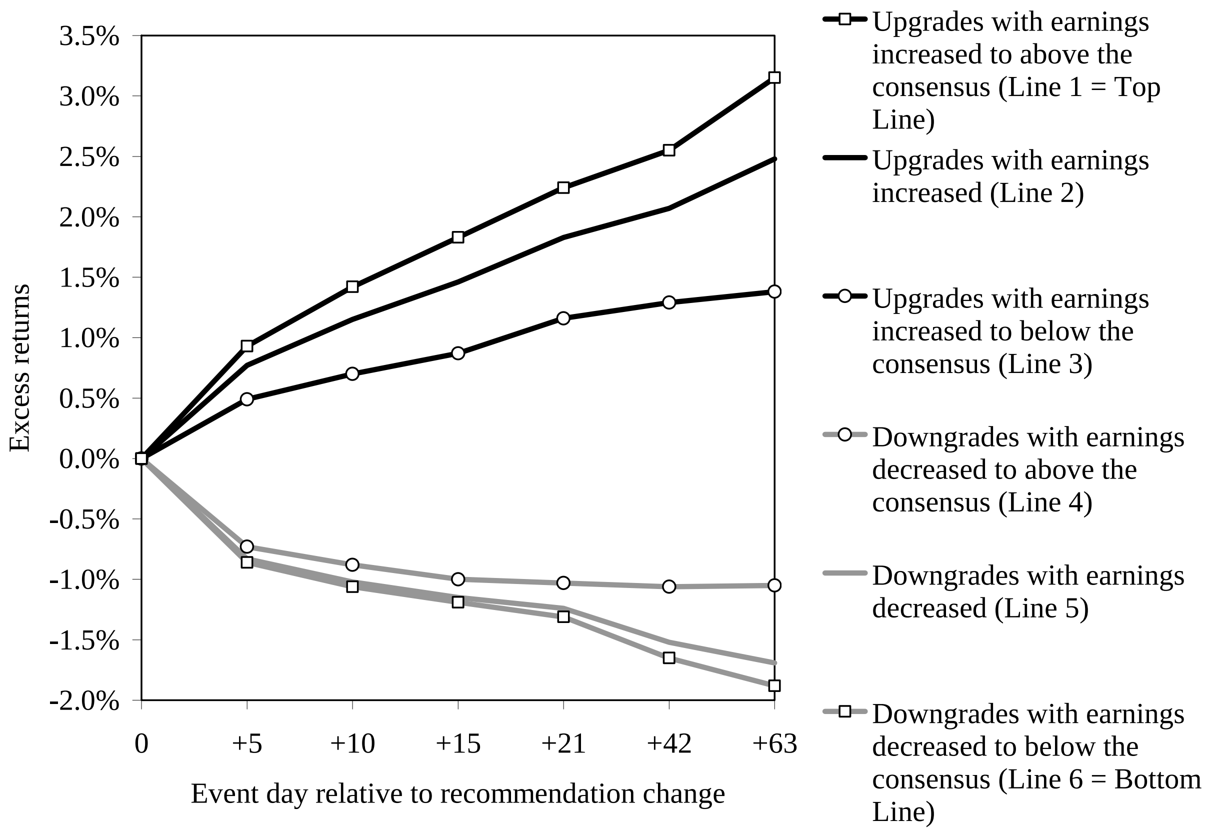
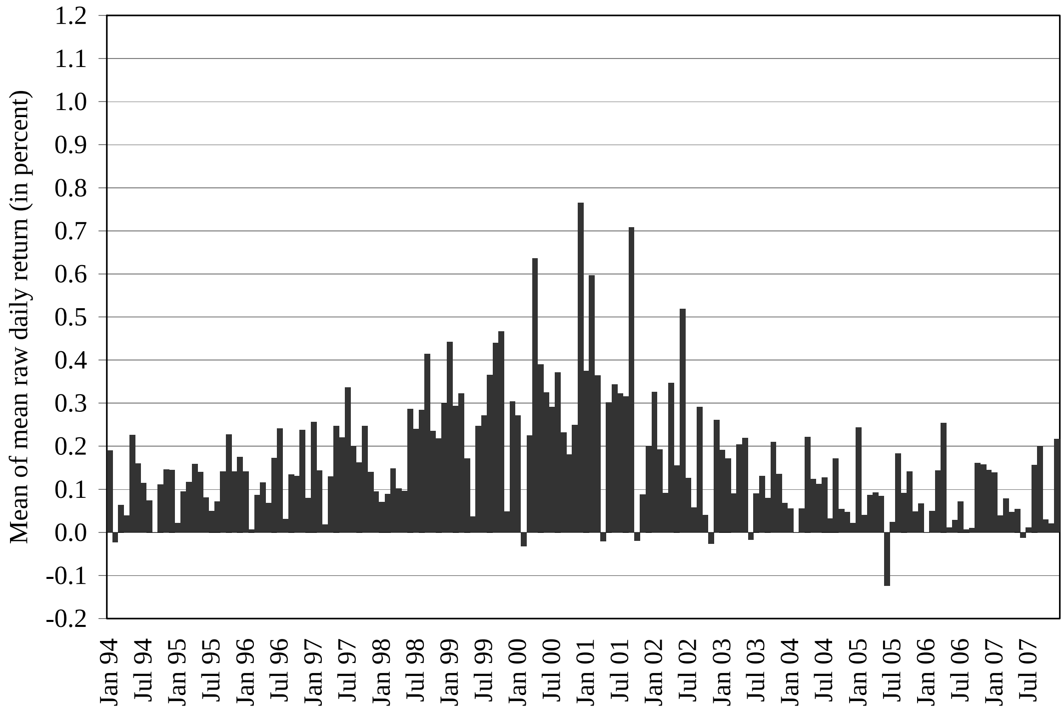


Figure 2. Stock returns by recommendation upgrades with earnings estimate increases and recommendation downgrades with earnings estimate decreases in event-time. The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles.



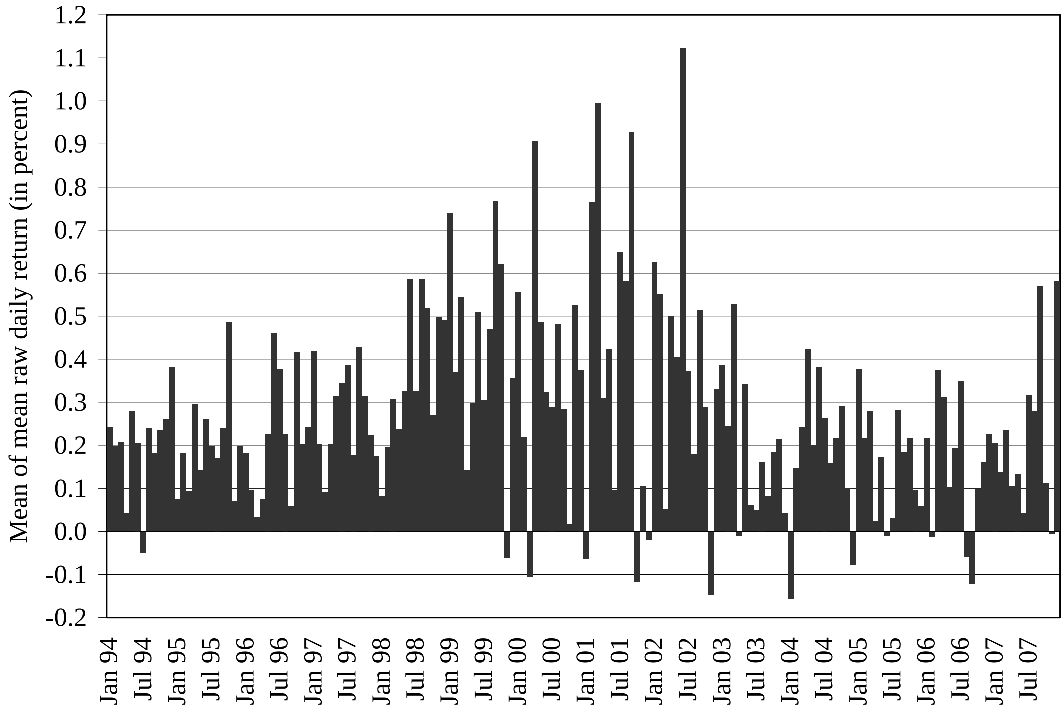


Figure 3. The drift after the recommendation changes in calendar-time. This figure presents the mean each month (rather than the mean for all months between 1994 and 2007) of the mean of the raw daily returns for the long minus short portfolios in Table 8 (top figure) and Table 9 (bottom figure). The top figure uses all upgrades in long portfolios and all downgrades in short portfolios. The bottom figure uses upgrades with earnings increased in long portfolios and downgrades with earnings decreased in short portfolios. The portfolio formation interval equals the portfolio holding period length and is ten days.