What Drives the Value of Analysts' Recommendations:

Earnings Estimates or Discount Rate Estimates?

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Abstract

An analyst changes his recommendation of a stock to indicate to investors that his valuation of the stock differs from the market's valuation. Explicitly or implicitly, the difference in valuation ultimately arises from disagreement about earnings estimates and/or discount rate estimates. We argue that recommendation changes that are based on changes in earnings estimates are characterized by harder information, greater verifiability, and shorter forecast horizons than recommendation changes that are based on discount rate estimates, so they are less subject to analysts' cognitive and incentive biases. Therefore, earnings-based recommendation changes should be more informative to investors than discount rate-based recommendation changes. We find that both the initial price reaction and the drift after recommendation changes are 50%-200% bigger for earnings-based recommendation changes 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.

May 16, 2011

* Kecskés is at the Virginia Polytechnic Institute and State University, Michaely is at Cornell University and the Interdisciplinary Center, and Womack is at the Rotman School of Management at the University of Toronto. We greatly appreciate the comments of Anup Agrawal, Alon Brav, Kobi Boudoukh, Alex Edmans, Ned Elton, Eli Fich, Umit Gurun, Christopher Hennessy, Özgür Ince, Paul Irvine, Avner Kalay, Andrew Karolyi, Jonathan Lewellen, Karl Lins, Roger Loh, Evgeny Lyandres, Patricia O'Brien, Christopher Polk, Enrique Schroth, Russ Wermers, Avi Wohl, Amir Yaron, and seminar participants at the 2011 American Finance Association meetings, Claremont McKenna College, the Copenhagen School of Business, Cornell University, Drexel University, the 2011 European Winter Finance Conference, the 2010 Financial Intermediation Research Society meetings, Georgia Tech, Imperial College, the Interdisciplinary Center, London Business School, the London School of Economics, the Norwegian School of Management, the Q Group, Tel Aviv University, the University of Alabama, the University of Amsterdam, the University of Illinois at Urbana-Champaign, l'Université du Luxembourg, the University of Miami, Universidade Nova de Lisboa, the University of Toronto, the University of Western Ontario, Virginia Tech, Washington University, and Wharton. Christopher Vincent provided excellent research assistance. This paper was formerly entitled "What Are Analysts Really Good At?"

1. Introduction

Sell-side analysts change their stock recommendations to indicate to investors that their valuation differs from the market's current valuation. It is well known that these pronouncements move the market in the target stock both at and after the news of the recommendation change.[1] In this study, we examine why some recommendation changes are more informative than others within the framework of the discounted cash flow valuation model.[2] According to this fundamental model, the value of an asset is the discounted present value of its future cash flows. Therefore, the difference between the analyst's estimated price and the market price should arise from differences in either estimates of future cash flows or discount rates.[3] We read a large sample of analyst reports, and we find that this dichotomy corresponds nicely to the motivations that analysts include in their reports: they cite either changes in their earnings estimates ("we now believe that earnings will be higher than the consensus") or, as the main alternative, recent stock price changes ("the stock price has dropped too much"). Absent a change in cash flow estimates, an opinion that prices declined or increased too much is equivalent to analysts supporting their recommendation changes with a change in their discount rate estimates relative to the market's. In this paper, we study how these two basic motivations for recommendation changes affect their informativeness to investors.

In reading 150 analyst reports, we find that analysts often explicitly justify their recommendation changes with earnings forecast changes, but they rarely mention the discount rate estimates that they implicitly use. Instead, they refer to undervaluation or overvaluation based on recent relative stock price changes or relative valuation ratios (e.g., price-to-earnings) using the firm's industry as the typical benchmark. Within the theoretical framework of the discounted cash flow valuation model, any recommendation change that is not motivated by a

[1] E.g., see Elton, Gruber, and Grossman (1986), Stickel (1995), Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), and Green (2006).
[2] Several previous studies provide context for our findings. Jegadeesh, Kim, Krische, and Lee (2004) document that analysts favor stocks with certain characteristics ("glamour" stocks, for example). Loh and Stulz (2011) examine how the market reaction to recommendation changes depends on how influential is the analyst issuing them (e.g., a star analyst or an analyst working for a prestigious broker).
[3] This is the case whether the analyst uses multiples valuation or discounted cash flow valuation. Although 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)).

change in earnings estimates must necessarily be motivated by a change in discount rate estimates even if this change is rarely stated explicitly.

We initially operationalize the dichotomy between recommendation changes based on changes in earnings estimates as opposed to discount rate estimates by first defining "earnings-based recommendation changes" as those that are accompanied by earnings estimate changes (in the next fiscal year or two). We then define "discount rate-based recommendation changes" as those that are not accompanied by earnings estimate changes; accordingly, they could also be accurately described as "non-earnings-based recommendation changes". We show below that these two types of recommendation changes differ dramatically in their informativeness to investors.

Analysts also issue recommendation changes accompanied by changes in long-term earnings estimate growth rates, but such "growth rate-based recommendation changes" are rare (only roughly 5% of recommendation changes). We find that our results do not change if we incorporate growth rate estimates into our analysis. Consequently, in most of the analysis, we focus on earnings-based and discount rate-based recommendation changes.

The natural null hypothesis is that the motivation of the recommendation change (a change in earnings estimates versus discount rate estimates) is independent of its informativeness to investors. If we reject the null hypothesis, one possible explanation, as we argue below, is 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 should be more informative and the market reaction to them should be larger.

We argue that the first difference in informativeness is that earnings-based recommendation changes are based on harder information. That is, analysts' earnings estimates are supported by hard numbers and detailed justification of those numbers whereas their discount rate estimates are based on risk assessments that are far more qualitative in nature. This difference is evident in the random sample of 150 analyst reports that we read to better understand what motivates analysts' recommendation changes. We find that analysts almost always 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 to justify their earnings estimates. By contrast, analysts rarely change their discount rate estimates explicitly; when they do change them implicitly, which occurs frequently, analysts typically simply express an opinion that the stock is mispriced without justification (e.g., the recent stock price change is overdone) or the firm is undervalued relative to its peers (e.g., relative to its historical price-to-earnings ratio). For example, analysts frequently point to big stock price run-ups to justify recommendation downgrades when not changing their earnings estimates. In doing so, they imply that their discount rate estimate is higher than the market's.

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 main evaluation criteria of the annual *Institutional Investor* magazine poll ranking of analysts. This ex post verification of analysts' earnings estimates incentivizes analysts to produce more accurate earnings estimates (e.g., Ljungqvist, Marston, Starks, Wei, and Yan (2007)). By contrast, discount rates are notoriously difficult to estimate accurately both ex ante and ex post (e.g., Fama and French (1997)).

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)). What this implies for our study is that analysts' short-term earnings estimates are more accurate than their discount rate estimates. Indeed, Brav, Lehavy, and Michaely (2005) find that analysts' expected returns are quite optimistic on average whereas their short-term earnings estimates are much less optimistic (e.g., Chopra (1998)).

These differences in informativeness also imply that earnings-based recommendation changes are less subject to analysts' cognitive and incentive biases than discount rate-based recommendation changes.[4] In summary, our arguments above suggest that, compared to discount rate-based recommendation changes, earnings-based recommendation changes are characterized by harder information, greater verifiability, and shorter forecast horizons, thus they should be more informative to investors.

Another possible explanation for rejecting the null hypothesis is that recommendation changes that we classify as "earnings-based" are driven by changes in both earnings estimates and discount rate estimates, so they have a more pronounced market reaction. (That is, even

[4] E.g., see McNichols and O'Brien (1997) for analysts' cognitive biases and Michaely and Womack (1999), Hong and Kubik (2003), Malmendier and Shanthikumar (2007), Kolasinski and Kothari (2008), and Ljungqvist, Marston, and Wilhelm (2009) for analysts' incentive biases.

though explicit discount rate estimates are rare in practice, they change implicitly and in the opposite direction to the change in earnings estimates). For example, when an analyst upgrades a stock and increases his earnings forecast, his earnings forecast increase may sometimes occur simultaneously with a decrease in his discount rate estimate.

We test these two alternative explanations against the null hypothesis. We measure informativeness using the initial price impact to recommendation changes as well as 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,[5] so the drift after earnings-based recommendation changes should be smaller because earnings information is more tangible and thus impounded more completely into prices on the recommendation day. On the other hand, the market underreacts to analysts' recommendation changes in general as well as to different types of corporate events including, importantly, earnings announcements.[6] If analysts' recommendation changes follow this pattern, then the drift should be bigger after earnings-based recommendation changes than after discount rate-based recommendation changes. In summary, the differential magnitude of the drift is unclear theoretically and is a question that we answer empirically.

Using recommendation changes from I/B/E/S between 1994 and 2007, we find that the initial price reaction is much larger 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% larger 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% larger than the initial price reaction to discount rate-based downgrades (-5.11% versus -1.72%).

In addition to the immediate event return, we also document a larger drift subsequent to the event for earnings-based recommendation changes. The average one-month drift after earnings-based upgrades is 182% larger than the drift after discount rate-based upgrades (1.83%

[5] E.g., see Lev and Sougiannis (1996), Chan, Lakonishok, and Sougiannis (2001), Daniel and Titman (2006), and Edmans (2011).

[6] The post-earnings announcement drift (e.g., Bernard and Thomas (1989, 1990)) is an important example because the market appears to underreact to quarterly earnings announcements, i.e., to information that is hard and highly verifiable. For evidence of underreaction to other corporate events, see, for example, Loughran and Ritter (1995) for seasoned equity offerings and Ikenberry, Lakonishok, and Vermaelen (1995) for share repurchases.

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 larger initial price reaction and a larger drift than discount rate-based recommendation changes.

These results are consistent with both of our alternative explanations. To distinguish between them, we perform two additional analyses. First, we examine how analysts motivate their recommendation changes in the aforementioned 150 reports that we read. For 88% of upgrades and for 80% of downgrades that we classify as "discount rate-based", the analyst explicitly or implicitly mentions some discount rate motivation. [7] By contrast, the analyst mentions some discount rate motivation for only 40% of upgrades and 12% of downgrades that we classify as "earnings-based". This suggests that a much smaller proportion of our "earnings-based" recommendation changes are motivated by changes in discount rate estimates compared to our "discount rate-based" recommendation changes.

Second, we use our full sample of earnings-based recommendation changes to estimate the incremental price impact of earnings estimate changes versus discount rate estimate changes. Our results suggest that most of the price impact of recommendation changes with earnings estimate changes is indeed driven by earnings estimate changes and not by discount rate estimate changes. Overall, then, our results are more consistent with the first alternative explanation than the second: it is the quality of the signals sent by analysts that matters (earnings-based versus discount rate-based) not their quantity (two versus one).

We also perform robustness tests to account for recommendation change characteristics and firm characteristics. Specifically, we consider 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 recommendation change as well as changes in the market's earnings estimates (to capture changes in the analyst's earnings estimate and discount rate estimate relative to the market's); 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. In additional analyses, we examine whether our results

[7] We consider changes in the analyst's risk estimate or changes in the stock price that the analyst considers excessive as implicit discount rate estimate changes.

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 the difference in the total price reaction between earnings-based and discount rate-based recommendation changes remains economically as well as statistically significant and robust.

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 estimate increases and selling downgrades with earnings estimate decreases. We find that the one-month 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 without regard to earnings estimates. Moreover, the profits from this trading strategy persist throughout our sample period.

Taken as a whole, the results show that recommendation changes based on changes in short-term earnings estimates are more informative than recommendation changes based on changes in discount rate estimates. This is consistent with the argument that earnings-based recommendation changes are characterized by harder information, greater verifiability, and shorter forecast horizons, thus they are less subject to analysts' cognitive and incentive biases.

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 all publicly traded U.S. firms available in 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 rate estimates issued between 1994 and 2007 are taken from I/B/E/S. For all observations in our sample, we must know the identity of the analyst. The recommendation must not be issued by an analyst employed by Lehman Brothers (because

I/B/E/S does not have earnings estimate data for Lehman Brothers), and 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, and the earnings forecast change concurrent with the recommendation change must be classifiable as an earnings estimate 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.[8] Appendix A.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. Appendix A.2 describes the details of the construction of our recommendation change categories.

Analysts issue long-term growth rate estimates much less frequently than they issue earnings estimates for the next fiscal year or two, so we can only measure long-term earnings growth rate estimate 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 concurrent growth rate estimate change (increase or decrease). For our analysis of growth rate estimate changes, we further split each of our six recommendation change categories above into three sub-categories based on growth rate estimate change, namely, increase, no change, and decrease. Appendix A.2 describes these details.

We calculate 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 A.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 one of

[8] 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 (2009)).

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 A.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. Given that 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 investors can earn returns starting from the day +1 return even for recommendations issued after the close of event day 0. We follow Daniel, Grinblatt, Titman, and Wermers (1997) and compute 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 the 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 control for 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 about 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 estimate changes are issued near quarterly 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.

About 10% of our sample recommendation changes are issued by star analysts and around 30% are issued by prestigious brokers. Consistent with Jegadeesh, Kim, Krische, and Lee (2004), recommendation changes are typically issued for big firms, growth firms, liquid firms, firms with low risk, firms with high institutional ownership, and firms with high analyst coverage. Across recommendation change categories, there is very little variation in these firm characteristics. In other words, we do not find that earnings-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, risk, institutional ownership, and analyst coverage.

We also examine the distribution of our six recommendation change categories (upgrades with earnings estimate increases, upgrades with no earnings estimate 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 estimate changes are roughly 58% and 46% of upgrades, respectively, whereas upgrades with earnings estimate increases are roughly 28% and 39%, respectively. We account for this structural change in our multivariate analysis using time fixed effects.

To better understand the institutional details of how our data are generated by analysts, we also read 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 concurrent earnings estimate decreases and downgrades with earnings estimate increases are *not* coding errors. For example, analysts state that they increase their earnings estimates because they are now more optimistic about the firm's cash flows, but they concurrently downgrade their recommendation because they believe that the firm is now overvalued because of the recent rise in the stock price. Overall, the I/B/E/S data appear to be consistent with the corresponding analyst reports.

The reports reveal several stylized facts about the reasons for which analysts disagree with the market and thus change their recommendation. First, 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)). Analysts do not often use discounted cash flow valuation: they only use this valuation technique in 17 of the 150 reports (11%) that we read. Second, analysts issue explicit discount rate estimates in only 15 of the 150 reports (10%). When they do issue explicit discount rate estimates, they typically simply report them without any detailed explanation of how they estimate their discount rates. More importantly, in only 2 of the 150 reports do analysts explicitly change their discount rate estimates. Third, analysts issue explicit long-term earnings 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 only 3% of these reports versus 5% in I/B/E/S.

3. Main Results

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

To test whether earnings-based recommendation changes are more informative than discount rate-based recommendation changes, we examine the total price reaction to recommendation changes in our six recommendation change categories (upgrades with earnings estimate increases, with no earnings estimate changes, with earnings estimate 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. (We examine the post-recommendation change drift later on.)

[Insert Table 2 about here]

Table 2 presents the results. Earnings-based recommendation changes have a significantly larger initial price reaction than discount rate-based recommendation changes. The average initial price reaction to upgrades with earnings estimate increases (earnings-based upgrades) is 3.55% compared to 2.13% for upgrades with no earnings estimate changes (discount rate-based upgrades) and 1.11% for upgrades with earnings estimate decreases. These patterns are similar for downgrades. The initial price reaction to downgrades with earnings estimate decreases (earnings-based downgrades) is -5.11% compared to -1.72% for downgrades with no earnings estimate changes (discount rate-based downgrades) and -0.35% for downgrades with earnings estimate increases. Non-parametric analysis (results not tabulated) 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. For downgrades, the corresponding figures are 75% and 63%, respectively.

The results in Table 2 clearly reject the null hypothesis that the motivation of the recommendation change is independent of its informativeness to investors, but they are consistent with both alternative explanations as discussed in the introduction. We now perform two additional analyses to distinguish between them.

At the time of a recommendation change, changes in analysts' estimates of earnings and discount rates may occur simultaneously and be negatively correlated. That is, since discount rate estimate changes are often unobservable, it is possible that the market reaction to earnings-based recommendation changes may also be driven by concurrent discount rate estimate changes. Given the results in Table 2, this possibility is not a major concern for downgrades. The initial price reaction to earnings-based downgrades (-5.11%) is almost three times the initial price reaction to discount rate-based downgrades (-1.72%). Thus even if earnings-based downgrades are subject to the same average discount rate increases as discount rate-based downgrades, the incremental impact of earnings estimate decreases (-3.39 percentage points) is substantial (at least twice as big). However, it is a potential concern for upgrades because the initial price reaction to earnings-based upgrades is 3.55% compared to 2.13% for discount rate-based upgrades, so the incremental impact of earnings estimate changes is more relevant.

We examine in two ways the possibility that recommendation changes that we classify as "earnings-based" may also be driven implicitly by changes in discount rate estimates. First, we examine our random sample of 150 analyst reports for the frequency with which analysts use discount rate estimate changes to motivate recommendation changes that we classify as "earnings-based" versus those that we classify as "discount rate-based". We include not just explicit discount rate estimate changes (these occur only in 2 out of the 150 reports) as motivations but also references to recent stock price changes and risk estimate changes. When an analyst motivates his recommendation change with a recent stock price change holding all else equal, the motivation for the recommendation change is an implicit discount rate estimate change. For example, analysts frequently point to big stock price drops to justify recommendation upgrades even if their earnings estimates and those of the market do not change. Such a justification suggests that the analyst's discount rate estimate has decreased relative to the market's, thus the analyst's valuation has increased relative to the market's, and so the analyst upgrades his recommendation.

[Insert Table 3 about here]

Table 3 presents our classification of motivations for recommendation changes from these analyst reports. Explicit or implicit discount rate estimate changes motivate 88% of upgrades that we classify as "discount rate-based" compared to only 40% of those that we classify as "earnings-based". For downgrades, the difference is even more pronounced: 80% for "discount rate-based" downgrades compared to only 12% for "earnings-based" downgrades. At a minimum, these two findings together suggest that significantly more recommendation changes that we classify as "discount rate-based" are motivated by discount rate estimate changes than recommendation changes that we classify as "earnings-based".

These results are also consistent with returns during the month before the recommendation change in Table 2. The average 21-day return before upgrades with earnings estimate increases is +2.16% compared to -1.02% for upgrades that we classify as “discount rate-based”. For downgrades, the corresponding return is -4.13% before downgrades with earnings estimate decreases compared to +1.43% for “discount rate-based” downgrades. In effect, "earnings-based" recommendation changes follow recent stock price changes in the same direction whereas "discount rate-based" recommendation changes follow recent stock price changes in the opposite direction. This corresponds nicely to the motivations that we find in the random sample of 150 analyst reports that we read: "discount rate-based" recommendation changes tend to be motivated by recent stock price changes ("the stock has become attractive based on price") much more frequently than "earnings-based" recommendation changes.

Second, we use our full sample of earnings-based recommendation changes and estimate the incremental price impact of earnings estimate changes by examining the initial price reaction to a range of earnings estimate changes while holding discount rate estimates fixed. Conceptually, holding fixed discount rate estimate changes, the variation in the initial price reaction to earnings estimate changes provides a minimum estimate of their incremental information content. It is straightforward to measure the variation in the analyst's earnings estimate change relative to the market's because both the analyst's earnings estimate and the consensus earnings estimate are observable. However, we cannot directly observe the analyst's and the market's discount rate estimates. Therefore, to proxy for the variation in discount rate estimate changes, we infer discount rate estimate changes from the “excess” stock price run-up before the recommendation change. Holding fixed the market's earnings estimate, a relative increase in the stock price implies a decrease in the market's discount rate estimate. This, in turn, implies an increase in the analyst's discount rate estimate relative to the market's (ΔDR_A-ΔDR_M).[9]

We measure the price run-up before the recommendation change as the excess return during the month ending two days before the recommendation day. We measure the variation in earnings estimate changes as the change in the analyst's earnings estimate minus the change in the market's earnings estimate (ΔE_A-ΔE_M) all divided by the stock price. The change in the market's earnings estimate is the change in the consensus earnings estimate during the month ending two days before the recommendation day. The stock price that we use as a scalar is the closing price per share two days before the recommendation day.

[9] It is possible that the analyst's discount rate estimate decreases by more than the market's. In this case, the initial price reaction should be increasing in the price run-up. However, our findings indicate that this is not the case.

We create quintiles for differential earnings estimate changes (ΔE_A-ΔE_M) independently of quintiles for differential discount rate estimate changes (ΔDR_A-ΔDR_M). We then compute the mean initial price reaction for each cell at the intersection of the two groups of quintiles. To estimate the incremental impact of earnings estimates changes, we compute and tabulate the difference between the two extreme quintiles for differential earnings estimate changes. We do so for each quintile of differential discount rate estimate changes. That is, for a given price run-up quintile (i.e., for a fixed differential discount rate estimate change), the difference between the extreme quintiles of differential earnings estimate changes provides a minimum estimate of the incremental information content of earnings estimate changes. To allow comparison between changes in estimates of earnings and discount rates, we also perform the same computations for differential discount rate estimate changes.

[Insert Table 4 about here]

Table 4 presents these conditional results for the initial price reaction to upgrades and downgrades. For upgrades (Panel A), the incremental impact of earnings estimate increases is given by the row difference (i.e., for fixed discount rate estimate changes) between column 5 (quintile 5) and column 1 (quintile 1) and is 2.94% on average (the column mean). For comparison, the incremental impact of discount rate estimate decreases is given by the column difference (i.e., for fixed earnings estimate changes) between row 1 and row 5 and is 1.09% on average (the row mean), and it is obviously much smaller. This strongly suggests that the market reaction to earnings-based recommendations is predominantly driven by new earnings information from the analyst than by new discount rate information.

The results for downgrades (Panel B) suggest even more strongly that earnings-based downgrades are not driven by discount rate estimate changes. The incremental impact of earnings estimate decreases is given by the row difference between column 1 (quintile 1) and column 5 (quintile 5) and is -5.68% on average. For comparison, the incremental impact of discount rate estimate increases is given by the column difference between row 5 and row 1 and is 0.47% on average, which is much smaller (and opposite to the direction that we would predict). Overall, the results of both panels suggest that recommendation changes that we classify as "earnings-based" derive most of their informativeness from changes in earnings estimates rather than changes in discount rate estimates. This supports our reference to such recommendation changes as "earnings-based". In summary, the results of our two analyses above (in Table 3 and Table 4) suggest that our main results (in Table 2) are more consistent with the first alternative explanation (significant incremental value from the earnings estimate changes alone) than the second alternative explanation (earnings estimate changes are accompanied by discount rate estimate changes in the opposite direction).

Next, we examine how the post-recommendation change drift differs for earnings-based and discount rate-based recommendation changes because prior studies find that the information content of analyst recommendations is not impounded into prices immediately. As discussed in the introduction, 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. The differential magnitude of the drift is unclear theoretically and is a question that we answer empirically. To this end, we measure the drift during various event windows after the recommendation change ([+1,+10], [+1,+21], [+1,+42], and [+1,+63]).

Table 2 presents the results. Like in the initial price reaction, the drift is significantly larger for earnings-based recommendation changes than for discount rate-based recommendation changes. For example, the average 21-day drift after upgrades with earnings estimate increases is 1.83% compared to 0.65% for upgrades with no earnings estimate changes (discount rate-based upgrades) and 0.36% for upgrades with earnings estimate decreases. These patterns are similar for downgrades. The 21-day drift after downgrades with earnings estimate decreases is -1.24% compared to -0.79% for downgrades with no earnings estimate changes (discount rate-based downgrades) and +0.23% for downgrades with earnings estimate increases. The market appears to underreact initially to earnings-based recommendation changes more than it underreacts to discount rate-based recommendation changes.[10] The magnitude of the drift is inconsequential for recommendation changes and earnings forecast changes that have the opposite sign.

[Insert Figure 1 about here]

[10] 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 the recommendation change takes place (i.e., by the number of quarters until the first fiscal year end). The results are the same across quarters.

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. The largest part 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 show that earnings-based recommendation changes are more informative than discount rate-based recommendation changes. We now use multiple regression analysis to test whether the univariate results are robust to controlling for 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 dummy variables for our recommendation change categories, except for recommendation changes with no earnings estimate 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 be more reputable than their peers (e.g., Fang and Yasuda (2009)). We therefore control for prestigious brokers as defined by *Institutional Investor* magazine (see Appendix A.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 aggregate recommendation changes, consensus earnings estimate changes, and stock returns, all measured prior to the recommendation change. 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.[11]

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 (e.g., see Brennan, Jegadeesh, and Swaminathan (1993) for size, Boehmer and Kelley (2009) for institutional investors, and Hong, Lim, and Stein (2000) for number of analysts). The initial price reaction to recommendation changes for such stocks should be smaller because such recommendations contain relatively less new 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.[12] 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 5 about here]

[11] If we measure these three variables over one month rather than one week, the results are the same.
[12] If we control for each of our market efficiency proxies individually, the results are the same.

Table 5 presents these 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, in Table 5, the initial price reaction is 1.27 percentage points higher for upgrades with earnings estimate increases compared to upgrades with no earnings estimate changes, whereas the corresponding figure in Table 2 is 1.42 percentage points. For upgrades with earnings estimate decreases, the initial price reaction is 1.35 percentage points lower compared to 1.02 percentage points in the univariate analysis.

The 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 more risky firms.[13] The initial price reaction is more positive for both upgrades and downgrades for firms with lower valuations (as measured by book-to-market) and firms with less momentum during the previous year.

The magnitude of the drift in the multivariate analysis (in Table 5) 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 estimate increases is 1.23 percentage points higher than for upgrades with no earnings estimate 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.[14]

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

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[13] If we also control for the dispersion of analysts' earnings estimates as an additional proxy for risk, the results are the same.

[14] 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 virtually eliminate auto-correlation and cross-correlation of returns. Our sample size decreases to 3,517 trading days and the results remain statistically significant.

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 5 suggest that this possible misclassification is not frequent. 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 the market's valuation drivers, the total price reaction is significantly bigger for earnings-based recommendation changes than for discount rate-based recommendation changes.

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 estimate 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 disagreement about future earnings between the analyst and the market. We examine this possibility by comparing the total price reaction for when the previous earnings estimate was above the consensus to when it was below the consensus. If the total price reaction is the same, then such recommendation changes are not driven by earnings estimate reiterations. In our tests, we use only discount rate-based recommendation changes and run our multiple regressions with the addition of a dummy variable for whether previous earnings estimate are above the consensus.

We find (in untabulated results) that for both upgrades and downgrades, the price reaction is not different when the analyst's previous estimate was above versus below the consensus. (For example, for the initial price reaction, the difference is five basis points for upgrades and ten basis points for downgrades.) This is the case for both the initial price reaction and the drift. The results suggest that recommendation changes with no earnings estimate changes are predominantly driven by discount rate estimate changes.

3.3. The Role of Growth Rate Estimate Changes

Recommendation changes based on changes in long-term earnings growth estimates 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 estimate changes on our results. First, we use a sub-sample of recommendation changes for which growth rate estimates do not change to examine the extent to which growth rate estimate changes play a role in our results. Second, we directly examine the incremental information content of growth rate estimate changes conditional on earnings estimate changes and discount rate estimate changes.

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

We examine firm characteristics and recommendation change characteristics across three long-term earnings growth rate estimate change categories: (1) recommendation changes with no changes in growth rate estimates, (2) recommendation changes with growth rate estimate increases, and (3) recommendation changes with growth rate estimate decreases. We find no difference across these categories in the proportion of recommendation changes 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 estimate changes around earnings announcements.

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 estimate increases, no changes, and decreases. (For expositional simplicity, we do not tabulate results for upgrades with decreases in earnings estimates or growth rate estimates and for downgrades with increases in earnings estimates or growth rate estimates.)

[Insert Table 6 about here]

Table 6 presents the results. 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 estimate changes in Table 6 (69,862 observations). For the full sample, the average initial price reaction to upgrades with earnings estimate increases is 3.55% compared to 2.13% for upgrades with no earnings estimate changes. For the sub-sample of no change in growth rate estimates, the corresponding figures are 3.81% and 2.23%, respectively. These patterns are similar for downgrades for the full sample. The initial price reaction to downgrades with earnings estimate decreases is -5.11% compared to -1.72% for downgrades with no earnings estimate changes. For the sub-sample, the corresponding figures are -5.50% and -1.77%, respectively. This absence of differences demonstrates that long-term earnings growth rate estimate changes do not play a significant role in the bigger total price reaction to earnings-based recommendation changes than to discount rate-based recommendation changes.

The results in Table 6 also suggest that growth rate estimate changes have little incremental information content compared to recommendation changes and earnings estimate changes. For upgrades, the pairwise differences in the initial price reaction and the drift associated with growth rate estimate changes are not statistically significant. This is also the case for downgrades with no earnings estimate changes. For downgrades with earnings estimate decreases, the initial price reaction to no growth rate estimate changes is significantly higher than for growth rate estimate decreases, but the opposite is the case for the drift.[15]

3.4. Recommendation Changes with Innovative Earnings Estimate Changes

We now 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 earnings estimates increased to below the consensus ("non-innovative"). We apply their findings to recommendation changes with concurrent earnings estimate changes. The total price reaction should be bigger for upgrades with earnings estimates increased to above the consensus ("innovative") than for upgrades with earnings estimates increased to below the consensus ("non-innovative"). Similarly, the total price reaction should be bigger for downgrades with earnings estimates decreased to below the consensus ("innovative") than for downgrades with earnings estimates decreased to above the consensus ("non-innovative"). Earnings estimates increased to above the consensus account for 62% of upgrades with earnings estimate increases, and earnings estimates decreased to below the consensus account for 78% of downgrades with earnings estimate decreases. We replicate Table 5 with the addition of dummy variables for earnings estimates increased to above the consensus and earnings estimates decreased to below the consensus.

[Insert Table 7 about here]

Table 7 presents the results. The incremental initial price reaction is 0.54 percentage points higher for upgrades with innovative earnings estimate increases and 1.82 percentage points lower for downgrades with innovative earnings estimate decreases (both relative to non-innovative earnings estimate changes). The incremental drift is 1.03 percentage points higher for upgrades with innovative earnings estimate increases but not different from zero for downgrades with innovative earnings estimate decreases.

[15] We redo Table 5 using the recommendation change categories in Table 6. The multivariate results (not tabulated) are the same as the univariate results in Table 6, so the univariate results for growth rate estimate 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 estimate decreases and downgrades with earnings estimate increases).

[Insert Figure 2 about here]

The patterns that we find during the month after the recommendation change are similar over shorter and longer horizons. Figure 2 presents the drift during the one, two, and three weeks and one, two, and three months after the recommendation change. As we see in Figure 2, the post-recommendation change drift is bigger for upgrades with earnings estimates increased to above the consensus and smaller for upgrades with earnings estimates increased to below the consensus. Once again, the results hold up for all horizons for up to three months after the recommendation change.

4. Robustness Tests

We perform a number of robustness tests of our results in Table 5. We present the results of these tests in Table 8. For expositional simplicity, the table reports the coefficient estimates for recommendation changes with earnings estimate changes but not for the control variables. If applicable, we also present results for new control variables that we use in Table 8 but not in Table 5.

[Insert Table 8 about here]

First, we check whether our results are driven by 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 5, we now exclude them altogether. The results in Table 8 Column 1 are very similar to the results in Table 5. The difference in the total price reaction between earnings-based and discount rate-based recommendation changes remains highly significant and on the same order of magnitude.[16]

[16] 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.

Second, we test whether our results are driven by the earnings surprise during the quarter before the recommendation day. Analysts might increase their earnings estimates after positive earnings surprises and decrease their earnings estimates after negative earnings surprises. Then both the initial price reaction and the drift might be affected by the earnings surprise before the recommendation change and not only by the earnings estimate change that accompanies the analyst's recommendation change. 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-to-market, and momentum during the three days centered on the quarterly earnings announcement date in the previous quarter. The results in Table 8 Column 2 are very similar to the results in Table 5. 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.[17]

Third, we examine whether our results are driven by the impact of star analysts (e.g., Emery and Li (2009)). Star analysts' recommendation changes might have a bigger total price reaction and star analysts might 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's analyst rankings as a proxy.[18] The results in Table 8 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 26 basis points higher for star analysts.

Fourth, we test whether our results are driven by particular analysts that issue disproportionately more earnings-based recommendations. Perhaps the explanation for star analysts collectively applies to particular analysts individually. To test this explanation, we

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[17] If we measure earnings surprises as reported earnings minus analysts' consensus earnings estimates all scaled by the stock price, the results are the same.

[18] We do not control for star analysts in Table 5 because we do not have data on star analysts during the last fourteen months of our sample. The data that we do have were generously shared with us by Doug Emery and Xi Li.

control for analyst fixed effects (so we drop firm-date pairs with more than one analyst). The results, in Table 8 Column 4, are unchanged.

Fifth, we repeat the same test but for particular brokerage firms rather than particular analysts. We control for broker fixed effects and we drop firm-date pairs with more than one broker. The results, in Table 8 Column 5, are again unaffected.

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 (2010)). 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 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. We use the mean previous recommendation level for firm-date pairs with more than one analyst. The results in Table 8 Column 6 are the same as in Table 5. 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 the Global Settlement. The prior 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 changed following 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 (in untabulated results) the same excess returns 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 the 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. A Trading Strategy

The results documenting the post-recommendation change drift in the months after the recommendation change naturally suggest a potentially profitable trading strategy. We examine an implementable strategy of buying upgrades with earnings estimate increases and selling downgrades with earnings estimate 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 recommendation changes 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 estimate increases and sell all downgrades with earnings estimate 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 compute summary statistics (e.g., mean raw return, four-factor alpha, etc.) for these portfolios.

We begin with a portfolio holding period that is one of the holding periods we have examined thus far, i.e., 1, 10, 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, $t = 1, 2, \ldots, 3{,}525$. 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 $t \leq 3{,}525/S$). 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/Nth 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:

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_t \text{ for t = 1, 2, … , 3,525.}$$

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, 10, 21, 42, 63}), we report the means of each of these four summary statistics for all S.

[Insert Table 9 about here]

Table 9 Panel A reports the results for the unconditional strategy and Table 8 Panel B for the conditional strategy. 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 estimate increases and 36% of downgrades have earnings estimate decreases. The difference in the number of daily returns and the number of firms arises because there are more unconditional signals (days with upgrades and downgrades) than conditional signals (days with upgrades with earnings estimate increases and at the same time downgrades with earnings estimate 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 9 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 implementing the standard four-factor asset pricing model to compute risk-adjusted returns. Moreover, for both strategies, the four-factor alphas are very similar to the corresponding figures in Table 2.[19] 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 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 9. First, the unconditional and conditional strategies are both significantly profitable and likely to be greater than transactions costs incurred by institutional investors. Second, each strategy is similarly profitable whether profitability is measured using raw returns or risk-adjusted returns. Third, the conditional strategy is roughly two-thirds more profitable than the unconditional strategy for all holding periods for up to three months after the recommendation change.

[Insert Figure 3 about here]

Figure 3 presents the raw profitability of our trading strategies over time during our sample period of 1994-2007. We implement the same trading strategies as in Table 9 for a portfolio formation interval and a portfolio holding period length of ten days. However, rather than computing a single mean of the raw daily returns during our sample period, we compute the mean each month. From the monthly time-series variation in the drift, we first observe that while the drift is more profitable for the conditional strategy (Figure 3 Panel B) than for the unconditional strategy (Figure 3 Panel A), it is also slightly more risky. The unconditional strategy earns negative returns during only 11 out of 168 months during our sample period

[19] The four-factor alphas in Table 9 multiplied by the length of the portfolio holding period roughly equal the corresponding excess returns elsewhere in Table 2.

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 and bust (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 estimate increases and the decrease in the relative frequency of upgrades with no earnings estimate 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.[20]

We also examine another trading strategy based on the results for earnings estimate changes relative to the consensus. Table 7 shows that upgrades with earnings estimates increased to above the consensus and downgrades with earnings estimates decreased to below the consensus have a bigger total price reaction than upgrades with earnings estimate increases and downgrades with earnings estimate decreases, respectively. We implement the trading strategy that consists of buying upgrades with earnings estimates increased to above the consensus and selling downgrades with earnings estimates decreased to below the consensus.

We find (in untabulated results) that this trading strategy yields higher but more variable profits than the profits in Table 9 Panel B. For the trading strategy based on earnings estimate changes relative to the consensus, mean returns are roughly 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 9 Panel B. However, the standard deviations of returns are also roughly 10% bigger. In summary, the strategy is more profitable but also somewhat more risky.

Finally, we perform several robustness tests of the results for the unconditional and conditional trading strategies (results not tabulated). 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 9 Panel A. For the conditional strategy, the means are roughly 10% lower and the standard deviations are roughly 5% lower compared to Table 9 Panel B. Our results are largely unchanged 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

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

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 9 Panel A. For the conditional strategy, the means are roughly 30% lower and the standard deviations are roughly unchanged compared to Table 9 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 of our robustness tests, the profits from the trading strategies remain statistically significant.

6. Conclusion

Normatively, the value of an asset should equal the present value of its future cash flows. This implies that differences of opinion about asset values are motivated, explicitly or implicitly, by differences in estimated cash flows and/or discount rates. In turn, differences of opinion between analysts and the market about the value of stocks are reflected in changes in analysts' recommendations. Using this framework, 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 than discount rate-based recommendation changes because they are characterized by harder information, greater verifiability, and shorter forecast horizons, thus they are less subject to analysts' cognitive and incentive biases.

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 to recommendation changes 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 post-recommendation change drift suggests that the full information content of both earnings-based and discount rate-based recommendation changes is not immediately impounded into prices.

The informativeness of recommendation changes may not only be driven by whether recommendation changes are based on changes in estimates of earnings or discount rates but also on whether they are more "innovative" (i.e., upgrades with earnings estimates increased to above (rather than below) the consensus and downgrades with earnings estimates decreased to below (rather than above) the consensus). We find that recommendation changes with innovative earnings estimate changes have a significantly larger incremental price impact. We also examine long-term earnings growth rate estimate 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 long-term earnings growth rate-based recommendation changes being characterized by softer information, less verifiability, and longer forecast horizons much 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 estimate increases and selling downgrades with earnings estimate 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 (2003), Chen and Zhao (2008), Campbell, Polk, and Vuolteenaho (2010), and Cohen, Polk, and Vuolteenaho (2009)). For example, Cohen, Polk, and Vuolteenaho (2003) 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 explain substantially more of the returns to information disseminated by analyst reports 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 earnings estimate 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).[22] We drop recommendation changes associated with the Global Settlement (leaves 213,034 firm-date-analyst triples).[23]

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

[22] To be conservative, we do not exclude previous recommendations that may be stale. Roughly 75% and 95% of our sample recommendation changes 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.

[23] 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.

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 because we study recommendation changes with earnings estimate 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 estimate increase, no change, or decrease (leaves 123,250 firm-date pairs).[24] 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 estimate 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.[25] 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

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

[25] 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.

define an "earnings estimate decrease" analogously. We define "no earnings estimate change" as an absence of both current FY1 and FY2 earnings estimates on the day of the recommendation change but a presence of previous earnings estimates for both FY1 and FY2.

We then define earnings estimate 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 estimate 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. However, many firms do not have a single previous growth rate estimate during the five years before the recommendation change. Therefore, for these firms, the (long-term earnings) growth rate estimate change is undefined even though the (short-term) 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.[26] 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 estimate 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 Earnings Estimates

We compute analyst coverage and the consensus earnings 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 earnings estimates issued during the year ending on the summary date (e.g., July 1, 1993 to June 30, 1994). We further keep only earnings 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 earnings estimates to compute analyst coverage (the number of earnings estimates) and the consensus earnings estimate (the mean earnings 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

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

Brown/Deutsche Morgan Grenfell (November 1996 to October 2008); Donaldson, Lufkin & Jenrette (November 1993 to October 2001); Goldman Sachs (November 1993 to October 2008); J. P. Morgan (November 1998 to October 2008); Kidder Peabody (November 1993 to October 1995); Lehman Brothers (November 1993 to October 2008); Morgan Stanley/Morgan Stanley Dean Witter (November 1993 to October 2008); Merrill Lynch (November 1993 to October 2008); Prudential Equity Group/Bache (November 1993 to October 2007); Sanford C. Bernstein (November 1993 to October 2008); 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 after the rating system change. For brokers without a rating system change, the vast majority of recommendations are 1s, 2s, and 3s both before and after the rating system changes of other brokers.

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Table 1
Descriptive Statistics

The sample comprises 123,250 recommendation changes between 1994 and 2007. 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 earn. est. increases	18,308	32.5	37.1	11.7	34.1
Upgrades with no earn. est. changes	30,121	53.5	16.0	11.8	32.4
Upgrades with earn. est. 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 earn. est. increases	6,918	10.3	36.0	10.6	30.5
Downgrades with no earn. est. changes	35,842	53.6	15.0	11.3	30.2
Downgrades with earn. est. 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 earn. est. increases	81.0	39.2	70.9	37.3	75.2	15.4
Upgrades with no earn. est. changes	81.6	39.9	70.7	36.6	75.5	15.7
Upgrades with earn. est. 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 earn. est. increases	81.1	35.5	71.1	37.3	75.3	15.2
Downgrades with no earn. est. changes	80.1	39.5	70.4	37.5	74.4	15.0
Downgrades with earn. est. 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 123,250 recommendation changes between 1994 and 2007. 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,+10]	[+1,+21]	[+1,+42]	[+1,+63]
All upgrades (56,341 observations)	-0.23***	2.45***	0.67***	0.99***	1.16***	1.36***
Upgrades with earnings estimate increases	2.16***	3.55***	1.15***	1.83***	2.07***	2.48***
Upgrades with no earnings estimate changes	-1.02***	2.13***	0.51***	0.65***	0.78***	0.93***
Upgrades with earnings estimate decreases	-2.72***	1.11***	0.15	0.36***	0.52***	0.40*
All downgrades (N=66,909 observations)	-0.31***	-2.81***	-0.67***	-0.85***	-1.09***	-1.21***
Downgrades with earnings estimate increases	4.00***	-0.35***	0.13	0.23	0.09	0.43
Downgrades with no earnings estimate changes	1.43***	-1.72***	-0.59***	-0.79***	-1.03***	-1.20***
Downgrades with earnings estimate decreases	-4.13***	-5.11***	-1.02***	-1.24***	-1.52***	-1.69***

Table 3
Selected Motivations for Recommendation Changes from Analyst Reports

This table presents selected motivations for recommendation changes from analyst reports. The sample comprises 150 recommendation changes constructed as follows. From the sample of 123,250 recommendation changes, 25 recommendation changes are randomly sampled for each of six recommendation change categories for a total of 150 recommendation changes. The corresponding analyst reports are then extracted from Investext. Each report is read to determine whether the recommendation change is motivated by a change in the analyst's discount rate estimate, the stock price, the analyst's risk estimate, or any of the preceding three.

	Recommendation change motivated by change in …			
	… discount rate estimate (DR)	… stock price (P)	… risk estimate (RISK)	… DR, P, or RISK
Upgrades with				
Earnings estimate increases (A)	0%	40%	0%	40%
No earnings estimate changes (B)	4%	76%	32%	88%
Earnings estimate decreases	0%	52%	28%	72%
p-value for (A) = (B)	0.000	0.009	0.002	0.000
Downgrades with				
Earnings estimate increases	4%	60%	12%	72%
No earnings estimate changes (B)	0%	76%	8%	80%
Earnings estimate decreases (A)	0%	12%	4%	12%
p-value for (A) = (B)	n/m	0.000	0.561	0.000

Table 4
The Price Impact of Changes in Estimates of Earnings and Discount Rates for Earnings-Based Recommendation Changes

This table presents the initial price reaction to earnings-based recommendation changes as a function of the variation in changes in estimates of earnings and discount rates. The sample comprises recommendation changes between 1994 and 2007 consisting of 18,308 upgrades with earnings estimate increases and 24,149 downgrades with earnings estimate decreases. The initial price reaction during the [-1,0] event window is measured as returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. The variation in earnings estimates changes is measured as the change in the analyst's earnings estimate minus the change in the market's earnings estimate all divided by the stock price. The change in the market's earnings estimate is the change in the consensus earnings estimate during the month ending two days before the recommendation day. The stock price is the closing price per share two days before the recommendation day. The variation in discount rate estimate changes is inferred from the stock price run-up before the recommendation change. Holding fixed the change in the market's earnings estimates, a rise in the stock price implies a decrease in the market's discount rate estimate, and thus an increase in the analyst's discount rate estimate relative to the market's. The price run-up before the recommendation change is measured as the excess return during the month ending two days before the recommendation day. Excess returns are measured as returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles. Quintiles are created for differential earnings estimate changes independently of quintiles for differential discount rate estimate changes, and the mean initial price reaction is computed for each cell.

Panel A: The Initial Price Reaction to Earnings-Based Upgrades as a Function of the Variation in Estimates of Earnings and Discount Rates

	Differential earnings estimate change: ΔE_A-ΔE_M						
Price run-up ($\uparrow P \Rightarrow \downarrow DR_M \Rightarrow \uparrow (DR_A - DR_M)$)	Quintile 1 (min. diff. ΔE)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (max. diff. ΔE)	Row mean	Row diff. (Q5-Q1)
Quintile 1 (min. price run-up)	3.25%	3.96%	4.88%	4.77%	5.74%	4.57%	2.49%
Quintile 2	2.04%	2.92%	3.44%	4.28%	5.34%	3.50%	3.30%
Quintile 3	2.17%	2.26%	2.84%	3.85%	4.94%	3.08%	2.77%
Quintile 4	1.46%	2.53%	2.57%	3.59%	4.15%	2.83%	2.69%
Quintile 5 (max. price run-up)	2.31%	2.46%	2.96%	3.65%	5.78%	3.64%	3.47%
Column mean	2.24%	2.80%	3.31%	4.02%	5.27%	Column mean →	2.94%
Column diff. (Q1-Q5)	0.94%	1.50%	1.92%	1.12%	-0.04%	1.09%	← Row mean

Panel B: The Initial Price Reaction to Earnings-Based Downgrades as a Function of the Variation in Estimates of Earnings and Discount Rates

	Differential earnings estimate change: ΔE_A-ΔE_M						
Price run-up ($\uparrow P \Rightarrow \downarrow DR_M \Rightarrow \uparrow (DR_A - DR_M)$)	Quintile 1 (min. diff. ΔE)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (max. diff. ΔE)	Row mean	Row diff. (Q1-Q5)
Quintile 1 (min. price run-up)	-9.41%	-6.62%	-5.19%	-4.83%	-2.84%	-6.69%	-6.57%
Quintile 2	-8.41%	-6.86%	-4.80%	-3.50%	-2.35%	-5.34%	-6.06%
Quintile 3	-7.08%	-5.43%	-4.31%	-3.13%	-2.24%	-4.23%	-4.84%
Quintile 4	-8.17%	-5.91%	-4.68%	-3.39%	-2.06%	-4.32%	-6.11%
Quintile 5 (max. price run-up)	-7.53%	-6.97%	-5.33%	-4.00%	-2.70%	-5.07%	-4.83%
Column mean	-8.42%	-6.38%	-4.83%	-3.64%	-2.40%	Column mean →	-5.68%
Column diff. (Q5-Q1)	1.88%	-0.35%	-0.14%	0.83%	0.14%	0.47%	← Row mean

Table 5
Stock Returns for Recommendation Changes and Earnings Estimate 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 123,250 recommendation changes between 1994 and 2007. 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 estimate 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 estimate increase dummy variable	1.272***	1.232***	1.428***	0.969***
	(19.272)	(10.579)	(11.850)	(5.556)
Earnings estimate 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 6
Comparisons of Stock Returns by Recommendation Change Category and Earnings Growth Rate Estimate Change Category in Event-Time

This table presents mean excess returns by recommendation change category and earnings growth rate estimate 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 76,714 recommendation changes with between 1994 and 2007. 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 estimate increases and			
No growth rate estimate changes	9,868	3.81	1.83
Growth rate estimate increases	1,102	3.91	1.61
Difference		-0.10	0.22
With no earnings estimate changes and			
No growth rate estimate changes	17,705	2.23	0.76
Growth rate estimate increases	516	2.21	0.50
Difference		0.02	0.26
Downgrades			
With no earnings estimate changes and			
No growth rate estimate changes	21,318	-1.77	-0.65
Growth rate estimate decreases	564	-2.21	-0.59
Difference		0.44	-0.06
With earnings estimate decreases and			
No growth rate estimate changes	13,406	-5.50	-1.22
Growth rate estimate decreases	1,993	-7.25	-0.46
Difference		1.75***	-0.76**

Table 7
Stock Returns for Recommendation Changes with Innovative Earnings Estimate Changes Controlling for Recommendation Change Characteristics and Firm Characteristics in Event-Time

This table presents stock returns for recommendation changes with innovative earnings estimate changes. The specifications are the same as in Table 5 with the addition of dummy variables for "innovative" earnings estimate changes. "Innovative" earnings estimates changes are increases in earnings estimates to above the consensus and decreases in earnings estimates to below the consensus. Only selected regression results are tabulated.

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

Table 8
Robustness Tests

This table presents variations of the regressions in Table 5. Compared to Table 5, each column changes the sample and/or control variables as follows. In column (1), recommendation changes with earnings announcements during the previous week are excluded and the earnings announcement dummy 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. 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 est. 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)
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 est. 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)
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 est. decrease dummy variable	-2.928*** (-33.698)	-2.901*** (-33.120)	-2.920*** (-35.339)	-2.566*** (-31.480)	-2.525*** (-32.475)	-2.925*** (-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 est. decrease dummy variable	-0.432*** (-3.317)	-0.482*** (-3.617)	-0.412*** (-3.396)	-0.576*** (-4.644)	-0.495*** (-4.207)	-0.443*** (-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 9
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 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 estimate increases and downgrades with earnings estimate decreases. In this panel, the sample comprises recommendation changes between 1994 and 2007 consisting of 18,308 upgrades with earnings estimate increases, which are bought, and 24,149 downgrades with earnings estimate 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										
Portfolio formation interval = length of portfolio holding period (days)	Portfolio type	Means of the following statistics								
		Number of daily returns	Mean number of firms	Mean of raw daily returns (%)	Holding period raw return (%)	Standard deviation of raw daily returns (%)	Four-factor alpha from daily returns (%)	Holding period four-factor alpha (%)	t-statistic of four-factor alpha (%)	Four-factor alphas significant at 5% level
1	Long	3,508	16.1	0.178	0.178	1.357	0.154	0.154	8.24	100%
	Short	3,515	19.0	-0.317	-0.317	1.346	-0.331	-0.331	-18.01	100%
	Long-short	3,506	35.1	0.493	0.493	1.348	0.483	0.483	21.19	100%
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%
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%
r	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 Estimate Increases and Downgrades With Earnings Estimate 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%
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%
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%

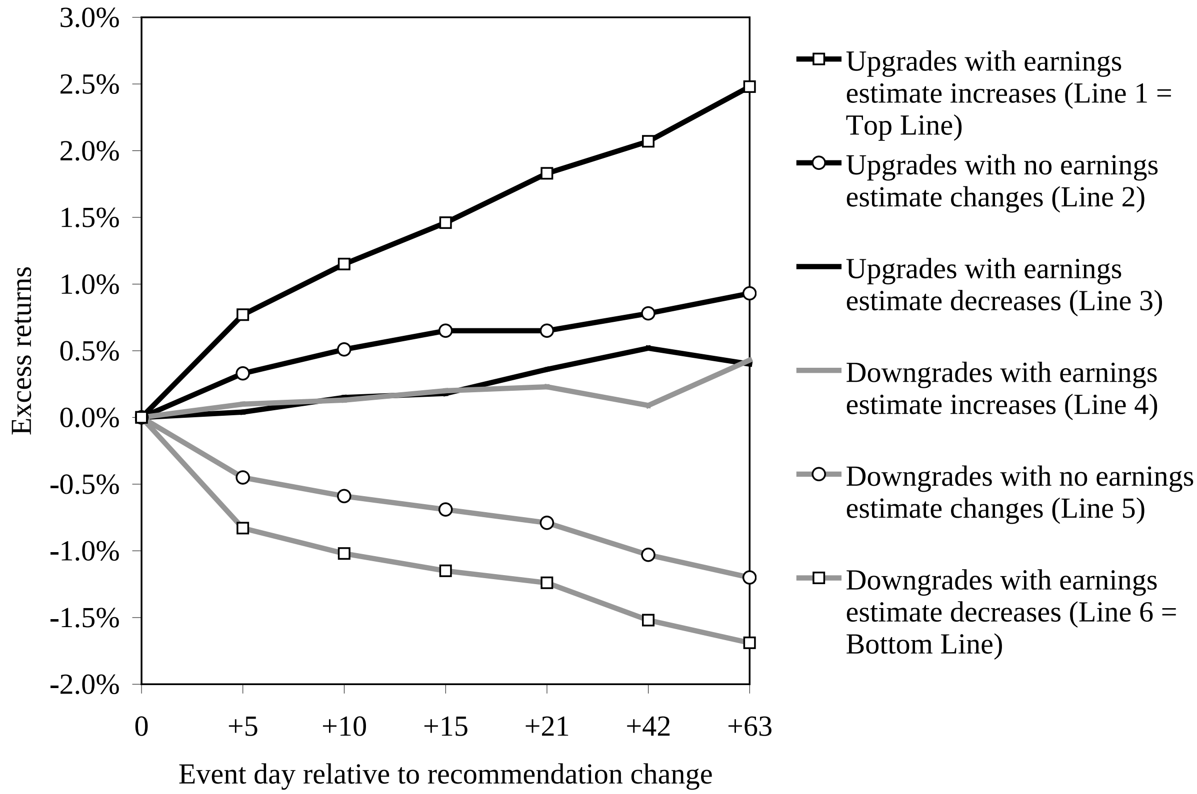


Figure 1. Stock returns by recommendation upgrades and downgrades and earnings estimate increases, no changes, and decreases in event-time. The sample comprises 123,250 recommendation changes between 1994 and 2007. Excess returns are returns in excess of benchmark portfolios matched on size quintiles,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

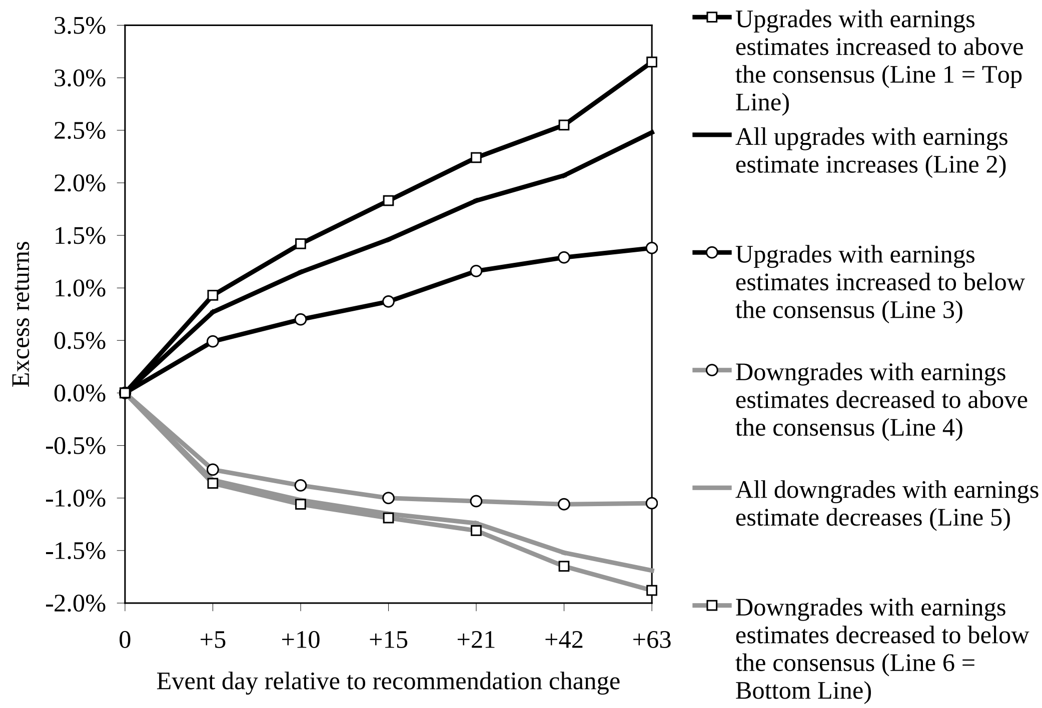
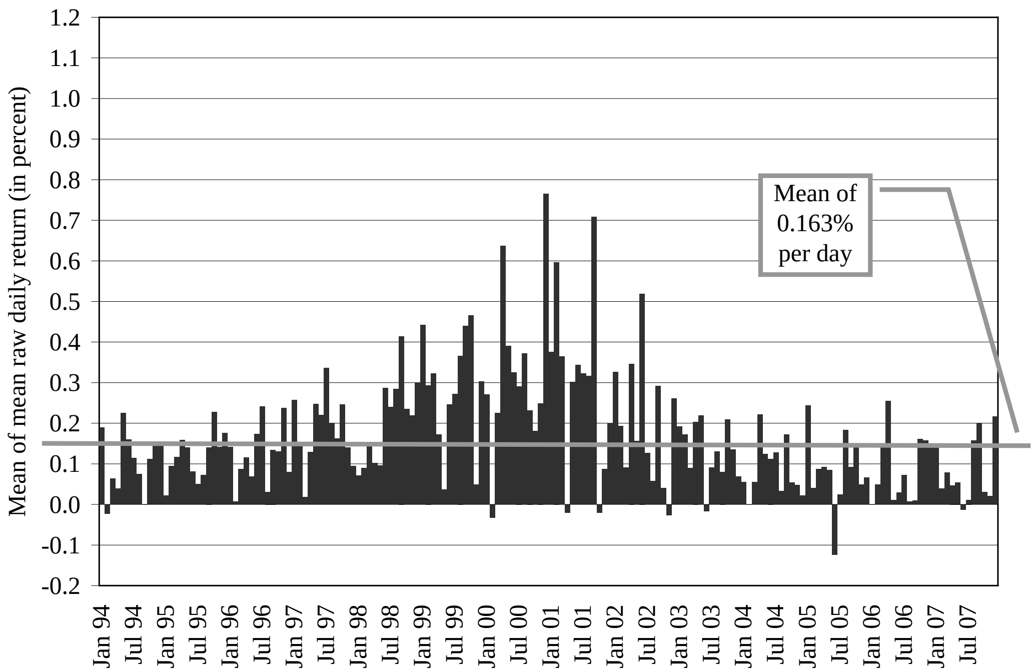


Figure 2. Stock returns for recommendation changes and earnings estimate changes relative to the consensus. Recommendation change categories are split into two sub-categories based on whether the analyst's earnings are above or below the consensus. The sample comprises 123,250 recommendation changes between 1994 and 2007. Excess returns are returns in excess of benchmark portfolios matched on size quintiles, book-to-market quintiles, and momentum quintiles.

Panel A. Portfolios formed using all upgrades and all downgrades



Panel B. Portfolios formed using upgrades with earnings estimate increases and downgrades with earnings estimate decreases

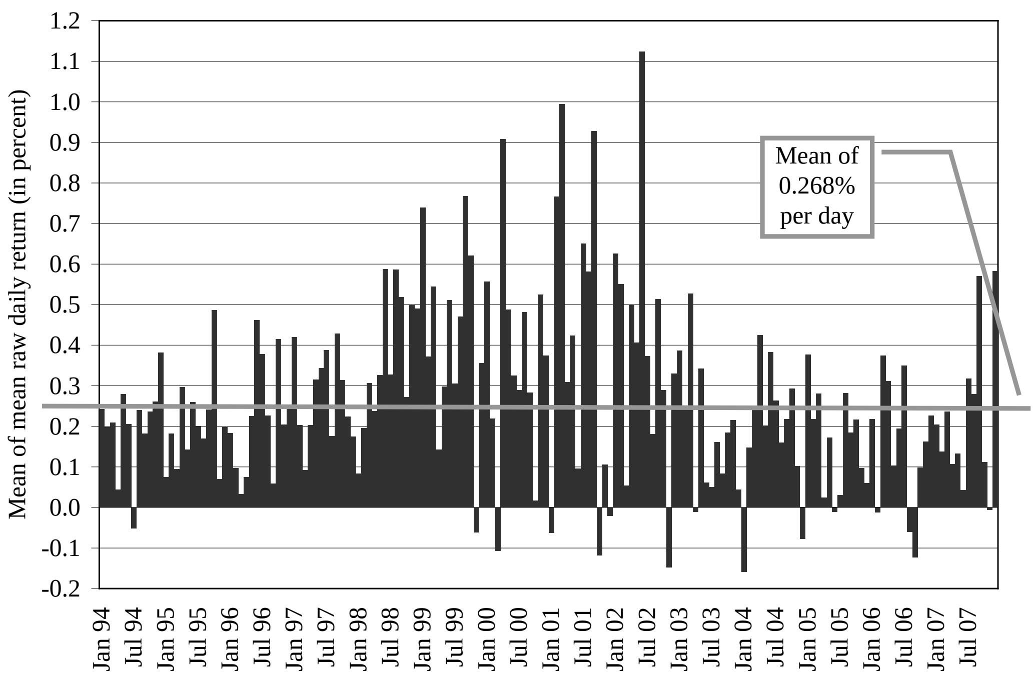


Figure 3. The drift after the recommendation changes in calendar-time. This figure presents the mean each month of the mean of the raw daily returns for the long minus short portfolios in Table 9 Panel A (top figure) and Table 9 Panel B (bottom figure). The top figure uses all upgrades in long portfolios and all downgrades in short portfolios. The bottom figure uses upgrades with earnings estimate increases in long portfolios and downgrades with earnings estimate decreases in short portfolios. The portfolio formation interval equals the portfolio holding period length and is ten days.