Internet Appendix for

Do Professional Rankings Affect Analyst Behavior? Evidence From a Regression Discontinuity Design

Michael J. Jung
University of Delaware
mjung@udel.edu

Yiqing Lü
New York University Shanghai
yiqing.lu@nyu.edu

Hong Wu
City University of Hong Kong
hong.wu.pitt@gmail.com

Yuhai Xuan
University of California, Irvine
yuhai.xuan@uci.edu

Appendix A. The Voting Procedure for Analyst Rankings in *Institutional Investor*

Each year, *Institutional Investor* (*II*) polls buy-side institutions for the best sell-side analysts. The list of voting institutions come from *II*'s internal database of subscribers, many of which are included in *II*'s list of the top 300 institutional investors and top 100 hedge funds. The heads of research of sell-side brokerage firms can also augment the list by submitting their clients. Other buy-side institutions interested in voting can directly contact *II*, although they must verify their eligibility related to active management and the thresholds of assets under management (AUM). *II* begins the confidential polling process around May of each year, and the process lasts approximately four weeks.

Votes for sell-side analysts are ordinal and weighted by each buy-side institution's AUM and converted into composite scores. For example, a first-place vote from the largest institutions translates into 24 points, while a fourth-place vote from the smallest eligible institutions translates into 1 point. When multiple voters from the same buy-side institution vote for different analysts in the same industry, the points are divided in such a way that the total points allocated to different analysts do not exceed the institution's "voting power" for a single analyst.

Analysts who place within the top positions require a minimum number of votes. First-place analysts require at least 15 votes, while second-place, third-place, and runners-up require a minimum of 10 votes. Runners-up also need a composite score that is within 35% of the third-place analyst's score. All other analysts need at least five votes to be included anywhere in the rankings. The rankings are published in October, often accompanied by interviews with buy-side voters and sell-side analyst winners. The amount of publicity top-ranked analysts receive in the October issue varies from year to year, but generally, the all-star analysts are highlighted, while runner-up analysts are mentioned infrequently.

Table A1: II-Ranked Analyst Composite Scores

Rank	N	Mean Score	Min	1st Quartile	Median	3rd Quartile	Max
First-place	849	19.76	9.24	16.24	19.09	22.57	44.60
Second-place	851	14.70	6.98	12.44	14.28	16.52	29.34
Third-place	845	11.79	6.39	10.12	11.47	13.19	22.58
First runner-up	754	9.89	5.09	8.56	9.71	10.95	19.11
Other runner-ups	1,032	8.12	4.37	7.15	7.99	9.10	15.50
Difference between third-place and first runner-up	750	1.57	0.00	0.54	1.28	2.37	6.82
After matching *II* data with IBES data–difference between third-place and first runner-up	736	1.57	0.00	0.54	1.26	2.37	6.82

Appendix B. The Regression Discontinuity Design

Regression discontinuity (RD) designs can be used to measure treatment effects when a treatment is based on whether an underlying continuous variable (or forcing variable) crosses a threshold. Under the condition that there is no other source of discontinuity, the treatment effect induces a discontinuity in the outcome of interest at the threshold. Thus, the outcomes on the two sides of the threshold are unequal, and the difference between these two directional limits measures the treatment effect. A necessary condition for the validity of the RD design is that the forcing variable itself is continuous at the threshold (Hahn et al. 2001).

Formally, let y denote the outcome of interest and z the forcing variable, with $\bar{z}$ being the threshold above which there is treatment. Further, we define the two limiting values of the outcome variable as follows:

$$y^{+} = \lim_{\delta \to 0} E[y \,|z = \bar{z} + \delta]\,;$$

$$y^{-} = \lim_{\delta \to 0} E[y \,|z = \bar{z} - \delta].$$

Then the local average treatment effect is given by

$$d = \; y^{+} - y^{-}.$$

In the context of analyst ranking, the forcing variable is the *II*-voting composite score earned by a given analyst in a given industry-year, and the ideal threshold is one in which scores just above the threshold earn an analyst all-star distinction and scores just below it do not. In our context, given the institutional details of the *II* voting process, the best way to study the treatment effect of the rankings is to compare the outcomes (e.g., forecast properties) of the third-place analyst and the first runner-up (i.e., fourth-place) analyst. There are several reasons for choosing this pair of analysts within each industry-year. First, among analysts, only the analysts ranked in the top three are considered all-stars. Second, the minimum number of votes required to achieve first place is higher than it is for all other places (see Appendix A for details of *II*'s voting process), which means that a first-place rank is not exactly comparable to other ranks. Third, the difference in composite scores between the top three places are not guaranteed to be close, while by construction, the composite scores of the runner-up analysts must be within at least 35% of the third-place analyst. Therefore, in the spirit of Thistlethwaite and Campbell (1960), we use the third-place analyst as the award winner and the first runner-up analyst as the one who just missed the award.

Formally, let Analyst A be ranked i in the voting process and Analyst B be ranked $i+1$ (one place below A), then it must be the case that

$$Score_A > Score_B,$$

or equivalently

$$\Delta Score_{AB} = Score_A - Score_B > 0.$$

In addition to the score levels, the difference in scores can be used as the forcing variable for the RD design, and the threshold for the treatment can be 0. The RD design measures the treatment effect by comparing outcomes for situations when $\Delta Score_{AB}$ is just above and when it is just below zero. This comparison achieves the quasi-experimental design that underlies RD, with the latter set of observations acting as a control for the former.

More details on estimating causal effects using RD designs, including the difference between sharp and fuzzy designs, the selection of nonparametric estimators for $y^+$and y^-, and the choice of bandwidths can be found in Imbens and Lemieux (2008) and Lee and Lemieux (2010).

Appendix C. Summary of Sample Size Differences Across Tables

Table 3:

Starting with all third-place analysts and all first runner-up analysts, we retrieve their quarterly forecasts from November of the current year to October of the next year. We then require requisite data for all control variables. This gives us a global sample size of 80,420 observations with 1,507 analyst pairs on which we can further construct our local sample for RD tests. After imposing the optimal bandwidth of 1.555 using the approach in Calonico et al. (2014), we have a local sample size of 42,328 forecast-level observations used in Columns (1) and (2). For comparison, we impose a bandwidth of 1.5, which leads to 41,634 observations used in Columns (3) and (4), and a bandwidth of 2.0, which leads to 49,398 observations used in Columns (5) and (6).

Table 4:

Using recommendation revisions as the dependent variable leads to a global sample size of 15,637 recommendation-level observations. After imposing the same optimal bandwidth used in Table 3, the sample size becomes 6,853.

Table 5:

The starting sample size is the same as in Table 3, Columns (1) and (2). When a firm's institutional ownership by transient institutions is above (below) the industry median, the firm is partitioned into the high (low) transient ownership group. Both partitions sum to 42,328 observations.

Table 6:

Starting with the same 1,507 analyst pairs from Table 3, we retrieve the three-day cumulative abnormal returns around each analyst's forecast revision date. Next, we exclude forecast revisions issued by both the third-place analyst and the first runner-up analyst in the same three-day window. We further impose the restriction that for each pair of analysts, their forecast revisions must pertain to the same firm in the same quarter. This leads to a sample size of 7,501 observations. After imposing the same optimal bandwidth used in Table 3, the sample size becomes 6,870 at the forecast level.

<u>Table 7:</u>

Panel A: Starting with the same 1,507 analyst pairs from columns (1) and (2) in Table 3, we retrieve their participation in conference calls based on the conference call transcripts. This match results in 8,166 analyst-quarter-firm observations. After imposing the same optimal bandwidth used in Table 3, we have 4,480 observations.

Panel B: Starting with from the regression sample in column (1) and (2) in Table 3, we retrieve each analyst's new initiation of coverage of a firm in the year after the ranking. We find 2,598 such initiations, at the analyst-year-sector level. We then require dependent variables, the next year market-to-book or market cap to be available. After imposing the same optimal bandwidth used in Table 3, we have 1,997 observations for all columns.

Panel C: Starting with the same 1,507 analyst pairs from columns (1) and (2) in Table 3, we manually search of each analyst's employment history on LinkedIn. We find this information for 326 analysts. The regression is thus at the analyst level.

<u>Table 8:</u>

Panel A: Using forecast boldness as the dependent variable leads to a global sample size of 55,611 at the analyst-sector-year-firm-quarter-level observations. After imposing the same optimal bandwidth used in Table 3, the sample size becomes 28,834.

Panel B: Using forecast frequency as the dependent variable leads to a global sample size of 54,765 analyst-sector-year-firm-quarter-level observations. After imposing the same optimal bandwidth used in Table 3, the sample size becomes 28,752.

Table 9:

Using forecast bias as the dependent variable leads to a global sample size of 80,119 observations. After imposing the same optimal bandwidth used in columns (1) and (2) in Table 3, the sample size becomes 42,173 at the forecast level.

Appendix D: Analyst Ranking and Alternative Measures of Forecast Optimism

This table presents the regression analysis of the effect of analyst ranking on two alternative measures of forecast optimism: annual forecast optimism and price target optimism. The dependent variable *Annual forecast optimism* in columns (1) and (2) is calculated as the annual EPS forecast minus the median of all annual forecasts in the same quarter, scaled by the stock price in the previous year end. The dependent variable *Price target optimism* in columns (3) and (4) is calculated as the annual price target forecast minus the median of all price target forecasts in the same quarter, scaled by the stock price at the previous year end. The key independent variable is *Third-place analyst*, an indicator variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. We use the optimal bandwidth of 1.555 in Table 3 for consistency. We introduce polynomials of up to order 2 that are different for the third-place and first runner-up analysts and control for firm fixed effects and year-quarter fixed effects in all regressions. In columns (2) and (4), we further control for firm characteristics including book size, book-to-market ratio, sales growth, ROA, leverage, and forecast horizon, and analyst characteristics including gender, experience and past all-star status. Standard errors are clustered at the firm level and included in the parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variable definitions are discussed in Section 3.3 of the paper.

	(1)	(2)	(3)	(4)
Dependent variable:	Annual forecast optimism		Price target optimism	
Third-place analyst	0.072**	0.084**	1.796**	1.876**
	(0.034)	(0.034)	(0.756)	(0.758)
Firm FE & Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes
Analyst Controls	No	Yes	No	Yes
N	44,059	44,059	27,210	27,210
R^2	0.129	0.140	0.192	0.194

Appendix E: Determinant Tests

Table E.1 Determinants of analyst ranking among all-star and runner-up analysts

This table presents the regression analysis of the determinants of ranking among all-star and runner-up analysts. We include all top-three ranked analysts and all runners-up (i.e., not just the third-place and first runner-up analysts). The dependent variable is the negative of the rank of the analyst, where first place is the best (least negative) and last runner-up is the worst (most negative). The dependent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if she is a first runner-up analyst. The independent variables are measured for the year before the rankings. Apart from the variables used in the main analysis, we introduce *Broker size*, calculated as the number of analysts in the brokerage firm; *Top 10 institutional investor*, set to one (zero otherwise) if at least one stock covered by the analyst is owned by at least one of the top ten largest institutional investors that year; *Number of industries*, calculated as the number of industries an analyst is covering. Standard errors are clustered at the analyst level and included in the parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var.:	− (Rank of the analyst)	
Forecast optimism	0.149	0.263
	(0.322)	(0.260)
Forecast frequency	−0.004	−0.002
	(0.012)	(0.009)
Forecast bias	−0.109	−0.048
	(0.091)	(0.068)
Forecast boldness	0.003	0.003
	(0.005)	(0.004)
Past star		2.061***
		(0.064)
Broker size		0.000
		(0.001)
Conference call priority		0.578***
		(0.219)
Top 10 institutional investor		0.007
		(0.101)
Number of industries		−0.101
		(0.185)
Experience		0.001
		(0.003)
Year FE	Yes	Yes
N	4,134	4,008
R^2	0.005	0.253

Table E.2 Determinants of being third-place vs. fourth-place

This table presents the regression analysis of the determinants of being ranked as a third-place analyst. We include only third-place and first runner-up analysts and use the optimal bandwidth of 1.555 in Table 3 for consistency. The dependent variable is *Third-place analyst*, a dummy variable that equals one if the analyst is a third-place analyst and zero if the analyst is a first runner-up analyst. The independent variables are measured for the year before the rankings. Apart from the variables used in the main analysis, we introduce *Broker size*, calculated as the number of analysts in the brokerage firm; *Top 10 institutional investor*, set to one (zero otherwise) if at least one stock covered by the analyst is owned by at least one of the top ten largest institutional investors that year; *Number of industries*, calculated as the number of industries an analyst is covering. Standard errors are clustered at the analyst level and included in the parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var.:	Third-place analyst	
Forecast optimism	−0.134	−0.118
	(0.172)	(0.181)
Forecast frequency	−0.007	−0.007
	(0.005)	(0.005)
Forecast bias	0.005	0.013
	(0.040)	(0.040)
Forecast boldness	0.002	0.003
	(0.003)	(0.003)
Past star		0.045
		(0.057)
Broker size		−0.000
		(0.000)
Conference call priority		0.191
		(0.151)
Top 10 institutional investor		0.004
		(0.069)
Number of industries		−0.007
		(0.105)
Experience		0.001
		(0.002)
Year FE	Yes	Yes
N	825	795
R^2	0.005	0.011