Rating on a Curve*

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ABSTRACT

We document that if an analyst is covering a strong pool, the best firm is rated less highly than it would be otherwise, and if the analyst is covering a weak pool, the worst firm is rated less badly than it would be otherwise. These relative ratings affect dispersion in recommendations. Blindly following recommendations (long strong buy, short hold and sells) would generate returns of 39 bps per month, but going long strong buys from analysts with the best pools and shorting the holds and sells of analysts with the worst pools would yield 74 bps per month – nearly double!

RATING ON A CURVE

The debate about rating on a curve, which is a debate about rating based on a sample benchmark versus using a population benchmark, pervades many facets of human life. In political elections, the most popular person in the party may not be the most popular in the country. In sports, compensation of athletes may depend on whether they are a big fish in a small pond or a small fish in a big pond. In corporations, compensation of CEOs would depend on the peers they are benchmarked to (Faulkender and Yang (2010)). In portfolio performance, the alpha depends on the benchmark. In academia, a student grade in a class may depend on the average performance of the class, and faculty tenure may depend on the peer schools being used as a benchmark.

This paper examines the possibility of sell-side analysts basing their recommendation ratings on a curve. The null hypothesis is that analysts do absolute rating: they give an overvalued stock a "Sell" recommendation and give an undervalued stock a "Buy" recommendation.[1] The alternate hypothesis is that analysts also do relative rating: their recommendations are also affected by the relative quality of the stock with respect to the quality of the other stocks they cover.[2] The question about whether analysts do relative rating with respect to a market or an industry has been addressed before (Kadan et al 2013), but the question about whether analysts do relative rating with respect to the portfolio of stocks they cover has not been addressed before.[3]

We motivate the basic idea of analysts rating on a curve with this telling example. In October of 2013, Greenfield recommended Facebook as a Strong Buy while Kessler recommended

[1] Here is an example of an absolute rating system from DBSVHK: "**STRONG BUY** [>20% total return over the next 3 months, with identifiable share price catalysts within this time frame] **BUY** [>15% total return over the next 12 months for small caps, >10% for large caps] **HOLD** [-10% to +15% total return over the next 12 months for small caps, -10% to +10% for large caps] **FULLY VALUED** [negative total return i.e. > -10% over the next 12 months] **SELL** [negative total return of > -20% over the next 3 months, with identifiable catalysts within this time frame]."

[2] Here is an example of a relative rating system from JP Morgan: "**Overweight** [Over the next six to twelve months, we expect this stock will outperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] **Neutral** [Over the next six to twelve months, we expect this stock will perform in line with the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] **Underweight** [Over the next six to twelve months, we expect this stock will underperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe.] …"

[3] The website https://www.marketwatch.com/tools/guide.asp explains how different analysts rate firms. Of the 69 analysts whose ratings could be classified, we found that 23 use expected raw returns, 27 use expected market-adjusted returns, 15 use expected industry-adjusted returns, and only 4 use expected relative returns (where "relative" means relative to the stocks they cover). But this is what they say; what they do may be different.

Facebook as a Hold. Greenfield was covering Facebook, Netflix, Twenty-first Century, Pandora Media, and AMC network in October 2013, and Facebook's target return (analyst's target price divided by price before the announcement) was the highest among these stocks covered by Greenfield. Kessler was covering Facebook, Apple, Baidu, E-bay, Expedia, Google, and Priceline.com in October 2013, and Facebook's target return was the lowest among these stocks covered by Kessler.

Figure 1 below illustrates this idea and, more importantly, pins down the research design and predictions of this paper.

Overvalued → Undervalued

	Absolute Rating	Stock A Sell	Stock B Underperform	Stock C Hold	Stock D Buy	Stock E Strong Buy
Analyst A	Coverage Recommendation	Covered **Sell**	Covered **Hold**	Covered **Strong Buy**		
Analyst B	Coverage Recommendation			Covered **Sell**	Covered **Hold**	Covered **Strong Buy**

Figure 1

Suppose the universe has only 2 analysts covering 5 stocks between them. These five stocks cover the spectrum from highly overvalued (Stock A) to highly undervalued (Stock E). If analysts do absolute rating, stock A, stock B, stock C, stock D and stock E, will get ratings of Sell, Underperform, Hold, Buy, and Strong Buy, respectively. This is shown in the first row of Figure 1. Absolute ratings would not be affected by the coverage of an analyst. However, an alternative hypothesis based on rating on a curve will predict a different result. If analyst A is covering stock A, stock B, and stock C, his recommendations will be Sell, Hold, and Strong Buy, respectively. If analyst B is covering stock C, stock D, and stock E, her recommendations will be Sell, Hold, and Strong Buy, respectively.

This gives us our three testable predictions:

1) Note that stock C is the best stock for analyst A and gets a rating of Strong Buy, whereas it is the worst stock for analyst A and gets a rating of Sell. To generalize, if relative rating holds, the recommendation on a particular stock depends positively not only on the absolute quality of the stock, but also positively on the rank of the stock in the pool of stocks an analyst is covering.

2) The disagreement here is on Stock C. To generalize, the impact of relative rating is less pronounced for the "corner" stocks (like stock A or stock B).

3) Disagreements amongst analysts, as measured in this case by the spread of recommendations, is also affected by the spread of the relative quality of the stock in the pools of different analysts.

The first part of the paper empirically tests these predictions. We first compute a measure of quality of a stock, global target return. All analysts, besides giving a recommendation on the stocks they carry, also give a target price for the stocks. This is their view of what the price should be. We define the target return of a stock s in month t by analyst a as this target price divided by the market price of the previous day of recommendation. For each stock s in month t, we estimate the global target return as the median target return amongst all analysts covering this stock. We assume that this global target return is a measure of the global quality of the stock s in month t.

Using two different research designs that control for "investment banking pressure" – one, an OLS regression (the dependent variable is the recommendation of analyst a on stock s in month t) with higher-dimensional fixed effects (stock-month effect, and analyst-stock fixed effect), the other an ordered logistic regression (the dependent variable is the recommendation of analyst a on stock s in month t) with time-fixed effects – we find evidence in favor of both testable implications 1 and 2. Ratings on a stock for an analyst in a month are positively correlated with the rank of the stock in the pool of stocks an analyst is covering in that month. The economic significance of the rank is substantial. A stock would have 0.431 grade higher if it is the best stock among the covered stocks than the case where it is the worst stock among the covered stocks; this result is from the OLS regression. We also notice in the OLS regression that the impact of relative rating is less pronounced for the "corner" stocks; the 0.431 number drops to 0.216.

Again using two different research designs – one, an OLS regression, the other an ordered logistic regression – we document that the spread of analyst recommendations on stock s in month t is positively affected by the spread of the relative quality of the stock in the pools of different analysts in the month. This is evidence in favor of testable implication 3.

The second part of the paper looks at return implications. We categorize all stocks into two dimensions: quality of pool and recommendation. We define the quality of pool of analyst a in month t as the mean of the global target return of all covered stocks in the pool in that month. We then divide all analysts into terciles by the quality of their pools each month: Worst Pool, Normal Pool, and Best Pool. For the recommendation letter, we create for each stock s in time t these categories: Strong Buy, Buy and Hold/Underperform/Sells. As there are so few Underperform/Sell recommendations, we put Hold/Underperform/Sells in one bucket. The sample size in this bucket is now comparable to the sample size in the Strong Buy or Buy buckets.

We find that blindly following recommendations (long strong buy, short hold and sells) would generate returns of 39 bps per month. However, using the logic of relative ratings documented in our paper, going long strong buys from analysts with the best pools and shorting the holds and sells of analysts with the worst pools yields 74 bps per month – nearly double! Surprisingly, the worst recommended stocks from the best pools (0.88%) even out-perform the best recommended stocks from the worst pools (0.64%).

The literature on analyst stock recommendations is vast. It can be categorized under a few headings. The first classification is the obvious: do analyst recommendations have informational content? The answer is yes.[4] The second classification would be the relationship between analyst stock recommendations and their earnings forecasts. The link is complex.[5] The third classification would be the "conflict of interest bias". This is a growing literature, and many conflicts have been analyzed. There is some consensus that analyst recommendations are more optimistic for

[4] An early paper is by Bjerring, Lakonishok and Vermaelen (1983), who show that an investor following the recommendations of a Canadian brokerage house would have achieved significantly positive abnormal returns. Altinkilic and Hansen (2009) show that analyst recommendation revisions have little information content, but Li et al (2015) dispute that. Li et al (2015) also provide a good literature review and references on this subject. The classic research design used here is the event study, and a representative paper is by Womack (1996), who shows that analysts have market timing and stock picking abilities. The availability of high-frequency data and accounting for time-stamp delays do indeed confirm that analysts' recommendations are informative (Bradley et al (2014)). Howe, Unlu and Yan (2009) show that analyst recommendations contain market- and industry-level information about future returns and earnings. Jegadeesh et al (2004) find that a quarterly change in consensus recommendations is a robust return predictor that appears to contain information orthogonal to a large range of other predictive variables. Barber et al (2001) pioneered the research design of trading strategies – purchase (sell short) stocks with the most (least) favorable consensus recommendations – and found abnormal gross returns but insignificant net returns with this strategy.

[5] Bradshaw et al (2004) show that buy-and-hold investors would earn higher returns relying on present value models that incorporate analysts' earnings forecasts than relying on analysts' recommendations.

"affiliated" stocks.[6] The fourth classification would be the "optimism bias."[7]

Given this vast literature, we need to control for many variables. Fortunately, the use of high-dimensional fixed effects helps us control for many of these variables. The stock-analyst fixed effect controls for variables like analyst specialization in certain industries, endogenous coverage selection (McNichols and O'Brien (1997)), etc. The stock-time fixed effect controls for time-varying characteristics of the stock (which controls for market capitalization, corporate investment, growth opportunity, institutional ownership (Firth, et al (2013), Ljungqvist, et al (2007)), corporate news (Li, et al (2015)), earnings announcement (Yezegel (2015)), undervaluation/overvaluation). We also control for the "investment banking pressure" variable proposed by Ljungqvuist, et al (2007).We, however, cannot use analyst-time fixed effects because it is very highly correlated with the pool of the analyst, which is our variable of interest.

Where does our paper fit into this vast literature? The literature has documented that analyst recommendations may be affected by their conflicts of interests or their optimism. To the best of our knowledge, our paper is the first to document that analyst recommendations may also be affected by their relative rating within their covered stocks. Four other papers in the analyst literature have related ideas. Hartzmark and Shue (2017) show that investors mistakenly perceive earnings news today as more (as less) impressive if last period's earnings surprise was bad (good). So their paper is about relative intertemporal comparison of an investor, whereas our paper is about

[6] The early work here is by Michaely and Womack (1999), who show that stocks that underwriter analysts recommend perform more poorly than "buy" recommendations by unaffiliated brokers prior to, at the time of and subsequent to the recommendation date. O'Brien et al (2005) show that banking ties increase analysts' reluctance to reveal negative news. Ljungqvist et al (2006) find no evidence that aggressive analyst behavior increased their bank's probability of winning an underwriting mandate. Ljungqvist et al (2007) find that analysts' recommendations relative to consensus are positively associated with investment banking relationships and brokerage pressure, but this bias decreases with the presence of institutional investor owners. Barber, Lehavy and Trueman (2007) found abnormal gross returns with this trading strategy – purchase (sell short) stocks with the most (least) favorable consensus recommendations – but the returns were higher for recommendations issued by independent research firms than they were for recommendations issued by investment banks. Clarke et al (2007), using a sample of all-star analysts who switch investment banks, find no evidence that issuing optimistic earnings forecasts or recommendations affects investment banking deal flow. Agrawal and Chen (2008) show that conflicted analysts do indeed give optimistic stock recommendations but are not able to systematically mislead investors. Kadan et al (2009) document the unintended consequences of the Global Analyst Research Settlement in 2003, which was intended to curb conflicts of interest, but which made recommendations less informative. Mola and Guidolin (2009) and Firth et al (2013) show that analysts are more optimistic on stocks held by affiliated mutual funds.

[7] Cowen, Groysberg and Healy (2006) show that optimism comes less from underwriting conflicts of interest and more because analysts cater to trading incentives of retail investors. Malmendier and Shanthikumar (2014) show that non-strategic distorters are optimistic – they issue both positive recommendations and optimistic forecasts – while strategic distorters speak in two tongues, issuing overly positive recommendations (to curry favor from management) but less optimistic forecasts.

relative cross-sectional comparison by an analyst. Chang et al. (2017) show that analysts overweight recent earnings seasonality, implying an intertemporal comparison. Harford, Jiang, Wang and Xie (2018) show that analysts strategically allocate more effort to firms important to their careers, which improves their information environment compared to those for other firms. In our paper, analysts give higher rating to stocks with relatively higher quality. So we focus on the first moment, whereas Harford, et al (2018) focus on the second moment. Wang (2017) shows that analysts issue significantly more pessimistic forecasts when they observe salient negative performances of unrelated industries in the portfolio of stocks they analyze. Wang (2017) hypothesizes a positive correlation due to the common country factor, whereas we hypothesize a negative correlation because, in our context of relative grading, a deterioration in the quality of stock j necessarily means that this analyst is more likely to give a higher recommendation for stock i. Our empirical results are different because Wang (2017) only analyzes situations when there are big negative industry shocks (which are situations where his hypothesis is likely to hold), whereas our analysis is for all situations.[8]

The paper is organized as follows. Section I describes the data. Section II provides summary statistics. Section III presents two different research designs and empirical results that provide formal evidence showing that analysts rate on a curve. Section IV shows that disagreements amongst analysts is also affected by the spread of the relative quality of the stock in the pools of different analysts. Section V presents the return implications of relative rating. Section VI concludes.

I. Data

The data used in our main study are constructed from three datasets: Thomson Reuter's I/B/E/S, CRSP, and Thomson Financial SDC U.S. New Issues database. I/B/E/S covers sell-side analysts issuing stock recommendations. CRSP contains stock price information at daily frequency. SDC database reports debt and equity underwriting information. Our sample period is from February of 1999 to June of 2017.[9]

8 The idea of relative rating is not new. There is a big literature in behavioral economics on this. In finance, Hartzmark (2015) shows that both retail traders and mutual fund managers are more likely to sell the extreme winning and extreme losing positions in their portfolio ("the ranking effect"). The effect indicates that trades in a given stock depend on how the stock compares to other positions in an investor's portfolio.

9 Our sample period starts from February of 1999 due to the data availability of IBES target price data database.

For the I/B/E/S data, since our focus is on rating on a curve, we need analysts who cover a pool of stocks, and so we exclude analyst-months where the analyst is analyzing less than three stocks in the month. We also exclude all cases in which analysts submit recommendation to I/B/E/S anonymously. For recommendations issued by the same analyst to the same stock at the same month, we only keep the latest one. All recommendations from "Zacks Investment Research" before 2006 are deleted, as "Zacks Investment Research" use the same analyst ID ("amaskcd" code in I/B/E/S) for all its recommendation issues. And finally, since we need an objective benchmark for a stock at the given time, we exclude the stock-month observations without target price. After the above screening, our unbalanced panel consists of 10,449 different analysts covering 7,570 different stocks for 220 months (February of 1999 to June of 2017). Given that analysts and stocks come and go in our panel, this amounts to 559,033 analyst-months, 460,089 stock-months, and 5,022,576 analyst-stock-months. As much of our analysis is at the analyst-stock-month level, which has more than 5 million data points, this big data allows us to use higher-dimensional fixed effects.

We use the SDC data to construct Ljungqvuist, et al (2007) "investment banking pressure" variable, $IBP_{b,s,t}$. This variable measures the possible conflict of interest that analysts face to be partial to stocks that have an underwriting relationship with a bank. It is a measure of the time-varying strength of a company's relationship with a particular bank. The variable is constructed as follows. For firm s in quarter t, we determine whether it extended an underwriting mandate to bank b or any of b's predecessors (but not b's successors). If so, we accumulate the proceeds from the deals that bank b and its predecessors managed for company s in the preceding five years, and divide by the total raised by the company. As banks often merge, we allow banks to inherit their predecessors' relationships only if the M&A deal fulfil all of the following conditions: (1) the M&A deal is complete; (2) both target and acquirer in this deal are brokers; (3) either target and acquirer has ever appeared in I/B/E/S dataset (i.e., one of them once issued an analyst report); and (4) either target or acquirer stopped giving recommendations. As corporate families exist, we form corporate families on the basis of SDC's ultimate parent CUSIP identifier, and allow subsidiaries and parent companies to share the same relationship with banks.

II. Summary Statistics

IBES provides data on the recommendation ratings ($rec_{a,s,t}$) by analyst a for stock s in month t. They are grouped into 5 different categories. The best recommendation is "Strong Buy" which corresponds to 1, the second-best recommendation is "Buy" which corresponds to 2, the third category is "Hold" which corresponds to 3, the second-worst recommendation is "Underperform" which corresponds to 4, and the worst recommendation is "Sell" which corresponds to 5. We follow the same numerical rule as IBES.

In addition to the recommendation letter, one subset of IBES data (Detail History Price Target, Unadjusted) also provides the target price by analyst a for stock s in month t. It is the price that analysts believe is the intrinsic value of the stock. With the target price, we construct the target return ($TR_{a,s,t}$) suggested by the analyst a for stock s in month t. The target return ($TR_{a,s,t}$) is constructed as a ratio of the target price to the closing price of the stock on the previous working day to the announcement date of the analyst's report. We use the median target return by all analysts covering stock s in month t ($TR_{s,t}$) as a measure of the global target return for stock s in month t. We assume that this global target return of stock s in month t stands for its global quality. If a stock s has a global target return that is in the middle three quintiles (second to fourth quintile rank of the global pool in a particular month), we call it a *middle stock*. $Middle_{s,t} = 1$ of middle stock; 0 otherwise. If a stock s has a global target return that is in the first or fifth quintile rank of the global pool in a particular month, we call it a *corner stock*. $Corner_{s,t} = 1$ of corner stock; 0 otherwise.

After constructing the global target returns for all stocks, we sort the stocks within an analyst's covered pool and assign each stock a rank according to its global target return. We normalize the rank of each stock s as its percentile position in the pool of analyst a in month t ($rank_{a,s,t}$). If an analyst is covering N stocks in a month, position variable of the stock with the highest global target return equals to 1 (N/N) while the position of the stock with the lowest global target return would be 1/N.

[Insert Table I here]

Panel A of Table I gives us the summary statistics at the analyst-month level. We first notice in Panel A in Table I that the median number of stocks analyzed by a representative analyst in a typical month in our panel is 10. The minimum, by construction, is 3. This reveals something very important: analysts usually analyze a portfolio of stocks. Given this fact, it is possible that analysts rate on a curve, which implies that recommendation of a stock may be influenced by the other stocks in their portfolio. Second, the mean target return of covered stocks, which is a measure of the quality of pool of an analyst, is 17%. More importantly, pool quality amongst analysts varies a lot; the standard deviation of pool quality is 16%. Third, within an analyst pool, there is variation in quality in stocks covered; the median of the spread of quality is 27%. Fourth, the median spread of recommendations of a typical analyst is 2, which means that analysts tend to differentiate the stocks from the other stocks they cover.

Panel B of Table I gives us the summary statistics at the stock-month level. We first notice that a typical stock in our sample is covered by 10 analysts in a typical month. The typical stock in our sample has a global target return of 16.3%. A typical stock is given a recommendation of 2.25, but more importantly, the recommendations for the same firm by different analysts in the same month differ; the median of the spreads is 2. A typical firm has different ranks within analyst pools; for some analysts this firm is relatively undervalued compared to the rest of his pool, whereas for other analysts this firm is relatively overvalued compared to the rest of his pool. We see this because the median of the spreads of percentile rank for the same firm amongst analysts is 40%.

Panel C of Table I gives us the summary statistics at the analyst-stock-month level. As the literature before us has showed, the representative analyst in a typical month gives a positive recommendation. The median recommendation is 2, which is a "Buy". The median target return of a stock in an analyst's pool in a month t is 15.1%, which gives it a percentile rank of 55.6% in an analyst's pool.

III. Relative Rating

In this section, we propose two empirical models to test whether analysts rate their covered stocks based on a curve. Our purpose is to investigate whether the position (or rank) of a given stock in an analyst's pool affects the analyst's recommendation even after we control for the quality of the stock. Our null hypothesis is ***no*** rating on a curve based on the pool of the analyst, which implies that the position of a specific stock in an analyst's pool should not affect her recommendation.

The first model is a higher-dimensional fixed-effects model, and the second is the ordered logit regression model. The higher-dimensional fixed-effects model can exploit the variation of the relative rank variable across stock, analyst, and time to verify whether relative quality has any marginal impact on the recommendation with non-parametrically controlled fixed effects. However, because our dependent variables are categorical from 1 to 5 with a decreasing order of recommendation (from “Strong Buy” to “Sell”), using OLS with higher-dimensional fixed-effects can be biased. Thus, we also use the ordered logit regression to further verify the impact of the relative quality of a stock in the analyst’s pool on the recommendations. One disadvantage of the latter approach is that we cannot control for fixed effects other than time fixed-effects due to the limitation of our computing power.

A. Higher-dimensional fixed-effects model

The empirical model is specified as in Equation (1):

$$rec_{a,s,t} = \beta_1\, TR_{s,t} + \beta_2\, rank_{a,s,t} \times Middle_{s,t} + \beta_3\, rank_{a,s,t} \times Corner_{s,t} + \theta\, IBP_{a,s,bt} + \eta_{s,t} + \gamma_{a,s} + \epsilon_{it}, \qquad (1)$$

where

$rec_{a,s,t}$ = recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell;

$TR_{s,t}$ = the global target return for a given stock *s* in month *t* measured by the median target return of all analysts covering the stock in month t;

$rank_{a,s,t}$ = the rank of stock *s* in the pool of analyst *a* covering N stocks in month *t*= equals 1 for the stock with the highest global target return in his pool, and 1/N for the stock with the lowest global target return;

$Middle_{s,t}$ = 1 if a stock s has a global target return that is in the second to fourth quintile ranks of the global pool in month t, 0 otherwise;

$Corner_{s,t}$ = 1 if a stock s has a global target return that is in the first or fifth quintile rank of the global pool month t, 0 otherwise;

$IBP_{a,s,b,t}$ measures the possible conflict of interest that analyst a faces to be partial to stock s that have an underwriting relationship with a bank b in month t;

$\eta_{s,t}$ represents fixed-effects capturing stock-month characteristics; and

$\gamma_{a,s}$ represents fixed-effects capturing analyst-stock characteristics.

If analysts give high recommendations to stocks with high global target return in month t, we should observe a significantly negative β_1. This is because “Strong Buy” is 1 and “Sell” is 5.

However, the variable of interest in the model is $rank_{a,s,t}$. If analysts do not rate on a curve, the rank of a stock in the pool of the analyst should not matter, and β_2 and β_3 should not be different from 0.

If analysts rate on a curve, the rank of a stock in the pool of the analyst should matter, and higher ranked stocks should get better recommendations, and so β_2 and β_3 should be negative and significantly different from 0.

In addition to this, as we explained in Figure 1, the impact of relative quality is less severe for stocks whose global target returns are extreme. These are the corner stocks. The corner stocks are the best and worst stocks at the given month identified as in the first and fifth quintiles according to the global target. If true, we would expect β_2 to be more negative than β_3. This test would also mitigate the concern that the estimated effect is coming from noise.

[Insert Table II here]

Column (1) shows the results of using just one independent variable, $TR_{s,t}$. β_1 is negative and significant. Unsurprisingly, the higher a stock's global target return is, the better recommendation a stock gets. It is indeed true that analysts' recommendations are affected positively by the global quality of the stock.

Column (2) includes our variable of interest, $rank_{a,s,t}$, and is our main result. Surprisingly, even after controlling for global target return, the relative position of the stock in the pool of stocks the analyst is covering is significantly correlated with the recommendations. The significantly negative coefficient of relative position implies that a stock would get a better recommendation if it belongs to the best stocks in the given pool of the analyst. The economic significance of the rank is also substantial. A stock would have 0.431 grade higher if it is the best stock among the covered stocks than the case when it is the worst stock among the covered stocks.

Column (3) investigates whether the impact is heterogenous depending on the stock's universal position in the global pool. According to Figure 1, if analysts are indeed rating on a curve, then the main effect should be focused on stocks located in the middle range. In other words, the universal best (worst) stocks would be less likely to be affected by the rating on a curve because their ranks would be highly likely to be the same across all analysts. Both β_2 and β_3 are negative and significantly different from 0, but β_2 is more negative than β_3. This tells us that we indeed observe the mitigated impact for the corner stocks, the stocks in the first and fifth quintiles.

From column (4) to column (7), we additionally control for two higher-dimensional fixed-effects, the analyst-stock fixed-effects and stock-month fixed-effects, to test whether the impact of rank would remain after controlling for those two higher-dimensional fixed-effects. These are powerful tests because the analyst-stock fixed effect controls for the match between the stock and the analyst (which controls for variables like analyst specialization in certain industries, endogenous coverage selection) and the stock-month fixed effects controls for time-varying characteristics of the stock (which controls for market capitalization, corporate investment, growth opportunity, institutional ownership, corporate news, earnings announcement, undervaluation/overvaluation). Note that when we control for the stock-month fixed-effects in columns (6) and (7), we drop $TR_{s,t}$, the global target return for a given stock s in month *t*, because this variable is subsumed by the latter variable.

We notice in column (4) to column (7), that although the magnitude of β_2 shrinks substantially after controlling for the higher-dimensional fixed-effects, it is still negative and statistically significant at the 1% significance level.

In sum, the results based on the higher-dimensional fixed-effects model support that analysts tend to rate their covered stocks on a curve, a curve that is specific to the analyst. This implies that they would give a better recommendation to their best stocks depending on their own covering pools.

B. Ordered Logistic Regressions

As mentioned, since our dependent variable is an ordered categorical value, the natural research design is to use an ordered logistic regression. We use a very similar model to Equation (1) in the ordered logistic model:

$$rec_{a,s,t} = \beta_1 \, TR_{s,t} + \beta_2 \, rank_{a,s,t} \times Middle_{s,t} + \beta_3 \, rank_{a,s,t} \times Corner_{s,t} + \theta \, IBP_{a,s,b,t} + \tau_t + \epsilon_{it} \qquad (2)$$

where

$rec_{a,s,t}$ = recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell;

$TR_{s,t}$ = the global target return for a given stock s in month *t* measured by the median target return of all analysts covering the stock;

$rank_{a,s,t}$ = the rank of stock s in the pool of analyst a covering N stocks in month t= 1 for the stock with the highest global target return in his pool, and 1/N for the stock with the lowest global target return;

$Middle_{s,t}$ = 1 if a stock s has a global target return that is in the second to fourth quintile ranks of the global pool in month t, 0 otherwise;

$Corner_{s,t}$ = 1 if a stock s has a global target return that is in the first or fifth quintile rank Of the global pool in month t, 0 otherwise;

$IBP_{a,s,b,t}$ measures the possible conflict of interest that analyst a faces to be partial to stock S that have an underwriting relationship with a bank b in month t; and

τ_t captures time fixed-effects controlling time specific characteristics.

We cannot control for fixed-effects other than time fixed-effects due to the limitation of our computing power. As specified in the previous subsection, if analysts' recommendations are correlated with their own expected returns, the coefficient β_1 would be significantly negative. The coefficient of the variable of interest, β_2 and β_3, would also be negative, if an analyst rates on her own curve. We also test whether the impact of relative quality is less severe for the corner stocks following the same definition.

[Insert Table III here]

In general, Table III confirms the main results that the relative position of a stock in the analyst's pool matters . Both β_2 and β_3 are negative and significantly different from 0. This implies that a stock would get a better recommendation if it belongs to the best stocks in the given pool of the analyst. But β_2 is more negative than β_3 , which tells us that we indeed observe the mitigated impact for the corner stocks, the stocks in the first and fifth quintiles.

In sum, the results show strong evidence for the rating on a curve behaviour by analysts. To summarize, our results suggest that an analyst's recommendation on a stock is determined by not only the objective quality but also the relative quality among the stocks covered by the analyst. A stock tends to be recommended higher by an analyst if it is one of the best stocks that she is covering; however, the same stock is likely to be recommended lower by another analyst if it is one of the worst stocks of her pool.

IV. Disagreement Amongst Analysts

There is a large and important literature hypothesizing the reasons behind analyst disagreements. This literature focuses on dispersion in analyst earnings forecasts. The early literature claims that this is because of difference of opinions, but the issue is not settled.[10] In this section, we offer another reason why analysts disagree about a particular stock--because the relative ranking of the stock in the stocks they cover is different. Is this true? In the section, we run a test to check this.

To empirically test this, we estimate the following model using OLS regression with stock and time fixed-effects:

$$SP(rec_{s,t}) = \beta_1\, SP(rank_{s,t}) + \eta_s + \tau_t + \epsilon_{s,t}, \qquad (3)$$

where

$SP(rec_{s,t})$ is the Spread of Recommendations, $rec_{a,s,t}$, across all analysts for stock s in month t. Here $rec_{a,s,t}$ is the recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell;

$SP(rank_{s,t})$ is the Spread of Ranks, $rank_{a,s,t}$, across all analysts for stock s in month t. Here $rank_{a,s,t}$ = the rank of stock s in the pool of analyst a covering N stocks in month t = 1 for the stock with the highest global target return in his pool,

1/N for the stock with the lowest global target return;

η_s is the stock fixed-effects; and

τ_t is the time fixed-effects.

Since recommendations can be either 1, 2, 3, 4 or 5, the spread of recommendations can be 0, 1, 2, 3 or 4. This means that the dependent variable is an ordered categorical value; so the natural research design is to use an ordered logistic regression. Hence, we re-estimate (3) (without the stock fixed effect) using an ordered logistic regression.

[10] Diether, Malloy and Scherbina (2002) show that stocks with higher dispersion in analysts' earnings forecasts earn lower future returns than otherwise similar stocks. They interpret dispersion in analysts' forecasts as proxy for difference of opinion about a stock, and show that this evidence is consistent with the hypothesis that price reflect the optimistic view with short-selling constraint. However, Johnson (2004) offers a different explanation for this phenomenon based on the interpretation of dispersion as proxy for unpriced information risk (idiosyncratic risk), which is negatively related with returns. Sadka and Scherbina (2007) shows that analyst disagreement coincides with high trading costs, leading to persistent stock mispricing. Avramov, Chordia, Jostova, and Philipov (2009) shows that this negative cross-sectional relation between dispersion in analysts' earnings forecasts and future stock return may be explained by financial distress, proxied by credit risk.

[Insert Table IV here]

Table IV, columns (1) to (3) presents the OLS results of the impact of spread in percentile ranks on the spread of recommendations. As β_1 is positive, Column (1) shows that the spread of recommendations is indeed positively correlated with the spread of percentile ranks. After controlling for stock and time fixed-effects, columns (2) and (3) show that the impact of spread of percentile rank on the spread of recommendations is still significantly positive. The economic significance of the impact is also not negligible. One standard deviation increase in the spread in percentile rank can explain almost 10% of variation of the spread in recommendation.

Table IV, columns (4) and (5) presents the results of the ordered logistic regression. As β_1 is positive, Column (4) shows that the spread of recommendations is positively affected by the spread of percentile rank. The result does not change in column (5) where we add the month fixed effect.

V. Relative Ratings and Returns

In this section, we study whether the stocks affected by rating on a curve behavior show specific patterns in terms of returns. If the recommendations ratings are given based on a curve that is analyst pool specific, stocks with the same recommendations may not have similar future returns. In the world of rating on a curve, the quality of the analyst pool may be as important as the recommendation rating.

As we have shown in our previous formal tests, a stock could be recommended a "Strong Buy" (or "Sell") if the stock is the best (or worst) stock in the covering analyst's pool. This implies that some undervalued stocks covered in the strong quality pool might be depreciated by analysts and be recommended poorly with "Hold" or even "Sell" even if the global target returns of the stock is high. On the other hand, some overvalued stocks might be over-appreciated and be recommended "Strong Buy" or "Buy" by the analysts with weak covering pool even if they have low global target returns. Note that this would not happen if analysts recommend the stock based only on global target returns.

The testable hypothesis, therefore, is as follows. In the null, we expect that stocks with the same recommendation ratings would have similar future returns since they are recommended based on the global target returns. In the alternative hypothesis, we expect the stocks' future returns could be correlated with not only the recommendation but also with the quality of the pool of the analyst covering the stock.

To empirically test this, we categorize all stocks into two dimensions: quality of pool and recommendation. We define the quality of pool of analyst a in month t as the mean of the global target return of all covered stocks in the pool in that month. We call this $Q_{a,t}$. We then divide all analysts into terciles by the quality of their pools each month: Worst Pool, Normal Pool, Best Pool. For the recommendation letter, we create for each stock s in time t these categories: Strong Buy, Buy and Hold/Underperform/Sells. As there are so few Underperform/Sell recommendations, we put Hold/Underperform/Sells in one bucket. The sample size in this bucket is now comparable to the sample size in the Strong Buy or Buy buckets.

Each month we form nine portfolios: Strong Buy and Worst Pool, Strong Buy and Normal Pool, Strong Buy and Best Pool, Buy and Worst Pool, Buy and Normal Pool, Buy and Best Pool, Hold/Underperform/Sells and Worst Pool, Hold/Underperform/Sells and Normal Pool, Hold/Underperform/Sells and Best Pool. Stocks which fall in more than one quality pool are removed. All remaining stocks are equally weighted in each portfolio. The returns are estimated using the period from one day before the announcement of the report to 20 working days after the announcement. We run a time-series regression for each of these nine portfolios. It is important to note that these portfolios are rebalanced every month, and since the information needed for the rebalancing is not available in real time, these strategies cannot be employed in real time.

[Insert Table V here]

Table V, Panel A, presents the monthly raw returns of each of these 9 portfolios. Table V, Panel B, presents the monthly risk-adjusted returns (risk adjusted with the Fama-French 5-factor plus momentum factor) of each of these 9 portfolios. The returns are estimated using the period from one day before the announcement of the report to 20 working days after the announcement.

We find that blindly following recommendations (long strong buy, short hold and sells) would generate returns of 39 bps per month. However, using the logic of relative ratings documented in our paper, going long strong buys from analysts with the best pools and shorting the holds and sells of analysts with the worst pools yields 74 bps per month (0.97% - 0.23%) – nearly double! Surprisingly, the worst recommended stocks from the best pools (0.88%) even out-perform the best recommended stocks from the worst pools (0.64%).

The results are similar in the risk-adjusted case. We find that blindly following recommendations (long strong buy, short hold and sells) would generate risk-adjusted returns of

36 bps per month. However, using the logic of relative ratings documented in our paper, going long strong buys from analysts with the best pools and shorting the holds and sells of analysts with the worst pools yields 118 bps per month (1.24% - 0.06%) – more than triple! Surprisingly, the worst recommended stocks from the best pools (0.91%) even out-perform the best recommended stocks from the worst pools (0.36%).

V. Conclusion

Analyst A may rate a stock a "Buy" because it is the least overvalued amongst the portfolio of stocks she is rating, whereas Analyst B may rate the same stock a "Sell" because it is the least undervalued amongst the portfolio of stocks she is rating. If this happens, analysts are rating on a curve, where the curve is determined by the average quality of the pool of stocks that they are covering. Using two different research designs that control for "investment banking pressure" as well as two pairs of higher-dimensional fixed-effects in a panel data set – the match between the stock and the analyst and changing unobserved characteristics of the stock – we find that analysts do rate on a curve.

We next analyze the disagreement amongst analysts. We find that the dispersion in analyst forecasts is affected by these relative ratings.

We finally look at return implications. We find that blindly following recommendations (long strong buy, short hold and sells) would generate returns of 39 bps per month. However, using the logic of relative ratings documented in our paper, going long strong buys from analysts with the best pools and shorting the holds and sells of analysts with the worst pools yields 74 bps per month (0.97% - 0.23%) – nearly double! Surprisingly, the worst recommended stocks from the best pools (0.88%) even out-perform the best recommended stocks from the worst pools (0.64%).

Table I: Summary Statistics

The sample consists of 559,033 analyst-months covering 460,089 stock-months during the period from February of 1999 to July of 2017. We exclude analyst-months analyzing less than three stocks, all recommendations from "Zacks Investment Research" before 2006 (because this company uses the same analyst id for all analyst recommendations), and all cases in which analysts submit recommendation to I/B/E/S anonymously. Target return is defined as a ratio of target price to the closing price of the stock on the previous working date, recommendation is defined as a categorical variable which varies from 1 (best, "Strong Buy") to 5 (worst, "Sell"). The median target return by all analysts covering a stock in a month is a measure of the global target return of that stock in that month. Percentile rank is defined as a percentile of the stock in the analyst's pool sorted according to global target return. Dummy for the middle (corner) stocks in global pool is defined as a dummy variable which equals to 1 if a stock belongs to second to fourth (first or fifth) quintile of global target returns, and 0 otherwise.

Panel A: Summary statistics at analyst-month level

Variable	Abbreviation	Obs.	Mean	S.D.	P25	P50	P75
Number of stocks covered		559,033	11.310	6.943	6	10	15
Mean target return of covered stocks	$Q_{a,t}$	559,033	0.213	0.159	0.120	0.171	0.254
Spread of target returns of covered stocks		559,033	0.348	0.294	0.168	0.274	0.425
Mean recommendation of covered stocks		559,033	2.294	0.510	2.000	2.333	2.667
Spread of recommendations of covered stocks		559,033	1.820	0.921	1	2	2

Panel B: Summary statistics at stock-month level

Variable	Abbreviation	Obs.	Mean	S.D.	P25	P50	P75
Number of analysts following		460,089	11.416	6.778	6	10	15
Median target return of analysts	$TR_{s,t}$	460,089	0.213	0.227	0.092	0.163	0.263
Spread of target returns of analysts		460,089	0.455	0.380	0.214	0.349	0.562
Mean recommendation of analysts		460,089	2.271	0.497	1.923	2.250	2.600
Spread of recommendations of analysts	$SP(rec_{s,t})$	460,089	2.192	0.895	2	2	3
Spread of percentile rank in the analysts' pools	$SP(rank_{s,t})$	460,089	0.426	0.235	0.250	0.400	0.575
Dummy for the middle stocks in the global pool	$Middle_{s,t}$	460,089	0.601	0.490	0	1	1
Dummy for the corner stocks in the global pool	$Corner_{s,t}$	460,089	0.399	0.490	0	0	1

Panel C: Summary statistics at analyst-stock-month level

Variable	Abbreviation	Obs.	Mean	S.D.	P25	P50	P75
Recommendations	$rec_{a,s,t}$	5,022,576	2.307	0.925	2	2	3
Median target return of analysts on stock	$TR_{s,t}$	5,022,576	0.190	0.191	0.089	0.154	0.236
Percentile rank of the stock in the analyst's pool	$rank_{a,s,t}$	5,022,576	0.556	0.290	0.308	0.556	0.800

Table II: Effect of Relative Quality on Recommendations: A High-Dimensional Fixed Effect Model

This table presents the impact of relative quality of a stock on analysts' recommendations. The model is estimated using OLS with/without high dimensional fixed effects. The y-variable is $rec_{a,s,t}$, which is the recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell. $TR_{s,t}$ is the global target return for a given stock *s* in month *t* measured by the median target return by all analysts covering the stock; $rank_{a,s,t}$ = the rank of stock *s* in the pool of analyst *a* covering N stocks in month *t*, which equals 1 for the stock with the highest global target return in his pool, and equals 1/N for the stock with the lowest global target return; $Middle_{s,t}$ ($Corner_{s,t}$) is 1 if a stock s has a global target return that is in the second to fourth quintile (first or fifth quintile) ranks of the global pool in a particular month, 0 otherwise. $IBP_{a,s,b,t}$ measures the possible conflict of interest that analyst a faces to be partial to stock s that have an underwriting relationship with a bank b in month t. Standard errors are shown in parenthesis underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	$rec_{a,s,t}$ (1= Strong Buy, 5=Sell)						
$TR_{s,t}$	-1.026***	-0.663***	-0.856***	-0.450***	-0.548***		
	(0.009)	(0.010)	(0.011)	(0.008)	(0.009)		
$rank_{a,s,t}$		-0.431***		-0.268***		-0.022***	
		(0.005)		(0.004)		(0.005)	
$rank_{a,s,t}$			-0.469***		-0.285***		-0.030***
$\times Middle_{s,t}$			(0.005)		(0.004)		(0.006)
$rank_{a,s,t}$			-0.216***		-0.157***		0.002
$\times Corner_{s,t}$			(0.006)		(0.004)		(0.008)
$IBP_{a,s,b,t}$				-0.154***	-0.155***	-0.122***	-0.122***
				(0.024)	(0.024)	(0.023)	(0.023)
Constant	2.502***	2.673***	2.685***	2.538***	2.543***	2.319***	2.317***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Analyst-Stock FE	No	No	No	Yes	Yes	Yes	Yes
Stock-Month FE	No	No	No	No	No	Yes	Yes
Observations	5,022,576	5,022,576	5,022,576	4,735,398	4,735,398	4,731,240	4,731,240
R-squared	0.045	0.057	0.063	0.555	0.556	0.645	0.645

Table III: Effect of Relative Quality on Recommendations: An Ordered Logistic Regression Model

This table presents the impact of relative quality of a stock on analysts' recommendations using ordered logistics model. The y-variable is $rec_{a,s,t}$, which is the recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell. $TR_{s,t}$ is the global target return for a given stock s in month t measured by the median target return by all analysts covering the stock; $rank_{a,s,t}$ = the rank of stock s in the pool of analyst a covering N stocks in month t, which equals 1 for the stock with the highest global target return in his pool, and equals 1/N for the stock with the lowest global target return; $Middle_{s,t}$ ($Corner_{s,t}$) is 1 if a stock s has a global target return that is in the second to fourth (first or fifth) quintile rank of the global pool in a particular month, 0 otherwise. $IBP_{a,s,b,t}$ measures the possible conflict of interest that analyst a faces to be partial to stock s that have an underwriting relationship with a bank b in month t. The ordered logit standard errors are clustered by analyst. Standard errors are shown in parenthesis underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable				$rec_{a,s,t}$ (1= Strong Buy, 5=Sell)			
$TR_{s,t}$	-2.249***	-1.416***	-1.861***	-1.051***	-1.486***	-1.056***	-1.509***
	(0.047)	(0.047)	(0.052)	(0.046)	(0.010)	(0.050)	(0.011)
$rank_{a,s,t}$		-0.918***		-1.051***		-1.076***	
		(0.020)		(0.020)		(0.022)	
$rank_{a,s,t}$			-1.003***		-1.107***		-1.126***
$\times Middle_{s,t}$			(0.020)		(0.004)		(0.005)
$rank_{a,s,t}$			-0.462***		-0.637***		-0.652***
$\times Corner_{s,t}$			(0.022)		(0.005)		(0.006)
$IBP_{a,s,b,t}$						-0.435***	-0.442***
						(0.069)	(0.015)
Time FE	No	No	No	Yes	Yes	Yes	Yes
Observations	5,022,576	5,022,576	5,022,576	5,022,576	5,022,576	4,739,823	4,739,823

Table IV: Effect of Relative Quality on Spread of Recommendations

This table investigate whether relative quality can explain the analysts' disagreement on a firm. The models used are OLS with/without high dimensional fixed effects and ordered logistic regressions. The y-variable is the Spread of Recommendations, $SP(rec_{s,t})$ across all analysts for stock s in month t. Here $rec_{a,s,t}$, is the recommendation rating of analyst a on stock s in month t = 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform and 5 for Sell. $SP(rank_{s,t})$ is the Spread of Ranks across all analysts for stock s in month t. Here $rank_{a,s,t}$ is the rank of stock s in the pool of analyst a covering N stocks in month t, which equals 1 for the stock with the highest global target return in his pool, and equals 1/N for the stock with the lowest global target return. Standard errors are clustered by stock. Standard errors are shown in parenthesis underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
	Fixed Effects			Ordered-Logit	
Variable	$SPrec_{s,t}$ (0=No disagreement, 4=Maximum disagreement)				
$SP(rank_{s,t})$	1.727***	1.368***	1.329***	3.440***	3.440***
	(0.005)	(0.009)	(0.009)	(0.012)	(0.022)
Constant	0.723***	0.833***	0.983***		
	(0.002)	(0.003)	(0.001)		
Stock FE	No	Yes	Yes	No	No
Month FE	No	No	Yes	No	Yes
Observations	432,196	432,196	432,196	432,196	432,196

Table V: Relative Ratings and Returns

This table presents monthly raw returns and risk-adjusted returns (risk adjusted Fama-French 5-factor plus momentum factor) for nine portfolios. The portfolios are constructed as follows. We define the quality of pool of analyst a in month t as the mean of the global target return of all covered stocks in the pool in that month. We call this $Q_{a,t}$. We then divide all analysts into terciles by the quality of their pools each month: Worst Pool, Normal Pool, Best Pool. For the recommendation letter, we create these categories: Strong Buy, Buy and Hold/Underperform/Sells. As there are so few Underperform/Sell recommendations, we put Hold/Underperform/Sells in one bucket. The nine portfolios are: Strong Buy and Worst Pool, Strong Buy and Normal Pool, Strong Buy and Best Pool, Buy and Worst Pool, Buy and Normal Pool, Buy and Best Pool, Hold/Underperform/Sells and Worst Pool, Hold/Underperform/Sells and Normal Pool, Hold/Underperform/Sells and Best Pool. Stocks which fall in more than one quality pool are removed. All remaining stocks are equally weighted in each portfolio. The returns are estimated using the period from one day before the announcement of the report to 20 working days after the announcement.

Panel A: Raw Returns

Raw returns	Strong Buy	Buy	Hold and Sells	All recommendations	Strong Buy-Hold and Sells
Worst Pool	0.64%	0.74%	0.23%	0.42%	0.41%
Normal Pool	1.10%	1.08%	0.80%	0.96%	0.30%
Best Pool	0.97%	0.97%	0.88%	0.94%	0.10%
All pools	0.88%	0.90%	0.49%	0.70%	0.39%
Best-Worst	0.33%	0.23%	0.64%	0.52%	

Panel B: Alphas of 6 Factor (Fama-French 5 Factor and Momentum Factor) Model

FF5+Mom alphas	Strong Buy	Buy	Hold and Sells	All recommendations	Strong Buy-Hold and Sells
Worst Pool	0.36%	0.32%	0.06%	0.25%	0.29%
Normal Pool	1.17%	1.11%	0.70%	0.99%	0.47%
Best Pool	1.24%	1.53%	0.91%	1.22%	0.32%
All pools	0.92%	0.99%	0.56%	0.82%	0.36%
Best-Worst	0.88%	1.20%	0.85%	0.98%	

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