# What Drives the Value of Analysts' Recommendations: Earnings Estimates or Discount Rate Estimates?

AMBRUS KECSKÉS, RONI MICHAELY, and KENT WOMACK*

**Abstract**

When an analyst changes his recommendation of a stock, his valuation differs from the market's valuation because of differences in earnings estimates and/or discount rate estimates. We argue that earnings-based recommendation changes are characterized by harder information, greater verifiability, and shorter forecast horizons compared to discount rate-based recommendation changes, thus they are less subject to analysts' cognitive and incentive biases. Therefore, earnings-based recommendation changes should be more informative than discount rate-based recommendation changes. We find that both the initial price reaction to and the drift after recommendation changes are between 50% to 200% bigger for earnings-based than for discount rate-based recommendation changes. Trading on earnings-based recommendation changes earns average risk-adjusted returns of over 3% per month over the period 1994-2007.

February 21, 2010

JEL classifications: G14 (Information and Market Efficiency; Event Studies), G24 (Investment Banking; Venture Capital; Brokerage; Ratings and Ratings Agencies)
Keywords: Analysts, brokers, recommendations, earnings, growth rates, discount rates, information, market efficiency

---

* Kecskés is at the Virginia Polytechnic Institute and State University, Michaely is at Cornell University and the Interdisciplinary Center, and Womack is at the Tuck School of Business at Dartmouth College. Email: rm34@cornell.edu. We greatly appreciate the comments of Anup Agrawal, Alon Brav, Kobi Boudoukh, Alex Edmans, Umit Gurun, Andrew Karolyi, Özgür Ince, Jonathan Lewellen, Patricia O'Brien, Christopher Polk, Enrique Schroth, Amir Yaron, and seminar participants at Claremont McKenna College, Cornell University, Georgia Tech, Imperial College, the Interdisciplinary Center, the London School of Economics, the University of Alabama, the University of Amsterdam, the University of Illinois at Urbana-Champaign, the University of Miami, the University of Toronto, the University of Western Ontario, Virginia Tech, and Wharton. Christopher Vincent provided excellent research assistance.

# 1. Introduction

An analyst changes his recommendation of a stock to indicate to investors that his valuation of the stock differs from the market's valuation. Whether the analyst uses a multiples or discounted cash flow valuation approach, the difference in valuation must come from differences in estimates of cash flows, discount rates, and/or growth rates.[1] In this paper, we study how these valuation drivers (i.e., cash flows, discount rates, and growth rates) affect the informativeness of analysts' recommendations to investors.

Why should the informativeness of recommendation changes depend on whether they are based on changes in estimates of cash flows, discount rates, and/or growth rates? We argue below that, compared to discount rate-based recommendation changes, earnings-based recommendation changes are characterized by (1) harder information, (2) greater verifiability, and (3) shorter forecast horizons. Therefore, they are easier to produce and they are less subject to analysts' cognitive and incentive biases than discount rate-based recommendation changes. We refer to recommendation changes based on changes in earnings estimates as "earnings-based recommendation changes" and to recommendation changes based on changes in discount rate estimates (and, as we explain below, growth rates estimates) as "discount rate-based recommendation changes".[2]

The first difference in informativeness is that earnings-based recommendation changes are based on harder information whereas discount rate-based recommendation changes are based on softer information. This difference is evident in the random sample of 150 analyst reports that we read and examine to better understand the motives behind analysts' recommendation changes. We find that analysts almost always a produce a projected income statement to arrive at their earnings estimates for the next fiscal year or two (consistent with the findings of Asquith, Mikhail, and Au (2005)). Analysts also explain in detail the main items in their projected income statement in order to justify their earnings estimates. By contrast, analysts rarely change their

[1] Analysts typically use multiples rather than discounted cash flow valuation models (e.g., Asquith, Mikhail, and Au (2005)). Multiples valuation models are implicitly based on cash flow and discount rate estimates (e.g., Damodaran (2006) and Grinblatt and Titman (2001)). Recommendation changes are driven by differences in estimates of cash flows, discount rates, and/or growth rates regardless of whether it is the analyst's and/or the market's valuation drivers that change.

[2] As we explain below, the difference between earnings-based and discount rate-based recommendation changes is that the former are accompanied by earnings estimates changes whereas the latter are not. Thus discount rate-based recommendation changes may be accurately referred to as "non-earnings-based recommendation changes".

discount rate estimates and growth rate estimates let alone justify them with detailed explanations or models.

Second, investors can and do verify the accuracy of analysts' short-term earnings estimates ex post, namely, when the firm announces its earnings each quarter. Indeed, earnings estimate accuracy is one of the important evaluation criteria of the annual *Institutional Investor* magazine ranking of analysts. This 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)) as are growth rates (e.g., Chan, Karceski, and Lakonishok (2003)).

Third, the behavioral literature finds that the longer 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 and long-term earnings growth rate estimates. In fact, analysts' expected returns are optimistic on average (e.g., Brav, Lehavy, and Michaely (2005)) as are their growth rate estimates (e.g., Chan, Karceski, and Lakonishok (2003)).

The arguments above also imply that earnings-based recommendation changes are less subject to analysts' cognitive biases (e.g., McNichols and O'Brien (1997)) and incentive biases (e.g., Lin and McNichols (1998), Michaely and Womack (1999), Hong and Kubik (2003), Malmendier and Shanthikumar (2007), and Ljungqvist, Marston, and Wilhelm (2009)) than discount rate-based recommendation changes because of their different characteristics. For the same reason, long-term growth rate-based recommendation changes are qualitatively similar to discount rate-based (both are characterized by softer information, less verifiability, and longer forecast horizons) and different from earnings-based recommendation changes.

Overall, these observations imply that earnings-based recommendation changes should be more informative than discount rate-based recommendation changes. For example, upgrades with earnings estimates increases should have a more positive price reaction than upgrades with no earnings estimates changes, and downgrades with earnings estimates decreases should have a more negative price reaction than downgrades with no earnings estimates changes.

We test this prediction using recommendation changes from I/B/E/S between 1994 and 2007. We find that the I/B/E/S data are consistent with a random sample of 150 analyst reports from Investext that we examine. Roughly one-third of recommendation changes are concurrent with changes in analysts' earnings estimates in the same direction. Analysts only change their growth rate estimates for 5% of recommendation changes. They almost never explicitly change their discount rate estimates but they do change them implicitly. For example, analysts typically point to big stock price run-ups to justify downgrades with no earnings changes. In doing so, they imply that their discount rate estimate differs from the market's.

We find that the initial price reaction is bigger for earnings-based recommendation changes than for discount rate-based recommendation changes. For example, the average two-day initial price reaction to earnings-based upgrades is 66% bigger than the initial price reaction to discount rate-based upgrades (3.55% versus 2.13%). Similarly, the initial price reaction to earnings-based downgrades is 197% bigger than the initial price 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 price reaction (e.g., Stickel (1995), Womack (1996), and Barber, Lehavy, McNichols, and Trueman (2001), and Green (2006)). We therefore examine the drift after recommendation changes and indeed find evidence of continuation of the initial price reaction. The average 21-day drift after earnings-based upgrades is 182% bigger than the drift after discount rate-based upgrades (1.83% versus 0.65%). Similarly, the drift after earnings-based downgrades is 57% bigger than the drift after discount rate-based downgrades (-1.24% versus -0.79%). Overall, our results show that earnings-based recommendation changes have both a bigger initial price reaction and a bigger drift than discount rate-based recommendation changes.

We also examine the price impact of long-run earnings growth rate changes, and we find that our results are the same within the sub-sample of recommendation changes for which growth rates do not change. Moreover, for both earnings-based and discount rate-based recommendation changes, the total price reaction (initial price reaction and post-recommendation change drift) does not depend on whether growth rates increase, remain the same, or decrease. In sum, the incremental total price reaction conditional upon a concurrent growth rate changes is insignificant.

Our analysis controls for recommendation change characteristics and firm characteristics. We account for multiple recommendation changes on the same day; earnings announcements that are contemporaneous with recommendation changes; the prestige of the broker making the recommendation change; changes in the market's valuation of the firm prior to the recommendations change as well as changes in the market's expected earnings; market efficiency (as proxied by market capitalization, turnover, institutional ownership, and analyst coverage); and book-to-market, momentum, total return volatility, and industry and time effects. We also consider whether our results are driven by the previously documented post-earnings announcement drift after earnings surprises during the quarter before the recommendation change, by star analysts, particular analysts, particular brokers, or by the level of the previous recommendation. We find that although several of these control variables are significant, the difference in the total price reaction between earnings-based and discount rate-based recommendation changes is economically as well as statistically significant and robust to these controls.

Our results for the post-recommendation change drift naturally suggest a potentially profitable trading strategy. In particular, we test whether an investor can earn excess returns by buying upgrades with earnings increases and selling downgrades with earnings decreases. We find that the 21-day holding-period four-factor alpha from this strategy is 3.37% (45.9% annualized). This alpha is not only very significant economically and statistically on its own but is significantly greater than the alpha of 2.01% from buying all upgrades and selling all downgrades. Moreover, the profits from this trading strategy persist throughout our sample period.

Overall, the results show that recommendations based on changes in earnings estimates are more informative than recommendation changes based on changes in discount rate estimates. This is consistent with earnings-based recommendation changes being characterized by harder information, greater verifiability, and shorter forecast horizons, thus they are easier to produce and are less subject to analysts' biases.

A possible alternative interpretation of our results is that the total price reaction is bigger for earnings-based recommendation changes than for discount rate-based recommendation changes because the analyst sends two explicit signals (recommendations and earnings) rather just one (just recommendations). This implies that the total price reaction should be similar if there were an alternative second signal, for example recommendation changes with growth rate changes compared to recommendation changes with earnings changes because, in both cases, the analyst sends two signals. However, we find that the total price reaction is bigger for earnings-based recommendation changes than for growth rate-based recommendation changes. This is consistent with growth rate-based recommendation changes being characterized by softer information, less verifiability, and longer forecast horizons much like discount rate-based recommendation changes.

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 in 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 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 system change associated with the Global Settlement, the earnings estimate change associated with the recommendation change must be classifiable as an earnings increase, no change, or decrease, and the firm must be covered by at least two analysts (this last requirement excludes only 2,031 recommendation changes). Collapsing firm-date-analyst observations to firm-date observations leaves 123,250 recommendation changes (firm-date observations) comprising 7,040 unique firms and 3,517 unique trading dates.[3] Appendix Section 1 describes the details of our sample construction.

We split each of the two main recommendation change categories (upgrades and downgrades) into three sub-categories based on contemporaneous earnings estimate changes, namely, increases, no changes, and decreases. We thus have six recommendation change categories consisting of three categories for upgrades, i.e., with earnings increases, with no

[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 literature suggests that recommendation changes contain more information than recommendation levels (e.g., Jegadeesh, Kim, Krische, and Lee (2004) and Barber, Lehavy, and Trueman (2008)).

earnings changes, and with earnings decreases, and the same three categories for downgrades. Appendix Section 2 describes the details of the construction of our recommendation change categories.

We emphasize that, by definition, the difference between earnings-based and discount rate-based recommendation changes is that the former are accompanied by changes in earnings estimates whereas the latter are not. Analysts rarely explicitly mention their discount rate estimates in their reports, so such changes are necessarily implicit in recommendation changes with no earnings changes.[4] Moreover, discount rate-based recommendation changes may be based on changes in any valuation components other than earnings estimate changes (including discount rates, growth rates, and even cognitive and incentive biases), so they may be accurately referred to as "non-earnings-based recommendation changes". Moreover, earnings changes and discount rate changes may be correlated because both may be driven by common shocks (firm-specific or systematic). Since we observe recommendation changes and earnings changes but not discount rate changes, we would classify recommendation changes driven by common shocks (i.e., those affecting both earnings and discount rates) as earnings-based recommendation changes.

Analysts issue long-term growth rate estimates less frequently than they issue short-term earnings estimates, so we can only measure growth rate changes for 62% of our sample of recommendation changes (76,714 out of 123,250 observations). Moreover, only 5% of the recommendation changes in our sample (6,638 out of 123,250 observations) are actually accompanied by a growth rate estimate change (increase or decrease). For our analysis of growth rate changes, we further split each of our six recommendation change categories above into three sub-categories based on growth rate estimate changes, namely, increases, no changes, and decreases. Appendix Section 2 describes these details.

We compute the number of analysts covering a stock and consensus earnings estimate for the stock 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. Appendix Section 3 describes the details of these two computations. We classify an analyst as a "star" from November of the current year to October of the following year if the analyst is

[4] Like most of the literature (with the exception of Brav and Lehavy (2003) and Brav, Lehavy, and Michaely (2005)), we do not observe or infer actual discount rate changes in this paper.

one of the top ranked analysts in the October issue of *Institutional Investor* magazine in the current year. 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 October issue of *Institutional Investor* magazine in the current year. Appendix Section 4 provides our list of prestigious brokers.

Stock trading data are from CRSP. Factor returns are 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. Thus for recommendations issued after the close of event day 0, investors can trade at 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. Institutional ownership data are from Thomson's 13f filings data.

Turning now to our sample, we examine the characteristics of recommendation changes in different recommendation change categories. Among recommendation change characteristics, we compile data on recommendation changes around earnings announcements, recommendations issued by star analysts, and those issued by prestigious brokers. For firm characteristics, we consider market capitalization, book-to-market, turnover, total return volatility, institutional ownership, and analyst coverage.

[Insert Table 1 about here]

Table 1 presents the results. Just over one-half of recommendation changes are associated with no concurrent earnings estimate changes. Roughly one-third of upgrades have earnings estimate increases and the same fraction of downgrades have earnings estimate decreases. Fourteen percent of upgrades have concurrent earnings estimate decreases and 10% of downgrades have earnings estimate increases. Roughly one-quarter of both upgrades and downgrades are issued around earnings announcements. Not surprisingly, analysts are more likely to issue recommendation changes with earnings estimate changes around earnings announcements. Only roughly 15% of recommendation changes with no earnings changes are issued around earnings announcements whereas roughly one-third of recommendation changes with earnings estimate changes are issued around earnings announcements. We account for this concentration of earnings-based recommendation changes around earnings announcements in our multivariate analysis.

Roughly 10% of our sample recommendation changes are issued by star analysts and around 30% are issued by prestigious brokers. Recommendations are typically made on big firms, growth firms, liquid firms, firms with low total risk, firms with high institutional ownership, and firms with high analyst coverage. However, there is very little variation in these recommendation change characteristics and firm characteristics across recommendation change categories. In other words, we do not find that earning-based and discount rate-based recommendation changes differ by whether they are issued by star analysts or prestigious brokers nor do they differ by size, valuation, liquidity, total risk, institutional ownership, and analyst coverage.

We also examine the distribution of the six recommendation change categories (upgrades with earnings increases, upgrades with no earnings changes, etc.) over time (not tabulated). The proportion of earnings-based versus discount rate-based recommendation changes is stable over time for both upgrades and downgrades with one exception. The proportion of earnings-based upgrades increases and the proportion of discount rate-based upgrades decreases around the recommendation rating system changes in 2002 associated with the Global Settlement. Specifically, comparing the sub-periods 1994-2002 and 2003-2007, upgrades with no earnings changes are roughly 58% and 46% of upgrades, respectively, whereas upgrades with earnings increases are roughly 28% and 39%, respectively. We account for this structural change in our multivariate analysis using time fixed effects.

To better understand our data, we also examine a random sample of 150 analyst reports. For each of our recommendation change categories, we randomly sample twenty-five observations for which we extract the corresponding analyst reports from Investext. We find that our recommendation change categories based on I/B/E/S data are consistent with the analyst reports. Importantly, upgrades with earnings decreases and downgrades with earnings increases are not coding errors. For example, analysts state that they increase their earnings because they are now more optimistic about the firm's cash flows, but they downgrade their recommendation because they believe that the firm is now overvalued because of the recent rise in the stock price.

The reports reveal several stylized facts about the reasons for which analysts disagree with the market and thus change their recommendation. Analysts almost 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% of our observations (also consistent with Asquith, Mikhail, and Au (2005)). They also issue explicit growth rate estimates for 50% of our analyst report observations compared to 62% of our I/B/E/S observations. They change their growth rate estimates in 3% of their reports versus 5% in I/B/E/S. 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 Price Reaction to Recommendation Changes*

We argue that earnings-based recommendation changes are more informative than discount rate-based recommendation changes. Specifically, upgrades with earnings increases should have a more positive total price reaction (initial price reaction and post-recommendation change drift) than upgrades with no earnings changes. Similarly, downgrades with earnings decreases should have a more negative total price reaction than downgrades with no earnings changes.

We test this prediction by examining the total price reaction to recommendation changes in our six recommendation change categories (upgrades with earnings increases, upgrades with no earnings changes, upgrades with earnings decreases, etc.). We 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 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 recommendation changes have a significantly bigger initial price reaction than discount rate-based recommendation changes.

Specifically, the average initial price reaction to upgrades with earnings increases is 3.55% compared to 2.13% for upgrades with no earnings changes (discount rate-based upgrades) and 1.11% for upgrades with earnings decreases. These patterns are similar for downgrades. The initial price reaction to downgrades with earnings decreases is -5.11% compared to -1.72% for downgrades with no earnings changes (discount rate-based downgrades) and -0.35% for downgrades with earnings increases. Non-parametric analysis (not shown) suggests that these results are not driven by outliers. Specifically, the initial price reaction is positive for 74% of earnings-based upgrades compared to 64% of discount rate-based upgrades. The initial price reaction is negative for 75% of earnings-based downgrades compared to 63% of discount rate-based downgrades.

The pre-recommendation run-up suggests that, in many cases, there is news about the firm even before the recommendation change. For example, the average 21-day run-up to upgrades with earnings increases is 2.15% compared to -1.02% for upgrades with no earnings changes, which suggests that upgrades with earnings increases follow better news about the firm than upgrades with no earnings changes. Moreover, consistent with the random sample of 150 analyst reports that we examine, analysts upgrade stocks that they believe are undervalued and downgrade stocks that they believe are overvalued based on the pre-recommendation change run-up even if they believe that the firm's fundamentals are improving or worsening, respectively. For example, the 21-day run-up to upgrades with earnings decreases is -2.72%, which is even lower than the 21-day run-up to upgrades with no earnings changes. For downgrades, the patterns are similar and even more pronounced.

Many corporate events are characterized by underreaction to news (e.g., earnings announcements (Bernard and Thomas (1989, 1990)), seasoned equity offerings (Loughran and Ritter (1995)), and share repurchases (Ikenberry, Lakonishok, and Vermaelen (1995))). Analysts' recommendation changes are no exception (e.g., Womack (1996)). Therefore, we, too, examine the post-recommendation change drift. 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, the market appears to undervalue information about intangibles versus tangibles (e.g., Lev and Sougiannis (1996), Chan, Lakonishok, and Sougiannis (2001), Daniel and Titman (2006), and Edmans (2009)), so the drift after earnings-based recommendation changes should be smaller because earnings information is more tangible. On the other hand, if the magnitudes of the initial price reaction and drift are positively correlated, then the drift after earnings-based recommendation changes should be bigger. Therefore, the differential magnitude of the drift is an empirical question. To this end, we measure the drift 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. The drift is significantly bigger for earnings-based recommendation changes than for discount rate-based recommendation changes. For example, the average 21-day drift after upgrades with earnings increases is 1.83% compared to 0.65% for upgrades with no earnings changes (discount rate-based upgrades) and 0.36% for upgrades with earnings decreases. These patterns are similar for downgrades. The 21-day drift after downgrades with earnings decreases is -1.24% compared to -0.79% for downgrades with no earnings changes (discount rate-based downgrades) and +0.23% for downgrades with earnings increases. The market appears to underreact to earnings-based recommendation changes more than it underreacts to discount rate-based recommendation changes.[5]

It is possible that, the drift after upgrades is greater in magnitude than the drift after downgrades, due to analysts' optimism bias. Analysts are more likely to upgrade than downgrade if they are optimistically biased. If investors recognize this optimism bias, then the initial price reaction to upgrades should not completely impound the information content of upgrades relative to downgrades, and the drift should be bigger after upgrades than downgrades.

[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 up to 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 several months.

*3.2. Multivariate Analysis of the Total Price Reaction to Recommendation Changes*

Our results thus far suggest that earnings-based recommendation changes are more informative than discount rate-based recommendation changes. We now use multiple regression

[5] We also examine the effect 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). The results are the same across quarters.

analysis to test whether the univariate results are explained by recommendation change characteristics and firm characteristics.

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 except for recommendation changes with no earnings changes and control variables. We control for the following recommendation change characteristics. First, multiple recommendation changes by several analysts on the same day may be more informative than a single recommendation change by one analyst. We control for multiple recommendation changes using a dummy variable. Second, recommendation changes occurring around earnings announcements are more likely to be classified as earnings-based than discount rate-based (see Table 1). The total price reaction to such recommendation changes may be attributable to the earnings announcement rather than the recommendation change. We control for recommendation changes around earnings announcements using a dummy variable.

Third, 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 (e.g., Fang and Yasuda (2009)). We therefore control for prestigious brokers as defined by *Institutional Investor* magazine (see Appendix Section 4) using a dummy variable. Fourth, the total price reaction to a recommendation change may include a delayed response to information released before the recommendation change. We control for such information using previous recommendation changes, earnings changes, and stock returns. We measure previous recommendation changes as the number of upgrades minus the number of downgrades during the week ending two days before the recommendation day. We measure previous consensus earnings estimate changes as 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 measure previous stock returns as the raw return during the week ending two days before the recommendation day.[6]

We also control for firm characteristics. We assume that stocks that are bigger, more liquid, have greater ownership by sophisticated investors, and are covered by more analysts incorporate new information faster. The initial price reaction to recommendation changes for such stocks should be smaller because such recommendations contain relatively less new

[6] If we measure these three variables over one month rather than one week, the results are the same.

information. Moreover, the new information that they do contain should be impounded into prices faster so the drift should also be smaller. We use market capitalization, turnover, institutional ownership, and analyst coverage as proxies for the speed at which information is impounded into prices, i.e., market efficiency. Since these variables are highly correlated, we use principal components analysis to reduce the dimensionality of our data to the first principal component of these four variables (a linear combination of these variables), and we include this single composite market efficiency proxy in our regressions.[7]

Following Jegadeesh, Kim, Krische, and Lee (2004), we also control for market-to-book as a valuation proxy; momentum, measured during the first eleven months of the year ending the month before the recommendation day; and total return volatility, measured during the year ending the month before the recommendation day. Finally, we control for industry and time effects using industry fixed effects, defined based on two-digit SIC codes, and time fixed effects, defined based on calendar quarters during our sample period.

[Insert Table 3 about here]

Table 3 presents the results. The difference in the price reactions to earnings-based versus discount rate-based recommendation changes remains economically and statistically significant after accounting for recommendation change characteristics and firm characteristics. For example, compared to the initial price reaction to upgrades with no earnings changes, the initial price reaction is 1.27 percentage points higher for upgrades with earnings increases compared to 1.42 percentage points in the univariate analysis in Table 2. For upgrades with earnings decreases, the initial price reaction is 1.35 percentage points lower compared to 1.02 percentage points in the univariate analysis.

Our control variables have the expected coefficients with respect to the initial price reaction to recommendation changes. The initial price reaction is significantly bigger (more positive for upgrades and more negative for downgrades) on days with multiple recommendation changes, when the recommendation change occurs around an earnings announcement, when the recommendation change is issued by a prestigious broker, for firms with lower returns during the previous week, for firms that are priced less efficiently, and for firms with greater total risk.[8] The

[7] If we control for each of our market efficiency proxies individually, the results are the same.
[8] If we also control for the dispersion of analysts' earnings estimates as an additional proxy for risk, the results are the same.

initial price reaction is more positive for both upgrades and downgrades for firms with lower valuations (book-to-market) and firms with less momentum during the previous year.

The magnitude of the drift in the multivariate analysis (in Table 3) is very similar to the magnitude of the drift in the univariate analysis (in Table 2). For example, the average 21-day excess return for upgrades with earnings increases is 1.23 percentage points higher than for upgrades with no earnings changes 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 compared to their effect on the initial price reaction.[9]

Our results may be understated by possible misclassifications of our recommendation change categories. Specifically, we may misclassify some earnings-based recommendation changes as discount rate-based recommendation changes for two reasons. First, it is possible that an analyst does not change his earnings estimate but the market consensus estimate has changed. Consequently, the analyst may change his recommendation because he disagrees with the market's new earnings estimate. For example, an analyst may upgrade a stock without changing his earnings and discount rate estimates because the market's earnings estimate decreases and thus the stock price falls. We would classify this as a discount rate-based recommendation change because the analyst does not change his earnings estimate even though the cause of the recommendation change is the change in the market's earnings estimate relative to the analyst's.

The results in Table 3 show that we can rule out this possible misclassification. Specifically, we use three proxies for changes in the market's earnings and discount rate estimates, namely, recommendation changes, consensus earnings estimate changes, and stock returns, all measured prior to the recommendation change. Consensus earnings estimate changes proxy for changes in the market's expected cash flows whereas recommendation changes and stock returns proxy for both changes in the market's expected cash flows and/or discount rates. Even after controlling for changes in these market's valuation drivers, the total price reaction is significantly bigger for earnings-based recommendation changes than for discount rate-based recommendation changes.

[9] The statistical significance of the results may be overstated because of our sample size (123,250 observations). For the initial price reaction, this possibility is mitigated by the fact that our t-statistics are well into the double digits. Even if our sample size were to decrease by a factor of 25 (and thus our t-statistics by a factor of five), the results would remain statistically significant. Moreover, for the drift, which is smaller in magnitude than the initial price reaction, we examine whether our event-time results can be implemented in calendar-time, and, in doing so, we eliminate auto-correlation and cross-correlation of returns. Our sample size decreases to 3,517 trading days and the results remain statistically significant.

Second, we may misclassify recommendation changes driven by reiterations of analysts' previous earnings estimates as discount rate-based recommendation changes. Specifically, an analyst may upgrade a stock without changing his earnings estimate to emphasize that his previous earnings estimate was and remains above the consensus earnings estimate. Similarly, an analyst may downgrade a stock without changing his earnings to emphasize that his previous earnings was and remains below the consensus. We would classify this as a discount rate-based recommendation change because the analyst does not change his earnings estimate even though the cause of the recommendation change is differences in beliefs about future earnings between him and the market. We examine this possibility by comparing the total price reaction depending on whether the previous earnings estimate was above the consensus or below the consensus. If the total price reaction is the same, then such recommendation changes are not driven by earnings estimate reiterations. To test this possibility, we use only discount rate-based recommendation changes and run our multiple regressions with the addition of a dummy variable for whether previous earnings are above the consensus.

[Insert Table 4 about here]

The results in Table 4 suggest that we can also rule out this possible misclassification as significant. For both upgrades and downgrades, the price reaction is not different when the analyst's previous estimate was above versus below the consensus. This is the case for both the initial price reaction and the drift. Overall, the results suggest that recommendation changes with no earnings changes are predominantly driven by discount rate changes.

### *3.3. The Role of Growth Rate Changes*

We argue that growth rate-based recommendation changes are conceptually similar to discount rate-based recommendation changes in that both are characterized by softer information, less verifiability, and longer forecast horizons. We now directly examine the role of growth rate changes on our results. First, we use a sub-sample of recommendation changes for which growth rates do not change to examine whether growth rate changes play a role in our results. Second, we examine whether growth rate changes have any incremental information content to earnings changes and discount rate changes.

Analysts issue long-term (typically five-year) growth rate estimates much less frequently than they issue short-term earnings estimates. Specifically, there is no previous long-term growth rate for 38% of the recommendation changes. Therefore, we can measure growth rate changes for only 62% (76,714 observations) of the recommendation changes in our sample of 123,250 recommendation changes. Growth rates change for only 9% (6,638 observations) of the sub-sample (or 5% of the full sample). We find similar figures in the random sample of 150 analyst reports that we examine.

We examine firm characteristics and recommendation change characteristics across three growth rate categories: (1) recommendation changes with no changes in growth rates, (2) recommendation changes with growth rate increases, and (3) recommendation changes with growth rate decreases. We find no difference across these categories in the proportion of recommendations issued by star analysts or prestigious brokers or in any of the firm characteristics that we examine (market capitalization, book-to-market, turnover, total return volatility, institutional ownership, or analyst coverage). Contrary to our findings on earnings-based recommendation changes, we do not find a concentration of recommendation changes with growth rate changes around earnings announcements.

To examine the role of growth rate changes on our results, we compute excess returns during the [-1,0] and [+1,+21] event windows for earnings-based and discount rate-based recommendation changes as in Table 2 but with each of our six recommendation change categories split into three sub-categories, namely, those with growth rate increases, no changes, and decreases. (For expositional simplicity, we do not tabulate results for upgrades with earnings or growth decreases and for downgrades with earnings or growth increases.)

[Insert Table 5 about here]

Table 5 presents the results. (For expositional simplicity, we only tabulate results for selected categories.) First, the total price reaction is not significantly different between the full sample in Table 2 (123,250 observations) and the sub-sample of recommendation changes with no growth rate changes in Table 5 (69,862 observations). For the full sample, the average initial price reaction to upgrades with earnings increases is 3.55% compared to 2.13% for upgrades with no earnings changes. For the sub-sample of no change in growth rates, the corresponding figures are 3.81% and 2.23%, respectively. These patterns are similar for downgrades. The initial price reaction to downgrades with earnings decreases is -5.11% compared to -1.72% for downgrades with no earnings changes. For the sub-sample, the corresponding figures are -5.50% and -1.77%, respectively. This suggests that the bigger total price reaction to earning-based recommendation changes than to discount rate-based recommendation changes is driven by earnings and discount rates and not by growth rates.

Second, the results in Table 5 also suggest that growth rate changes have little incremental information content compared to earnings and discount rate changes. For upgrades, the pairwise differences in the initial price reaction and the drift associated with growth rate changes are not statistically significant. This is also the case for downgrades with no earnings changes. For downgrades with earnings decreases, the initial price reaction to no growth rate changes is significantly higher than for growth rate decreases, but the opposite is the case for the drift.[10]

The results in Table 5 also shed light on whether recommendation changes with earnings changes can be interpreted as a "double signal". It is possible that the total price reaction is bigger for 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. Using the same argument, recommendation changes with growth rate changes could also be interpreted by the market as a double signal versus no growth rate changes. While we find that the total price reaction is bigger for recommendation changes with earnings changes versus no earnings changes, we find that the incremental total price reaction to growth rate changes is insignificant. Thus, it is not the number of signals that matters but the quality of the signal. Those differences are consistent with our argument that earnings-based recommendation changes are conceptually different from growth rate-based recommendation changes in that the former compared to the latter are characterized by harder information, greater verifiability, and shorter forecast horizons.

### *3.4. Extreme Recommendation Changes and Large Earnings Forecast Changes*

Our results thus far suggest that earnings-based recommendation changes are more informative than discount rate-based recommendation changes because earnings-based recommendation changes are characterized by harder information, greater verifiability, and shorter forecast horizons compared to discount rate-based recommendation changes. We now extend this binary analysis to examine the information content of the magnitude of

[10] We redo Table 3 using the recommendation change categories in Table 5. The multivariate results (not tabulated) are the same as the univariate results in Table 5, so the univariate results for growth rate changes are robust to accounting for recommendation change characteristics and firm characteristics. The results are also the same for the categories that we do not tabulate (e.g., upgrades with earnings decreases and downgrades with earnings increases).

recommendation changes and earnings changes. The total price reaction should be more positive for upgrades if the analyst produces measurably more optimistic information about recommendations and/or earnings and similarly more negative for downgrades if the analyst produces more pessimistic information. To this end, we examine the incremental total price reaction to extreme recommendation changes and large earnings changes as well as earnings estimate changes relative to the consensus earnings estimate. In doing so, we also examine whether extreme recommendation changes explain the bigger total price reaction to earnings-based versus discount rate-based recommendation changes.

First, we examine extreme recommendation changes and large earnings estimate changes. Since different brokers use different recommendation rating scales and since some brokers change their rating scales around the Global Settlement, we convert all brokers to a three-point rating scale (Appendix Section 5 describes the procedure), and we define extreme recommendation changes as recommendation changes of two points on a three-point rating scale. We define "large" earnings estimate increases as earnings estimate increases (relative to the closing price per share two days before the recommendation day) of greater magnitude than the median earnings estimate increase computed using the sub-sample of recommendation changes with earnings estimate increases. We define large earnings decreases analogously. We examine the joint distribution of extreme recommendation changes and large earnings changes. Roughly 23% of recommendation changes are extreme recommendation changes both for earnings-based and discount rate-based recommendation changes as well as for small and large earnings changes.

[Insert Table 6 about here]

We then run regressions of excess returns on dummies for recommendation change categories and control variables as in Table 3 with the addition of dummies for interactions between earnings increases, no changes, and decreases and extreme recommendation changes and large earnings changes. Table 6 Panel A presents the results. The incremental initial price reaction is not different from zero for extreme upgrades with earnings increases compared to upgrades with no earnings changes. It is significant (0.40 percentage points lower) for extreme downgrades with earnings decreases. The incremental initial price reaction is also not different from zero for both extreme upgrades and extreme downgrades with no earnings changes. For large earnings changes, the incremental initial price reaction is 1.00 percentage points higher for upgrades with large earnings increases and 2.25 percentage points lower for downgrades with large earnings decreases. Both are highly significant. The incremental drift is not different from zero for either extreme upgrades with earnings increases or for extreme downgrades with earnings decreases. For large earnings changes, the incremental drift is 0.94 percentage points higher for upgrades. It is not different from zero for downgrades with large earnings decreases.

The return patterns during the months after the recommendation change do not change significantly as we examine shorter versus longer horizons. Figure 2 presents the drift during the one, two, and three weeks and one, two, and three months after the recommendation change. Compared to all upgrades with all earnings increases, the drift is bigger for large upgrades with earnings increases, larger still for all upgrades with large earnings increases, and largest for extreme upgrades with large earnings increases.

[Insert Figure 2 about here]

Second, we examine earnings estimate changes relative to the consensus. Gleason and Lee (2003) find that the total price reaction is larger for earnings forecasts increased to above the consensus ("innovative") than for stocks with earnings increased to below the consensus ("non-innovative"). Similarly, the total price reaction should be bigger for downgrades with earnings decreased to below the consensus ("innovative") than for downgrades with earnings decreased to above the consensus ("non-innovative"). Earnings increased to above the consensus account for 62% of upgrades with earnings increases, and earnings decreased to below the consensus account for 78% of downgrades with earnings decreases. We replicate Table 3 with the addition of dummies for earnings increased to above the consensus and earnings decreased to below the consensus.

Table 6 Panel B presents the results. The incremental initial price reaction is 0.54 percentage points higher for upgrades with innovative earnings increases and 1.82 percentage points lower for downgrades with innovative earnings decreases. The incremental drift is 1.03 percentage points higher for upgrades with innovative earnings increases but not different from zero for downgrades with innovative earnings decreases.

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. As we see in Figure 2, the post-recommendation drift is larger for upgrades with earnings increased to above the consensus and smaller for upgrades with earnings increased to below the consensus.

Overall, our conclusion is that extreme recommendation changes do not explain the bigger total price reaction to earnings-based versus discount rate-based recommendation changes. However, large earnings estimate changes and recommendation changes with innovative earnings estimate changes have a bigger total price reaction.

## 4. Robustness Tests

We perform various robustness tests of our results. We present the results of several of these tests in Table 7. For expositional simplicity, we only present results for the dummies for recommendation changes with earnings changes. If applicable, we also present results for new control variables that we use in Table 7 but not in Table 3.

[Insert Table 7 about here]

First, we check whether our results are driven by the recommendation changes that are contemporaneous with earnings announcements. While we have already controlled for earnings announcements during the week ending on the recommendation day in Table 3, we now exclude them altogether. The results in Table 7 Column 1 are very similar to the results in Table 3. The difference in the total price reaction to between earnings-based and discount rate-based recommendation changes remains highly significant, except for the initial price reaction to recommendation changes with earnings increases for which the coefficient estimates are smaller by roughly 50 basis points, and on the same order of magnitude.[11]

Second, we test whether our results are driven by the earnings surprise during the quarter before the recommendation change day. The concern might be that 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 price reaction and the drift are actually caused by the earnings surprise before the recommendation change and not by their announced earnings change that accompanies the recommendation change. Moreover, the drift that we document is actually a variation of post-earnings announcement drift. To test this explanation, we again exclude earnings announcements and control for whether the earnings surprise at the earnings announcement during the previous quarter is positive. We measure earnings surprises as returns in excess of returns on benchmark portfolios matched on size, book-

[11] We also account for earnings guidance using a sub-sample of recommendation changes for which earnings guidance data from First Call are available. Roughly 24% of the recommendation changes in this sub-sample occur around earnings guidance and roughly 11% occur around earnings guidance but not earnings announcements. If we control for earnings guidance, the results for this sub-sample are the same.

to-market, and momentum during the three days centered on the quarterly earnings announcement date in the previous quarter. The results in Table 7 Column 2 are very similar to the results in Table 3. Positive earnings surprises at the earnings announcement during the previous quarter are associated with a slightly lower initial price reaction and a slightly higher drift for both upgrades and downgrades.[12]

Third, we examine whether our results are driven by the larger impact star analysts (e.g., Emery and Li (2009)) might make. Conceivably star analyst's recommendation changes have a bigger total price reaction and star analysts issue disproportionately more earnings-based recommendation changes than discount rate-based recommendation changes. If this is the case, then the total price reaction to earnings-based versus discount rate-based recommendation changes could be caused by star analysts. To test this explanation, we control for whether the analyst issuing the recommendation change is a star analyst using *Institutional Investor* magazine results as a proxy.[13] The results in Table 7 Column 3 indicate that star analysts do not explain the bigger total price reaction to earnings-based versus discount rate-based recommendation changes. Moreover, star analysts are not associated with a bigger total price reaction except for the initial price reaction to upgrades, which is 25 basis points higher for star analysts.

Fourth, we test whether our results are driven by particular analysts that issue proportionately more earnings-based recommendations. Perhaps the explanation for star analysts collectively applies to particular analysts individually. To test this explanation, we control for analyst fixed effects and we drop firm-date pairs with more than one analyst. The results in Table 7 Column 4 are the same as in Table 3. Fifth, we conduct the same test checking whether our results are driven by particular brokerage firms. We control for broker fixed effects and we drop firm-date pairs with more than one broker. The results, in Table 7 Column 5, are again not affected.

Sixth, we examine whether our results change if we account for the level of the previous recommendation by the analyst (e.g., Loh and Stulz (2009)). While it is not clear that the total price reaction to earnings-based versus discount rate-based recommendation changes should depend on the level of previous recommendation, the incremental effect of an upgrade may be

[12] If we measure earnings surprises as announced earnings minus analysts' consensus earnings estimates all scaled by the stock price, the results are the same.
[13] We do not control for star analysts in Table 3 because we do not have data on star analysts during the last fourteen months of our sample.

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 control for the level of the previous recommendation by the analyst and we use the mean previous recommendation level for firm-date pairs with more than one analyst. The results in Table 7 Column 6 are the same as in Table 3. A higher level of the previous recommendation is associated with a lower total price reaction except for the drift after downgrades, which is not different from zero.

Seventh, we test whether our results hold 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 (e.g., Gintschel and Markov (2004)) and after the Global Settlement in April 2003 (e.g., Kadan, Madureira, Wang, and Zach (2009)). Perhaps the greater 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 find (in untabulated results) that earnings-based recommendation changes are associated with a bigger total price reaction than discount rate-based recommendation changes in each sub-period.

Finally, we consider whether our results are a function of the clustering of firms on the same dates within recommendation change categories. To remove such clustering, we collapse our firm-date observations to the date level by computing mean excess returns across firms in a given recommendation change category for a given date, and we redo Table 2. We find the same excess returns (not tabulated) as in Table 2, so our results are not affected by clustering of firms on the same dates within recommendation change categories.

Overall, our result that total price reaction is bigger for earnings-based recommendation changes than for discount rate-based recommendation changes is robust to numerous alternative empirical specifications.

## 5. Trading Strategy

Our results showing post-recommendation drift in the months after the recommendation change naturally suggest a potentially profitable trading strategy. We examine one such strategy of buying upgrades with earnings increases and selling downgrades with earnings decreases. We compare this strategy to a strategy of unconditionally buying all upgrades and selling all downgrades.

We form portfolios for two trading strategies based on the recommendation change categories for our sample of 123,250 firm-dates between 1994 and 2007. 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 increases and sell all downgrades with earnings decreases. 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 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., an 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 $(V_t/V_{t-1})-1$ where $V_t$ is the value of portfolio on day t. 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 is issued on the previous day but comes after the close, we trade on it at the open of the first day in the holding period.

Using this procedure, we create a single time-series of daily returns from a portfolio created from trading on the signal (e.g., buying all upgrades) and holding the same portfolio for S days before unwinding the portfolio and creating a new portfolio. 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 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 signals from all $S-1$ 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]

Table 8 presents the raw return results. Portfolios are formed almost every trading day during 1994-2007 (3,525 trading days) for the unconditional strategy compared to 95% 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 33% of upgrades have earnings increases and 36% of downgrades have earnings decreases. The difference in the number of daily returns and the number of firms arises because there are more unconditional signals (all upgrades and all downgrades) than conditional signals (upgrades with earnings increases and downgrades with earnings decreases) upon which we can trade.

Several patterns emerge when we examine the raw returns of the unconditional and conditional strategies across various holding periods. 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 therefore 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 side of the portfolios for both strategies. Thus the profitability of the long minus short portfolios does not appear to be result of short sales constraints.

Fourth, and most importantly, the magnitude of the raw returns for the conditional strategy is roughly two-thirds larger than the magnitude of raw returns for the unconditional strategy. The 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 earns 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 also presents the risk-adjusted returns results. 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 applying the four standard asset pricing factors. Moreover, for both strategies, the four-factor alphas are very similar to the corresponding figures in Table 2.[14] Furthermore, the four-factor alphas are still driven mainly by the positive drift of the upgrades rather than the negative drift of the downgrades. Finally, we assess the significance of the four-factor alphas by 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

[14] The four-factor alphas in Table 8 multiplied by the length of the portfolio holding period roughly equal the corresponding excess returns elsewhere in Table 2.

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. 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.

[Insert Figure 3 about here]

Figure 3 presents the profitability of our trading strategies over time during our sample period of 1994-2007. We implement the same trading strategies as in Table 8 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. From the monthly time-series variation in the drift, we first observe that while the drift is more profitable for the conditional strategy than for the unconditional strategy, it is also slightly 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 during the two years after the technology boom (2001-2002), but the most positive returns are also concentrated during this period. The structural change in Figure 3 between 1994-2002 and 2003-2007 coincides with the increase in the relative frequency of upgrades with earnings increases and the decrease in the relative frequency of upgrades with no earnings changes. Second, the profitability of the drift for both strategies is similar at the end of our sample period compared to the beginning. We conclude that our results have not disappeared in recent years.[15]

We also examine two other trading strategies based on the results for large earnings estimate changes and earnings estimate changes relative to the consensus. Table 6 Panel A shows that upgrades with large earnings increases and downgrades with large earnings decreases have a larger total price reaction than upgrades with small earnings increases and downgrades with small earnings decreases, respectively. Table 6 Panel B shows that upgrades with earnings increased to above the consensus and downgrades with earnings decreased to below the

[15] If we exclude technology firms from our sample, the results are the same.

consensus have a bigger total price reaction than upgrades with earnings increases and downgrades with earnings decreases, respectively. We implement one trading strategy that consists of buying upgrades with large earnings increases and selling downgrades with large earnings decreases. We implement another trading strategy that consists of buying upgrades with earnings increased to above the consensus and selling downgrades with earnings decreased to below the consensus.

We find that both of these trading strategies yield higher but more variable profits than the profits in Table 8 Panel B. For the trading strategy based on large earnings estimate changes, mean returns are roughly are 10%-30% bigger. For example, for the 21-day holding period, raw returns for the long minus short portfolio are 4.58% compared to 3.83% in Table 8 Panel B. However, the standard deviations of returns are roughly 35% bigger. For the trading strategy based on earnings estimate changes relative to the consensus, mean returns are roughly are 10% 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 8 Panel B. However, the standard deviations of returns are also roughly 10% bigger. In summary, both trading strategies are somewhat more profitable but also somewhat more risky.

Finally, we perform several robustness tests of the results for the unconditional and conditional trading strategies. We exclude firms with a stock price of less than five dollars and firms with market capitalization in the bottom quintile of the market capitalization of NYSE firms. For the unconditional strategy, the means are roughly 10% lower and the standard deviations are roughly unchanged compared to Table 8 Panel A. For the conditional strategy, the means are roughly 10% lower and the standard deviations are roughly 5% lower compared to Table 8 Panel B. We conclude that our results remain and are not driven by illiquid stocks. To be even more conservative, we exclude firms with a stock price of less than five dollars and firms with market capitalization below the fiftieth percentile of the market capitalization of NYSE firms. The firms that remain have market capitalizations of around $1 billion or more. For the unconditional strategy, the means are roughly 40% lower and the standard deviations are roughly 10% higher compared to Table 8 Panel A. For the conditional strategy, the means are roughly 30% lower and the standard deviations are roughly unchanged compared to Table 8 Panel B (e.g., for the 21-day holding period, raw returns for the long minus short portfolio are 2.60%).

Therefore, our results are robust to including only highly liquid stocks. In all our robustness tests, the profits from the trading strategies are statistically significant.

## 6. Conclusion

The value of an asset should equal the present value of its cash flows. This implies that differences of opinion about asset values are motivated by differences in estimated cash flows and/or discount rates. In turn, differences of opinion about the value of stocks between analysts and the market are reflected in changes in analysts' recommendations. In this paper, we study how estimates of cash flows, discount rates, and growth rates drive the informativeness and investment value of analysts' recommendations. We argue that earnings-based recommendation changes are more informative because they are characterized by harder information, greater verifiability, and shorter forecast horizons, thus they are easier to produce and are less subject to analysts' cognitive and incentive biases than discount rate-based recommendation changes.

If investors discern the greater informativeness of earnings-based recommendation changes compared to discount rate-based recommendation changes, then the price reaction should be bigger for the former than for the latter. We find evidence consistent with this prediction for both the initial price reaction and the post-recommendation change drift. These results are robust to various controls for recommendation change characteristics and firm characteristics. At the same time, 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.

The quality of the information content of recommendation changes may not only be driven by whether recommendation changes are based on earnings or discount rates but also on the magnitude of the changes. We examined the impact of extreme recommendation changes, recommendation changes with large earnings changes, and recommendation changes with "innovative" earnings changes (i.e., upgrades with earnings increased to above the consensus and downgrades decreased to below the consensus). We find that both recommendation changes with large earnings changes and recommendation changes with innovative earnings changes have a significant incremental impact. Extreme recommendation changes have a significantly larger price impact than non-extreme recommendation changes, but they are equally common among earnings-based and discount rate-based recommendation changes and have no price impact incremental to the price impact of earnings-based and discount rate-based recommendation changes.

We also examine growth rate changes, and we find that the total price reaction is bigger for earnings-based recommendation changes than for growth rate-based recommendation changes. These results are consistent with growth rate-based recommendation changes being characterized by softer information, less verifiability, and longer forecast horizons like discount rate-based recommendation changes.

Our results for the post-recommendation change drift suggest that investors may be able to earn excess returns by buying upgrades with earnings increases and selling downgrades with earnings decreases. We find that the alpha from this strategy is very economically and statistically significant both on its own (3.37% per month) and compared to buying all upgrades and selling all downgrades (2.01% per month). Moreover, the profits from this trading strategy persist throughout our sample period.

Finally, our evidence supports a recent body of the asset pricing literature that 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% 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 I/B/E/S does not have data for Lehman Brothers (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).[17] We drop recommendation changes associated with the Global Settlement (leaves 213,034 firm-date-analyst triples).[18]

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 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 that require at least one year of data (leaves 164,219 firm-date pairs). We drop firms with only one analyst covering them

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

[18] 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. Because of the Global Settlement and typically in anticipation of it, many brokers changed their rating system 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.

because we study recommendation changes with earnings changes relative to the consensus and the consensus is 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 (leaves 123,250 firm-date pairs).[19] 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 by collapsing firm-date-analyst triples to firm-date pairs as follows. Most firm-date-analyst triples (97%) 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 by firm-date-analyst triples in both the recommendations and earnings estimates databases.[20] 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.

[19] Eighty-five percent of these dropped recommendation changes are not associated with a previous earnings estimate.

[20] If we extend the window for potential matches to the fifteen calendar days centered on the recommendation day, we capture only a trivial number of additional matches, and the results are the same.

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 are often unable to compute the consensus for FY2 earnings estimates due to insufficient FY2 earnings 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 (typically five-year) earnings growth rate estimate changes similarly to our short-term earnings estimate changes with two exceptions. First, there is exactly no or one growth rate estimate for each firm-date-analyst triple 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 even though the earnings estimate change is defined.

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.[21] 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.

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 in equity research analysis according to *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

[21] If we extend the window for potential matches to the fifteen calendar days centered on the recommendation day, we capture only a trivial number of additional matches, and the results are the same.

2008); Prudential Equity Group/Bache (November 1993 to October 2007); Sanford C. Bernstein (November 1993 to October 2008); Schroder/Wertheim/Schroder Wertheim/Wertheim Schroder (November 1993 to October 2000); and UBS/Paine Webber (November 1993 to October 2008).

*A.5. Conversion of Five-Point Rating Scale to Three-Point Rating Scale*

Our conversion is in the spirit of the Global Settlement's regulatory requirement for brokers to issue only buy, hold, and sell recommendations. We convert the five-point rating scale used by I/B/E/S (1 is best and 5 is worst) to a three-point rating scale as follows. For brokers with a rating system change associated with the Global Settlement (typically in the second half of 2002), we convert 1s to 1, 2s to 2, and 3s, 4s, and 5s to 3 before their rating system change, and after their rating system change, we convert 1s and 2s to 1, 3s to 3, and 4s and 5s to 3. For brokers without a rating system change, we convert 1s to 1, 2s to 2, and 3s, 4s, and 5s to 3. We use a broker-specific rating system change date because different brokers change their rating system on different dates. Our conversion is supported by the distribution of recommendations. For brokers with a rating system change, the vast majority of recommendations are 1s, 2s, and 3s before the rating system change, but there are significantly fewer 1s and 2s and significantly more 3s, 4s, and 5s. For brokers without a rating system change, the vast majority of recommendations are 1s, 2s, and 3s both before and after the time of rating system change.

## References

Amir, Eli, and Yoav Ganzach, 1998, Overreaction and underreaction in analysts' forecasts, *Journal of Economic Behavior & Organization* 37, 333-347.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245-282.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2008, Ratings changes, ratings levels, and the predictive value of analysts' recommendations, working paper.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting Research* 27, 1-36.

Bernard, Victor L., and Jacob K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Brav, Alon, and Reuven Lehavy, 2003, An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics, *Journal of Finance* 58, 1933-1967.

Brav, Alon, Reuven Lehavy, and Roni Michaely, 2005, Using expectations to test asset pricing models, *Financial Management* Autumn, 5-37.

Campbell, John Y., Christopher Polk, and Tuomo Vuolteenaho, 2009, Growth or glamour? Fundamentals and systematic risk in stock returns, forthcoming *Review of Financial Studies*.

Chan, Louis K. C., Jason Karceski, and Josef Lakonishok, 2003, The level and persistence of growth rates, *Journal of Finance* 58, 643-684.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431-2456.

Chen, Long, and Xinlei Zhao, 2008, What drives stock price movement?, working paper.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003a, The value spread, *Journal of Finance* 58, 609-641.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003b, The price is (almost) right, forthcoming *Journal of Finance*.

Damodaran, Aswath, 2006. *Damodaran on Valuation: Security Analysis for Investment and Corporate Finance, Second Edition* (Wiley).

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605-1643.

Edmans, Alex, 2009, Does the stock market fully value intangibles? Employee satisfaction and equity prices, working paper.

Emery, Douglas R., and Xi Li, 2009, Are the Wall Street analyst rankings popularity contests?, *Journal of Financial and Quantitative Analysis* 44, 411-437.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics 43*, 153-193.

Fang, Lily H., and Ayako Yasuda, 2009, Are stars' opinions worth more? The relation between analyst reputation and recommendation values, working paper.

Ganzach, Yoav, and David H. Krantz, 1991, The psychology of moderate prediction: II Leniency and uncertainty, *Organizational Behavior and Human Decision Processes* 48, 169-192.

Gleason, Cristi A., and Charles M. C. Lee, 2003, Analyst forecast revisions and market price discovery, *The Accounting Review* 78, 193-225.

Gintschel, Andreas, and Stanimir Markov, 2004, The effectiveness of Regulation FD, *Journal of Accounting and Economics* 37, 293-314.

Green, T. Clifton, 2006, The value of client access to analyst recommendations, *Journal of Financial and Quantitative Analysis* 41, 1-24.

Grinblatt, Mark, and Sheridan Titman, 2001. *Financial Markets and Corporate Strategy, Second Edition* (McGraw-Hill/Irwin).

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313-351.

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181-208.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083-1124.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2009, Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations, forthcoming *Review of Financial Studies*.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21, 107-138.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101-127.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, Jr., 2009, Scaling the hierarchy: How and why investment banks compete for syndicate co-management appointments, *Review of Financial Studies* 22, 3977-4007.

Loh, Roger K., and René M. Stulz, 2009, When are analyst recommendation changes influential?, working paper.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23-51.

Malmendier, Ulrike, and Devin Shanthikumar, 2007, Do securities analysts speak in two tongues?, working paper.

McNichols, Maureen F., and Patricia C. O'Brien, 1997, Self-selection and analyst coverage, *Journal of Accounting Research* 35, 167-199.

Michaely, Roni, and Kent L. Womack, 1999, Conflicts of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653-686.

Stickel, Scott E., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* September-October, 25-39.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

**Table 1**
**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. Analysts are classified as "stars" and brokers are classified as "prestigious" based on the rankings of *Institutional Investor* magazine. Turnover and total return volatility are measured during the year ending the month before the recommendation day. Market capitalization, book-to-market, turnover, total return volatility, and institutional ownership are measured in percentiles.

| Panel A: Recommendation Change Characteristics | | | | | |
|---|---|---|---|---|---|
| Recommendation change category | Observations | Percent of upgrades or downgrades | Percent around earnings announcements | Percent issued by star analysts | Percent issued by prestigious brokers |
| All upgrades | 56,341 | 100.0 | 24.6 | 11.6 | 32.6 |
| Upgrades with earnings increases | 18,308 | 32.5 | 37.1 | 11.7 | 34.1 |
| Upgrades with no earnings changes | 30,121 | 53.5 | 16.0 | 11.8 | 32.4 |
| Upgrades with earnings decreases | 7,912 | 14.0 | 28.3 | 10.5 | 30.0 |
| All downgrades | 66,909 | 100.0 | 22.9 | 11.0 | 30.5 |
| Downgrades with earnings increases | 6,918 | 10.3 | 36.0 | 10.6 | 30.5 |
| Downgrades with no earnings changes | 35,842 | 53.6 | 15.0 | 11.3 | 30.2 |
| Downgrades with earnings decreases | 24,149 | 36.1 | 30.9 | 10.7 | 30.9 |

| Panel B: Firm Characteristics | | | | | | |
|---|---|---|---|---|---|---|
| Recommendation change category | Mean market capitalization (percentiles) | Mean B/M (percentiles) | Mean turnover (percentiles) | Mean total return volatility (percentiles) | Mean institutional ownership (percentiles) | Mean analyst coverage (number of analysts) |
| All upgrades | 81.0 | 40.2 | 70.7 | 37.1 | 75.2 | 15.5 |
| Upgrades with earnings increases | 81.0 | 39.2 | 70.9 | 37.3 | 75.2 | 15.4 |
| Upgrades with no earnings changes | 81.6 | 39.9 | 70.7 | 36.6 | 75.5 | 15.7 |
| Upgrades with earnings decreases | 78.7 | 43.7 | 70.7 | 38.5 | 74.4 | 14.8 |
| All downgrades | 78.7 | 40.7 | 70.8 | 38.7 | 74.1 | 14.6 |
| Downgrades with earnings increases | 81.1 | 35.5 | 71.1 | 37.3 | 75.3 | 15.2 |
| Downgrades with no earnings changes | 80.1 | 39.5 | 70.4 | 37.5 | 74.4 | 15.0 |
| Downgrades with earnings decreases | 75.9 | 44.1 | 71.3 | 40.7 | 73.3 | 13.8 |
| Standard deviations | 18.2 | 25.7 | 21.9 | 24.1 | 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 (56,341 observations) | -0.23*** | 2.45*** | 0.43*** | 0.67*** | 0.85*** | 0.99*** | 1.16*** | 1.36*** |
| Upgrades with earnings increases | 2.16*** | 3.55*** | 0.77*** | 1.15*** | 1.46*** | 1.83*** | 2.07*** | 2.48*** |
| Upgrades with no earnings changes | -1.02*** | 2.13*** | 0.33*** | 0.51*** | 0.65*** | 0.65*** | 0.78*** | 0.93*** |
| Upgrades with earnings decreases | -2.72*** | 1.11*** | 0.04 | 0.15 | 0.18 | 0.36*** | 0.52*** | 0.40* |
| All downgrades (N=66,909 observations) | -0.31*** | -2.81*** | -0.53*** | -0.67*** | -0.76*** | -0.85*** | -1.09*** | -1.21*** |
| Downgrades with earnings increases | 4.00*** | -0.35*** | 0.10 | 0.13 | 0.20 | 0.23 | 0.09 | 0.43 |
| Downgrades with no earnings changes | 1.43*** | -1.72*** | -0.45*** | -0.59*** | -0.69*** | -0.79*** | -1.03*** | -1.20*** |
| Downgrades with earnings decreases | -4.13*** | -5.11*** | -0.83*** | -1.02*** | -1.15*** | -1.24*** | -1.52*** | -1.69*** |

**Table 3**
**Stock Returns for Recommendation Changes and Earnings Changes**
**Controlling for Recommendation Change Characteristics and Firm Characteristics in Event-Time**

This table presents regressions of excess returns on recommendation change category dummy variables and control variables in event-time. Returns are presented during various event windows relative to the recommendation day. The sample comprises upgrades and downgrades 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 variable for recommendation changes with no earnings changes, which is the default category. The earnings announcement dummy variable equals one if there is a quarterly earnings announcement during the week ending on the recommendation day. The recommendation change by a prestigious broker dummy variable 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. 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, momentum, and total return volatility are measured in percentiles. Turnover and total return volatility are measured during the year ending the month before the recommendation day. Momentum is measured during the first eleven months of the year ending the month before the recommendation day. Industry fixed effects are defined based on two-digit SIC codes. Time fixed effects are defined based on calendar quarters during our sample period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Below each coefficient estimate is its corresponding t-statistic in parentheses.

| | Excess returns for upgrades during | | Excess returns for downgrades during | |
|---|---|---|---|---|
| | [-1,0] | [+1,+21] | [-1,0] | [+1,+21] |
| Earnings increase dummy variable | 1.272*** | 1.232*** | 1.428*** | 0.969*** |
| | (19.272) | (10.579) | (11.850) | (5.556) |
| Earnings decrease dummy variable | -1.347*** | -0.340** | -2.934*** | -0.443*** |
| | (-15.648) | (-2.240) | (-37.254) | (-3.889) |
| Multiple recommendation changes on the same day dummy variable | 3.963*** | 1.024*** | -6.889*** | -0.308 |
| | (19.594) | (2.870) | (-37.415) | (-1.156) |
| Earnings announcement dummy variable | 0.786*** | 0.407*** | -1.012*** | 0.440*** |
| | (11.392) | (3.344) | (-11.759) | (3.532) |
| Recommendation change by a prestigious broker dummy variable | 1.231*** | 0.040 | -1.141*** | -0.035 |
| | (19.210) | (0.351) | (-14.231) | (-0.301) |
| Number of upgrades minus number of downgrades during the previous week dummy variable | -0.144 | 0.437* | -0.369** | 0.028 |
| | (-0.998) | (1.719) | (-2.121) | (0.113) |
| Percent change in the consensus earnings estimate during the previous week | 0.294 | 0.243 | -1.367*** | 0.121 |
| | (1.570) | (0.737) | (-7.693) | (0.471) |
| Percent raw return during the previous week | -0.045*** | -0.012** | 0.018*** | -0.023*** |
| | (-13.121) | (-1.986) | (4.784) | (-4.081) |
| Market efficiency proxy | -0.402*** | -0.392*** | 0.254*** | 0.196*** |
| | (-17.417) | (-9.628) | (9.322) | (4.975) |
| Book-to-market | 1.336*** | 0.361 | 0.965*** | -0.470* |
| | (9.712) | (1.486) | (5.814) | (-1.959) |
| Momentum | -1.718*** | 0.070 | -0.583*** | -0.370* |
| | (-14.451) | (0.334) | (-3.937) | (-1.724) |
| Total return volatility | 4.486*** | -0.158 | -5.003*** | -1.975*** |
| | (28.820) | (-0.575) | (-26.258) | (-7.164) |
| Industry fixed effects? | Yes | Yes | Yes | Yes |
| Time fixed effects? | Yes | Yes | Yes | Yes |
| Observations | 55,520 | 55,520 | 65,690 | 65,690 |
| Adjusted $R^2$ | 0.090 | 0.009 | 0.096 | 0.007 |

**Table 4**
**Test of Whether Discount Rate-Based Recommendation Changes Are Driven By Changes in Earnings Estimates or Discount Rates Estimates**

This table presents the same regressions as Table 3 with the following exceptions. The sample comprises recommendation changes between 1994 and 2007 corresponding to 65,963 firm-dates of which 30,121 are upgrades with no earnings changes and 35,842 are downgrades with no earnings changes. Since the sample comprises only recommendation changes with no earnings changes, dummies for earnings increases and earnings decreases are deleted. A dummy variable for previous earnings estimates above the consensus earnings estimate is added. Only selected regression results are tabulated.

| | Excess returns for upgrades during | | Excess returns for downgrades during | |
|---|---|---|---|---|
| | [-1,0] | [+1,+21] | [-1,0] | [+1,+21] |
| Previous earnings above the consensus dummy variable | -0.048 | 0.043 | 0.096 | -0.117 |
| | (-0.593) | (0.298) | (0.977) | (-0.825) |
| Control variables | Yes | Yes | Yes | Yes |

**Table 5**
**Comparisons of 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. For expositional simplicity, results are only tabulated for selected categories. 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.

| | Observations | Excess returns during [-1,0] | Excess returns during [+1,+21] |
|---|---|---|---|
| Upgrades | | | |
| With earnings increases and | | | |
| No growth rate changes | 9,868 | 3.81 | 1.83 |
| Growth rate increases | 1,102 | 3.91 | 1.61 |
| Difference | | -0.10 | 0.22 |
| With no earnings changes and | | | |
| No growth rate changes | 17,705 | 2.23 | 0.76 |
| Growth rate increases | 516 | 2.21 | 0.50 |
| Difference | | 0.02 | 0.26 |
| Downgrades | | | |
| With no earnings changes and | | | |
| No growth rate changes | 21,318 | -1.77 | -0.65 |
| Growth rate decreases | 564 | -2.21 | -0.59 |
| Difference | | 0.44 | -0.06 |
| With earnings decreases and | | | |
| No growth rate changes | 13,406 | -5.50 | -1.22 |
| Growth rate decreases | 1,993 | -7.25 | -0.46 |
| Difference | | 1.75*** | -0.76** |

**Table 6**
**Stock Returns for Recommendation Changes and Earnings Estimate Changes Split Into Various Sub-Categories Controlling for Recommendation Change Characteristics and Firm Characteristics in Event-Time**

Panel A presents stock returns for extreme recommendation changes and large earnings estimate changes. This panel presents the same regressions as Table 3 with the addition of dummies for interactions between earnings increases, no changes, and decreases and extreme recommendation changes and large earnings changes. Extreme recommendation changes are defined as recommendation changes of two points on a three-point rating scale. Large earnings estimate increases are defined as earnings estimate increases (relative to the closing price per share two days before the recommendation day) of greater magnitude than the median earnings estimate increase using the sub-sample of recommendation changes with earnings estimate increases. Panel B presents stock returns for earnings estimate changes relative to the consensus. This panel presents the same regressions as Table 3 with the addition of dummies for earnings estimates increased to above the consensus and earnings estimates decreased to below the consensus. Only selected regression results are tabulated.

Panel A: Stock Returns for Extreme Recommendation Changes and Large Earnings Changes

| | Excess returns for upgrades during | | Excess returns for downgrades during | |
|---|---|---|---|---|
| | [-1,0] | [+1,+21] | [-1,0] | [+1,+21] |
| Earnings increase dummy variable | 0.807*** | 0.803*** | 1.475*** | 0.420* |
| | (8.850) | (4.988) | (8.994) | (1.765) |
| Earnings increase and extreme recommendation change dummy variable | -0.086 | 0.342 | -0.373 | -0.178 |
| | (-0.717) | (1.622) | (-1.423) | (-0.470) |
| Large earnings increase | 0.995*** | 0.938*** | 0.180 | 1.250*** |
| | (9.728) | (5.193) | (0.817) | (3.909) |
| No earnings changes and extreme recommendation change dummy variable | 0.150 | 0.637*** | -0.041 | -0.249 |
| | (1.593) | (3.826) | (-0.377) | (-1.564) |
| Earnings decrease dummy variable | -1.253*** | -0.294 | -1.710*** | -0.446*** |
| | (-11.073) | (-1.475) | (-15.789) | (-2.835) |
| Earnings decrease and extreme recommendation change dummy variable | 0.564*** | 0.451 | -0.400*** | -0.270 |
| | (3.071) | (1.392) | (-2.926) | (-1.363) |
| Large earnings decrease | -0.479*** | 0.016 | -2.250*** | 0.015 |
| | (-3.014) | (0.059) | (-18.313) | (0.084) |
| Control variables | Yes | Yes | Yes | Yes |

Panel B: Stock Returns for Earnings Estimate Changes Relative to the Consensus

| | Excess returns for upgrades during | | Excess returns for downgrades during | |
|---|---|---|---|---|
| | [-1,0] | [+1,+21] | [-1,0] | [+1,+21] |
| Earnings increased dummy variable | 0.950*** | 0.617*** | 0.843*** | 0.600** |
| | (10.520) | (3.872) | (4.535) | (2.228) |
| Earnings increased to above the consensus dummy variable | 0.542*** | 1.033*** | 0.937*** | 0.585* |
| | (5.237) | (5.659) | (4.169) | (1.795) |
| Earnings decreased | -1.599*** | -0.541*** | -3.375*** | -0.471*** |
| | (-15.971) | (-3.061) | (-39.359) | (-3.790) |
| Earnings decreased to above the consensus dummy variable | 0.804*** | 0.638** | 1.816*** | 0.114 |
| | (4.902) | (2.204) | (12.907) | (0.558) |
| Control variables | Yes | Yes | Yes | Yes |

**Table 7**
**Robustness Tests**

This table presents variations of the regressions in Table 3. Compared to Table 3, 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 variable is excluded. In column (2), the same regression is run as in column (1) but there is a dummy variable for whether the earnings surprise at the earnings announcement during the previous quarter was positive. In column (3), there is a dummy variable 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), recommendation changes with more than one broker per firm-date pair are dropped and broker fixed effects are included. In column (6), there is a control for the level of the previous recommendation by the analyst. In column (7), there is a dummy variable for recommendation changes with unclassifiable earnings changes. Only selected regression results are tabulated. The results for upgrades are presented in Panel A (initial price reaction) and Panel B (drift), and the results for downgrades are presented in Panel C (initial price reaction) and Panel D (drift).

Panel A: Initial Price Reaction for Upgrades

| | Excess returns during [-1,0] | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Earnings increase dummy variable | 0.808*** | 0.810*** | 1.251*** | 1.147*** | 1.211*** | 1.276*** |
| | (11.225) | (11.076) | (17.919) | (16.390) | (18.141) | (19.334) |
| Earnings decrease dummy variable | -0.986*** | -0.974*** | -1.294*** | -1.223*** | -1.204*** | -1.352*** |
| | (-10.634) | (-10.307) | (-14.145) | (-13.494) | (-13.911) | (-15.712) |
| Positive earnings surprise dummy variable | | -0.279*** | | | | |
| | | (-4.501) | | | | |
| Star analyst dummy variable | | | 0.255** | | | |
| | | | (2.393) | | | |
| Level of the previous recommendation | | | | | | -0.306*** |
| | | | | | | (-7.514) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

Panel B: Drift for Upgrades

| | Excess returns during [+1,+21] | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Earnings increase dummy variable | 1.270*** | 1.244*** | 1.239*** | 1.207*** | 1.268*** | 1.234*** |
| | (9.267) | (8.839) | (9.914) | (9.577) | (10.589) | (10.594) |
| Earnings decrease dummy variable | -0.303* | -0.323* | -0.290* | -0.226 | -0.233 | -0.343** |
| | (-1.717) | (-1.774) | (-1.772) | (-1.386) | (-1.501) | (-2.256) |
| Positive earnings surprise dummy variable | | 0.217* | | | | |
| | | (1.816) | | | | |
| Star analyst dummy variable | | | 0.127 | | | |
| | | | (0.666) | | | |
| Level of the previous recommendation | | | | | | -0.154** |
| | | | | | | (-2.152) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

| Panel C: Initial Price Reaction for Downgrades | | | | | | |
|---|---|---|---|---|---|---|
| | Excess returns during [-1,0] | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Earnings increase dummy variable | 0.793*** | 0.693*** | 1.454*** | 1.366*** | 1.363*** | 1.429*** |
| | (5.633) | (4.910) | (11.449) | (11.173) | (11.642) | (11.865) |
| Earnings decrease dummy variable | -2.928*** | -2.901*** | -2.920*** | -2.566*** | -2.525*** | -2.925*** |
| | (-33.698) | (-33.120) | (-35.339) | (-31.480) | (-32.475) | (-37.148) |
| Positive earnings surprise dummy variable | | -0.051 | | | | |
| | | (-0.659) | | | | |
| Star analyst dummy variable | | | -0.129 | | | |
| | | | (-0.959) | | | |
| Level of the previous recommendation | | | | | | -0.394*** |
| | | | | | | (-7.382) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

| Panel D: Drift for Downgrades | | | | | | |
|---|---|---|---|---|---|---|
| | Excess returns during [+1,+21] | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Earnings increase dummy variable | 0.993*** | 1.039*** | 1.048*** | 0.847*** | 0.895*** | 0.969*** |
| | (4.699) | (4.836) | (5.624) | (4.554) | (5.051) | (5.557) |
| Earnings decrease dummy variable | -0.432*** | -0.482*** | -0.412*** | -0.576*** | -0.495*** | -0.443*** |
| | (-3.317) | (-3.617) | (-3.396) | (-4.644) | (-4.207) | (-3.887) |
| Positive earnings surprise dummy variable | | 0.203* | | | | |
| | | (1.715) | | | | |
| Star analyst dummy variable | | | -0.281 | | | |
| | | | (-1.423) | | | |
| Level of the previous recommendation | | | | | | -0.005 |
| | | | | | | (-0.068) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 8**
**Summary of Daily Returns for Calendar-Time Portfolios**

This table presents daily returns statistics for portfolios in calendar-time formed based on recommendation changes. In Panel A, portfolios are formed using all upgrades and all downgrades. In this panel, the sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates consisting of 56,341 upgrades, which are bought, and 66,909 downgrades, which are sold short. In Panel B, portfolios are formed using upgrades with earnings increases and downgrades with earnings decreases. In this panel, the sample comprises recommendation changes between 1994 and 2007 corresponding to 42,457 firm-dates consisting of 18,308 upgrades with earnings increases, which are bought, and 24,149 downgrades with earnings decreases, which are sold. Calendar-time returns are computed as follows. The portfolio formation interval equals the portfolio holding period length. Firms are bought ("long" firms) and sold short ("short" firms) based on recommendation changes on the day before the portfolio formation date. 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 5% level are also tabulated.

| Panel A: Portfolios Formed Using All Upgrades and All Downgrades | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Means of the following statistics | | | | | | | | |
| Portfolio formation interval = length of portfolio holding period (days) | Portfolio type | 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% |

| Panel B: Portfolios Formed Using Upgrades With Earnings Increases and Downgrades With Earnings Decreases | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 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% |

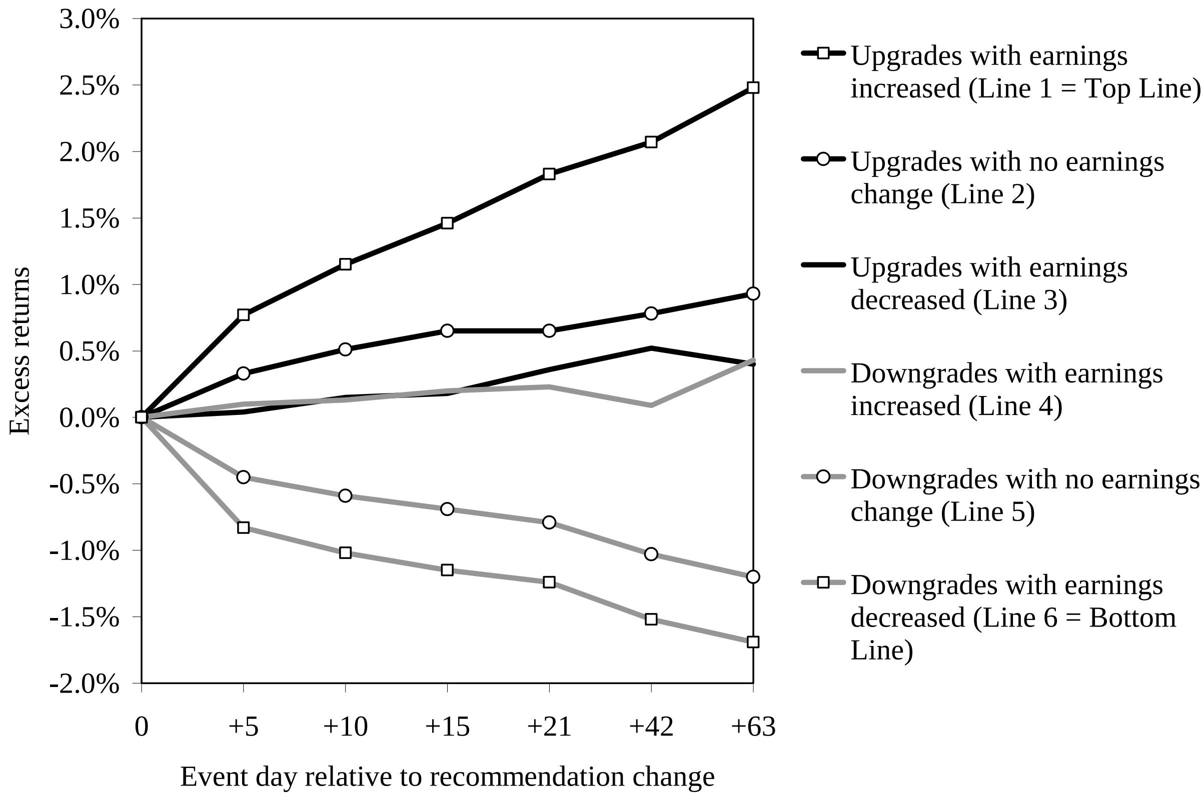



**Figure 1. Stock returns by recommendation upgrades and downgrades and earnings estimate increases, no changes, and decreases in event-time.** The sample comprises recommendation changes between 1994 and 2007 corresponding to 123,250 firm-dates. Excess returns are returns in excess of benchmark portfolios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

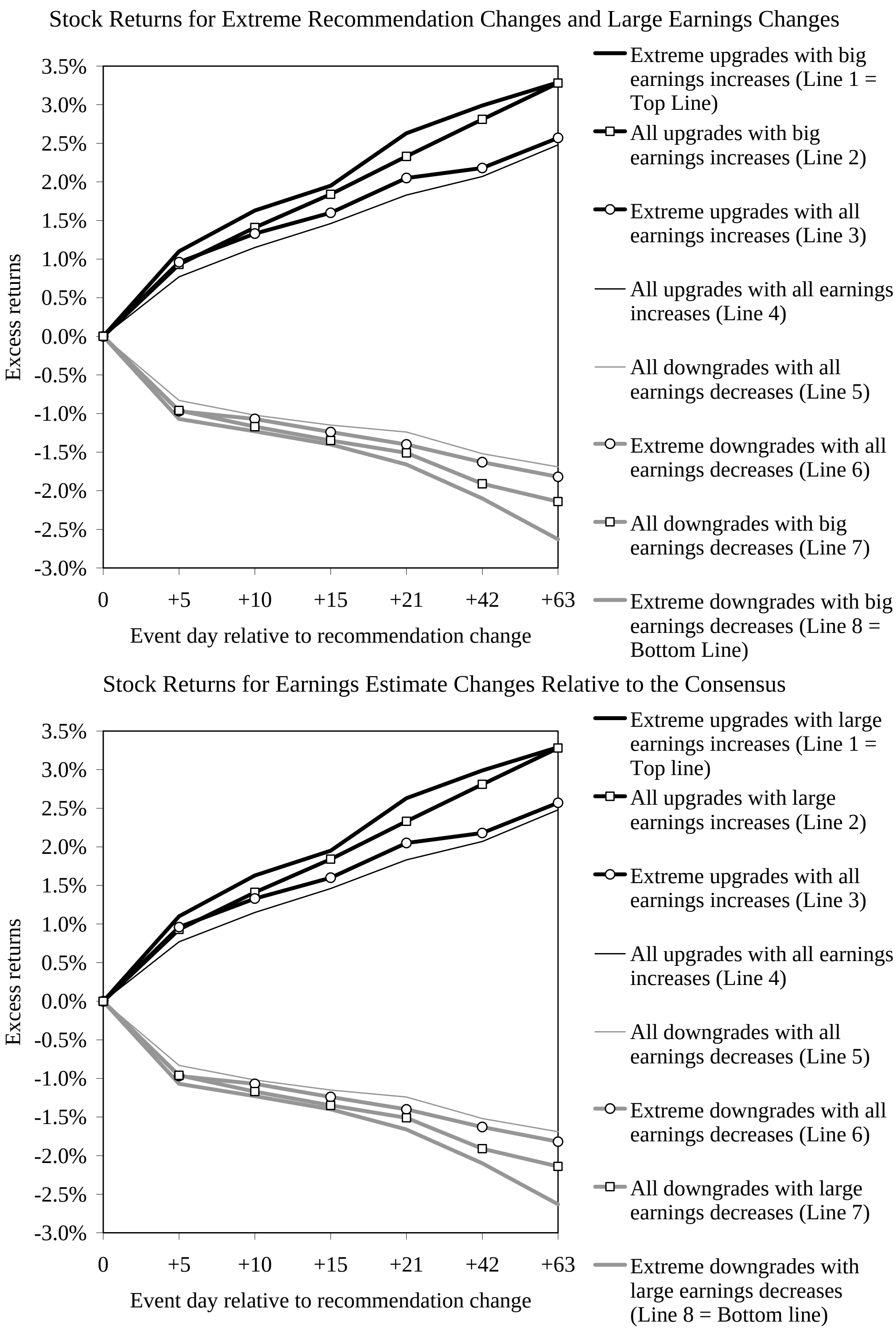
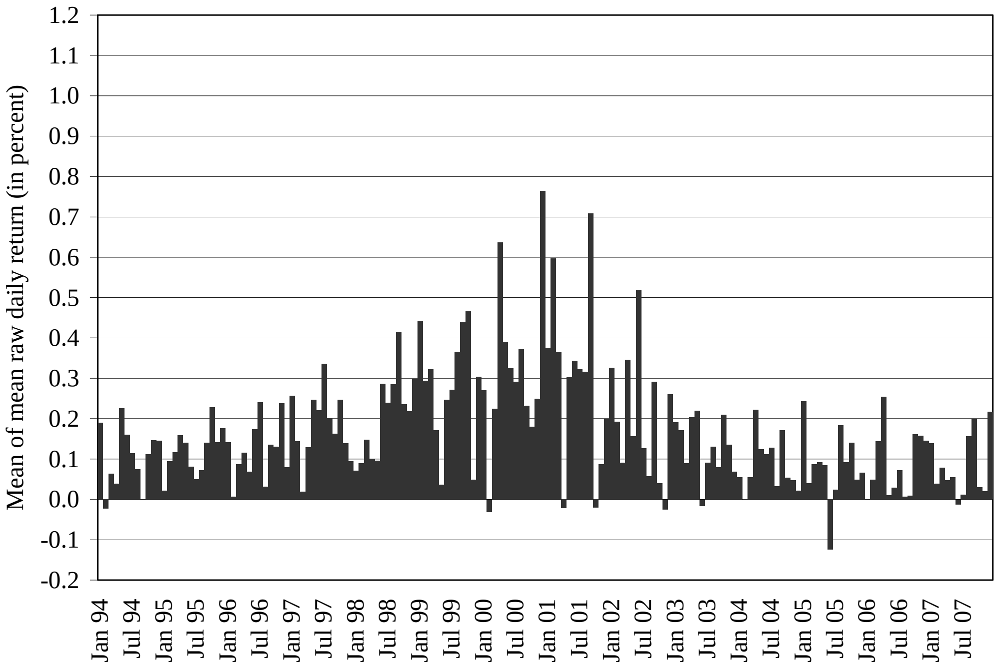



**Figure 2. Stock returns for extreme recommendation changes, large earnings changes, and earnings estimate changes relative to the consensus.** The top figure presents recommendation change categories split into extreme recommendation changes, large earnings estimate changes, and extreme recommendation changes with large earnings estimate changes. The bottom figure presents recommendation change categories split into two sub-categories based on whether the analyst's earnings are above or below the consensus. 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.

Portfolios formed using all upgrades and all downgrades




Portfolios formed using upgrades with earnings increases and downgrades with earnings decreases

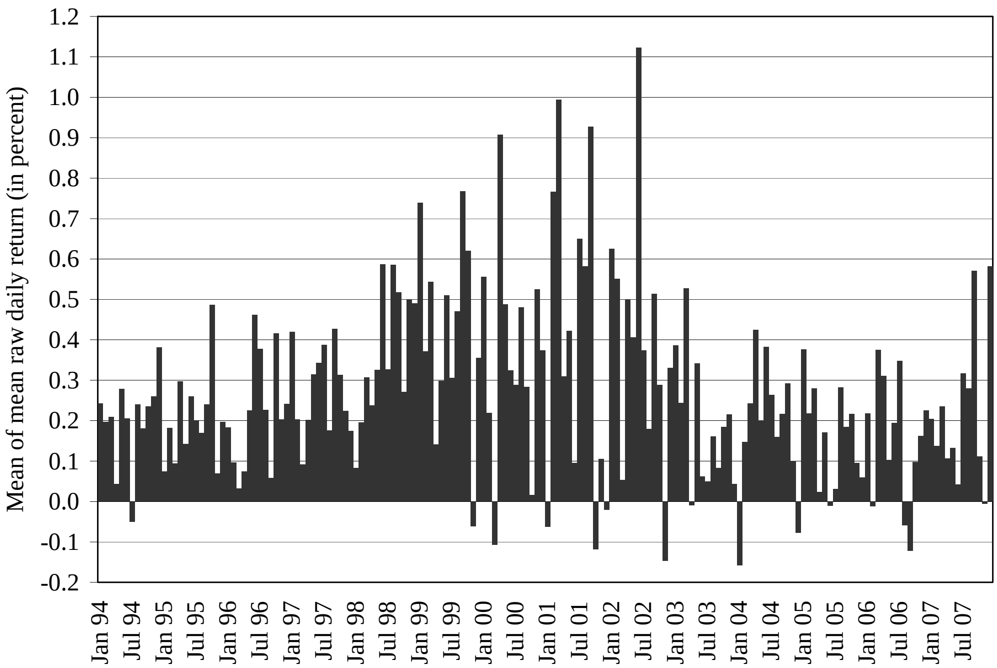



**Figure 3. The drift after the recommendation changes in calendar-time.** This figure presents the mean each month (rather than the mean for all months between 1994 and 2007) of the mean of the raw daily returns for the long minus short portfolios in Table 8 Panel A (top figure) and Table 8 Panel B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