Explaining (Some) Anomalies: The Role of Analyst Bias

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Abstract

Predictable biases in analyst earnings forecasts drive several popular anomalies. Analyst forecasts, both conservative and optimistic, distort share prices, but only for firms with hard-to-forecast earnings, like those with high credit risk, high idiosyncratic volatility, and other attributes linked to 14 popular low-return anomalies. For these firms, the risk-adjusted return spread between the least and most optimistic predicted analyst bias quintiles ranges from 6% to 19% per year, depending on the anomaly. The prevalence of analyst optimism among these firms emerges as a likely explanation for their overpricing and subsequent negative alphas.

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One of the classic tenets of finance is that high risk should generate high average returns. However, several efficient markets anomalies challenge this maxim because of their inverse relationship between high degrees of uncertainty (and presumably risk) and average returns. For example, Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), and Avramov, Chordia, Jostova, and Philipov (2009) show that high-credit-risk firms earn low subsequent returns, Diether, Malloy, and Scherbina (2002) find a negative relation between dispersion in analysts' earnings forecasts and subsequent returns, while Ang, Hodrick, Xing, and Zhang (2006) document that high idiosyncratic volatility stocks subsequently underperform.

The puzzling inverse relationships between average returns and these three metrics of risk derive from an omitted variable that more plausibly explains the anomalous relationships. Many other anomalies also stem from omitted variable biases that are tied to the same root cause: stocks identified as having high levels of uncertainty tend to have earnings that are difficult to forecast and value. For these stocks, investors are particularly receptive to analyst opinions—however irrational those opinions—causing share prices to deviate from fair value. Moreover, the most overly optimistic forecasts often concentrate in firms with difficult-to-forecast earnings.[1] For example, the average consensus forecast is 35% higher than actual earnings for firms in the worst credit rating quintile, but is 5% above actual earnings for firms in the best-rated quintile. Thus, we contend that the credit risk anomaly, as well as many other anomalies, largely arise from the convergence to fair value of prices that had been inflated by predictably optimistic analyst forecasts.

Buttressing our argument are three findings. First, analyst bias influences future returns more when the consensus contains the forecast of at least one "strategic" analyst. Strategic analysts, defined by Malmendier and Shanthikumar (2014), tend to be more optimistic in their buy recommendations compared to their earnings forecasts. As the authors argue, their optimistic recommendations stem from strategic motives rather than genuine optimism. Second, analyst bias correlates more with future returns when retail investors are relatively more important in owning the stock, suggesting that less sophisticated investors are more likely to be swayed by biased analyst opinions. This is unsurprising. With greater resources and incentives, institutions are better at assessing forecasts and their implications for stock prices, and better at properly weighting alternative and

[1] See Duru and Reeb (2002) and Cohen and Lou (2012).

less biased opinions, often valuing firms on their own. Finally, many firm characteristics linked to abnormally low returns are associated with both difficult-to-forecast earnings and a higher degree of unwarranted analyst optimism. The low-return anomalies linked to these characteristics tend to disappear or greatly shrink once we control for analyst bias. These characteristics include low past returns (i.e. momentum), low gross profitability, low returns on assets, high asset growth, high investment, high net operating assets, high net stocks issuance, high composite stocks issuance, high failure probability, high credit risk, high dispersion, high idiosyncratic volatility, high accruals, and negative earnings surprises. These represent the union of anomalies studied in Stambaugh, Yu, and Yuan (2012, 2015) and Avramov, Chordia, Jostova, and Philipov (2013).

Do the price movements behind these anomalies stem from the tendency of investors to blindly follow analysts' opinions irrespective of their merit? While keen observers of the stock market recognize that analyst forecasts move prices, research has yet to uncover exactly why prices move when analysts speak. If markets are efficient, the price movements generated by the news in analyst forecasts should be permanent. That is, subsequent price movements will be random. Moreover, to the extent that the analyst's view is predictable, and therefore not news, it should not move prices. If, alternatively, markets are affected by behavioral biases, then both predictable and unpredictable analyst opinions may move prices. However, we would know that these analyst-driven price movements emerged from animal spirits and not news if they are temporary—that is, they subsequently reverse. When these temporary price movements stem from a predictable analyst opinion, which cannot be news, the analysts' power to move prices must be due to investors' blind tendency to follow.

Prior research offers differing views on the role of analysts. For example, Womack (1996) identifies a positive link between analyst opinions and future stock returns. Womack's evidence portrays analysts as savants who recognize when a stock's price differs from a fair value that the price ultimately gravitates towards. Investors who mimic analysts' recommendations achieve superior performance. By contrast, La Porta (1996) and Dechow and Sloan (1997) show that stocks with the highest-earnings-growth forecasts tend to earn the lowest returns, often at earning announcements according to Skinner and Sloan (2002). This is a view of analysts as "Pied Pipers"—investors who march to their forecast tunes are doomed to underperform the market.

While a large body of research examines analyst bias, and some of it links the bias to returns, studying return anomalies to distinguish these two views is relatively rare.[2] In Teoh and Wong (2002), analysts systematically underestimate the accruals of new issues in their EPS forecasts, generating upwardly biased forecasts. While their paper does not suggest that forecast errors explain the accruals anomaly, it hints that recently issued stocks underperform (a fact documented by Loughran and Ritter 1995) because analysts fail to recognize the degree to which accruals influence their earnings forecasts. They find that the distortion in analyst earnings forecasts from accruals is predictable—issuing firms with high past accruals tend to have overly optimistic earnings forecasts in subsequent years and abnormally high accruals. Not only do analysts overshoot the rational earnings forecast, but—for issuers—the market overshoots the rational price as well.[3]

We find that analysts have biases for certain types of firms and that these biases are predictable (consistent with Teoh and Wong 2002). Among firms with hard-to-forecast earnings, those with consensus forecasts known to have the most optimistic bias subsequently have lower risk-adjusted returns, while firms with relatively conservative forecasts subsequently earn abnormally high returns. Moreover, the abnormal returns of firms with the most optimistic and conservative forecasts are associated with the predictable component of the forecast. Trading against this false optimism and pessimism leads to highly profitable market-neutral strategies. This profitability cannot be explained by risk or well-known stock return anomalies documented in the literature. The most likely explanation for these findings is that optimism and conservatism temporarily distort prices. Subsequently, distorted prices converge to fair values as more accurate earnings and revenue information is disseminated to the market. This obvious behavioral explanation distinguishes the "analyst-bias anomaly" from other major anomalies, which do not as readily reveal their root causes.

For example, among high-credit-risk stocks, those with predicted analyst bias in the highest quintile underperform those with bias in the lowest quintile by 150 basis points per month [bpm], and by 159 bpm after risk adjusting with the Fama and French (2015) 5-factor model. Because our sample's relatively large S&P-rated firms generate alphas of such magnitude, omitted risk variables

[2] Frankel and Lee (1998) and Bartram and Grinblatt (2018b) use analyst forecasts to derive fundamental values, showing how price deviations from fundamental values predict the cross-section of returns. Frankel and Lee (1998) link forecast biases to long- but not short-term returns. Kothari, So, and Verdi's (2016) literature survey on the effect of analysts forecasts on the cross-section of stock returns notes that market prices appears to underreact to predictable biases and acknowledges the need for further research on how analyst bias impacts expected returns.

[3] In our data, analyst optimism is not more prevalent for high-accruals stocks. Teoh and Wong (2002) did find such an association for firms with recent IPOs and their associated SEOs, but not for non-issuers (as seen in the top half of their Table 9). Recent IPOs are extremely rare in our sample, which requires firm-wide credit ratings.

are an unlikely explanation for the analyst bias anomaly. For firms with high idiosyncratic volatility, forecast dispersion, or many other attributes tied to hard-to-forecast earnings, return spreads across bias quintiles are smaller but still economically and statistically significant.

Analyst bias towards optimism, first documented in De Bondt and Thaler (1990) and Ali, Klein, and Rosenfeld (1992), is particularly high long before earnings are announced (Richardson, Teoh, and Wysocki, 2004). While the market appears to correct for the general level of analyst optimism across all stocks, it seems unable to distinguish between firms with the greatest and least amounts of optimism. Cross-sectional differences in optimism can be predicted by past analyst bias and a host of firm attributes, such as past returns, past earnings surprises, credit risk, and forecast dispersion, among others. Two-way portfolio sorts, as well as Fama-MacBeth regressions, clearly demonstrate that this predicted analyst bias (rather than its correlates) is the key driver of mispricing.

Our paper's focus on direct estimation of the bias in a firm's consensus forecast distinguishes it from studies like So (2013) that investigate whether quantitative earnings forecast models can generate alpha. So (2013) documents that regression predictions from firm characteristics produce unbiased earnings forecasts that deviate from the forecasts of analysts and provide the basis for profitable trading.[4] His findings indicate that analysts are slow to incorporate the information in firm characteristics. Implicitly, investors' earnings forecasts overweight the analyst forecasts and underweight the earnings implications of firm characteristics, resulting in share price deviations from fair value, especially among small or poorly performing firms.

As an alternative to So's (2013) use of accounting data to improve earnings forecasts, we (like Lim 2001) assess factors, like past biases, that directly predict the consensus forecasting bias on a stock-by-stock basis. Our more direct approach to bias prediction stems from the need for greater accuracy if one is to explain return anomalies in the literature caused by this bias. If one cannot improve upon the accuracy of the consensus forecast, direct prediction of the consensus bias is necessarily more accurate than indirect prediction from the difference between the consensus forecast and an unbiased alternative earnings forecast.[5] In this sense our approach is more closely related to Hughes, Liu, and Su (2008) [HLS], who select variables likely to cause irrational pessimism or optimism in

[4] Bartram and Grinblatt (2018a,b) directly estimate fundamental values from firm accounting characteristics.

[5] Earnings forecasts employing purely statistical techniques are likely to be noisier earning predictors than the consensus forecast given the added resources and information available to the analyst community. The emiprical evidence in Table 1 Panel C of So (2013) supports this conjecture.

analysts' forecasts. However, HLS find that analyst forecast bias does not affect stock prices. By contrast, our results show that a stock's alpha has a significant and economically strong inverse relationship to the predicted forecast bias.

So (2013) attributes the insignificant price impact of analyst bias in HLS to model misspecification due to the unobservability of analysts' private information and incentives; we attribute it to the scaling of the forecast error. Scaling forecast errors by the stock price, as in HLS, impedes detection of stock price distortions due to analyst bias. If an optimistic forecast raises both the forecast error and inflates the stock price, scaling the forecast error by the inflated stock price reduces the scaled forecast error because of the inflation one is trying to detect. Moreover, since price-earnings ratios vary widely in the cross-section, scaling earnings forecast errors by stock prices introduces noise into the scaled estimate. Both factors imply a lower perceived impact of forecast bias on prices than exists in reality. Scaling the forecast error by the absolute value of actual earnings, as we do, alleviates this concern. Our paper's empirical focus also differs from So (2013) and HLS in its extension to the understanding of several well-known asset pricing anomalies, their concentration among certain types of firms, and potential behavioral explanations.

In sum, our paper offers three empirical contributions. First, it documents that overly optimistic analyst forecasts are more prevalent among firms with high credit risk and other indicators of hard-to-forecast earnings. Second, it shows that cross-sectional differences in analyst optimism lead to an efficient markets anomaly: an investor can earn abnormal risk-adjusted profits by selling hard-to-forecast firms with the most overly optimistic consensus forecasts and buying those with the least optimistic forecasts. Third, we conclude that greater analyst optimism for stocks with high credit risk and other extreme anomaly attributes linked to hard-to-forecast earnings is the likely explanation for their overpricing and subsequent lower returns.

I. Data and Methodology

This section describes the filters used to create our data sample, the methodology for estimating analyst bias and relating it to stock returns, and summary statistics for the data.

Data Filters. Our sample starts with all NYSE, AMEX, or NASDAQ-listed common stocks on the CRSP Monthly Returns file that trade from 1986 to 2016.[6] In each month t of the sample period, we include each stock i in a trading strategy based on portfolio sorts or cross-sectional regression analysis (with coefficients representing portfolio returns). The trades employ a signal computed from a month $t-1$ estimate of the bias in stock i's I/B/E/S consensus earnings forecast. Our analysis excludes stocks that lack month $t-1$ share prices at or above $1, a month t CRSP return,[7] an I/B/E/S consensus forecast for the current fiscal year, or a month $t-1$ Standard & Poor's (S&P) long-term domestic issuer credit rating.[8] These requirements generate a sample of 245,763 firm-month observations with an average of 816 firms per month, or a total of 2,640 firms over the sample period. The need for both an S&P credit rating and an I/B/E/S forecast skew our sample towards larger firms. For example, the quintile of stocks with the lowest credit ratings, which tend to be the smallest firms, has an average market capitalization of about $1.23 billion.

Estimating Analyst Forecast Bias. To understand if forecast biases distort prices, we need to first estimate a firm's analyst forecast bias as of the forecast date. This bias is defined as the percentage difference between the firm's I/B/E/S consensus earnings forecast and an *unbiased* consensus forecast given the information available at that date. The bias is not directly measurable because we do not know what the available information is. To estimate forecast bias, we regress the future realized forecast error, or *ex post* bias, on a set of predictor variables. The realized forecast error is:[9]

$$AB_{i,t} = \frac{ConForecastEPS_{i,t}^{T} - EPS_{i}^{T}}{|EPS_{i}^{T}|}, \tag{1}$$

[6] October 1985 represents the first month that the credit ratings of firms reliably appear on WRDS.

[7] We adjust for delisting months using the standard treatment for delisting returns, i.e., compounding delisting returns with standard returns (see Beaver, McNichols, and Price, 2007).

[8] This filter is omitted only when we study failure probabilities. We prefer credit ratings as a measure of credit risk because they are non-model specific and publicly available simultaneously to all investors. A firm's credit rating is S&P's long-term issuer credit rating as listed in Compustat, or in Credit Ratings in WRDS when missing from Compustat. S&P defines the "long-term issuer credit rating is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's capacity and willingness to meet its long-term financial commitments (those with maturities of more than one year) as they come due." When averaging credit ratings across firms, we convert the 22 S&P letter ratings into numerical scores as follows: 1=AAA, 2=AA+,. . . , 10=BBB−, 11=BB+,. . . , 19=CCC−, 20=CC, 21=C, 22=D. Higher scores indicate higher credit risk. Ratings AAA to BBB− are considered investment grade and ratings BB+ to D are non-investment grade or high-yield.

[9] We exclude *ex post* bias observations with obvious reporting errors. Among these are rare cases where the earnings announcement precedes the firm's fiscal period end date or is reported to be exactly zero. To prevent small positive and negative values of actual EPS from unduly affecting our inferences, we also exclude *ex post* bias observations that are below the 1st and above the 99th percentiles for the sample. We similarly censor other variables with obvious outliers.

where EPS_i^T is firm i's actual EPS for the fiscal year FY1 (ultimately announced in month T) and $ConForecastEPS_{i,t}^T$ is the month t analyst consensus forecast of that annual EPS.[10]

Even though it differs from the true bias, the prediction from this regression, or *ex ante* bias, is an appropriate substitute for the unmeasurable true bias. Rational expectations implies that the realized forecast error, $AB_{i,t}$, can be viewed as any unbiased estimate of this error plus mean zero noise that is uncorrelated with this estimate. That is

$$AB_{i,t} = \mathrm{E}[AB_{i,t}|\psi_t, \phi_t] + \nu_{i,t} \tag{2}$$

$$= \mathrm{E}[AB_{i,t}|\psi_t] + u_{i,t} + \nu_{i,t}, \text{ trivially implying} \tag{3}$$

$$\mathrm{E}[AB_{i,t}|\psi_t, \phi_t] = \mathrm{E}[AB_{i,t}|\psi_t] + u_{i,t}, \tag{4}$$

where ψ_t is the information available to an econometrician, and ϕ_t is the additional information available to analysts. $u_{i,t}$, the incremental noise from the cruder econometrician's information, correlates with both the unmeasurable analyst bias, $\mathrm{E}[AB_{i,t}|\psi_t, \phi_t]$, and the forecast error subsequently realized at the earnings announcement date. However, $u_{i,t}$ is uncorrelated with the econometrician's estimate of the forecast error. Thus, statistical analyses that use $\mathrm{E}[AB_{i,t}|\psi_t]$ as a regressor produce consistent estimates of the true coefficient on the unmeasurable forecast bias.[11] By contrast, the *ex post* bias cannot be used to asses whether bias influences stock prices. An *ex post* bias measure that looks ahead at future earnings to compute a stock's degree of analyst optimism could inversely correlate with future returns for reasons that have nothing to do with the analysts' optimism for a stock—but rather, because future returns are leading indicators of future realized earnings.

[10] Firm i's consensus forecast is an average of the most recent analyst EPS forecasts collected by I/B/E/S, although I/B/E/S sometimes throws out stale or outlier forecasts. The FY1 forecast refers to the earliest fiscal year earnings that have yet to be announced by month end t, with $t \leq T$. Typically, T is 1-3 months after the fiscal year end.

[11] Consider a regression of future returns on true analyst bias: $R = \gamma_0 + \gamma_1 \mathrm{E}[AB_{i,t}|\psi_t, \phi_t] + \delta$, which cannot be implemented because of the unobservable analyst bias regressor. This regression is identical to $R = \gamma_0 + \gamma_1 \mathrm{E}[AB_{i,t}|\psi_t] + \epsilon$ with $\epsilon = \gamma_1 u + \delta$, which can be estimated because its regressor is observable. Note that u (as well as ϵ) and $\mathrm{E}[AB_{i,t}|\psi_t]$ are uncorrelated because rational expectations makes u (and δ) orthogonal to the predictors of analyst bias used by the econometrician. Hence, γ_1's estimate (from the regression we can estimate) consistently estimates γ_1, the theoretical coefficient on the true but unknowable analyst bias. The same consistency applies in a multiple regression to coefficients on any control variables spanned by information the econometrician uses to predict analyst bias.

Our regression's forecast error prediction (dropping time subscripts for notational simplicity),

$$\begin{aligned}\widehat{AB}_i &= c_0 + c_1\, PastAB_i + c_2\, Dispersion_i + c_3\, Coverage_i \\ &\quad + c_4\, PastRet_i^- + c_5\, PastRet_i^+ + c_6\, SUE_i^- + c_7\, SUE_i^+ \\ &\quad + c_8\, D_{Small,i} + c_9\, D_{Value,i} + \mathbf{d}\, \mathbf{D}_{Rating,i} + \mathbf{e}\, \mathbf{D}_{Industry,i},\end{aligned} \tag{5}$$

comes from a set of variables (our ψ_t) known at least one month prior to the consensus forecast. The predictor variables include last year's actual bias ($PastAB$, computed the same number of months since the 10K earnings announcement), analyst *Dispersion*, analyst *Coverage*, negative and positive momentum ($PastRet_i^- = \min[PastRet, 0]$ and $PastRet_i^+ = \max[PastRet, 0]$, where $PastRet$ is the firm's cumulative past 6-month return, lagged one month to exclude the prior-month return), negative and positive prior earnings surprise ($SUE_i^-\, and\ SUE_i^+$), dummies for above prior-month-median values for small firms and value firms ($D_{Small,i}$ and $D_{Value,i}$), 15 rating dummies ($\mathbf{D}_{Rating,i}$),[12] and industry dummies ($\mathbf{D}_{Industry,i}$) for 19 of the 20 industries in Moskowitz and Grinblatt (1999).[13]

The coefficients for the above prediction, $c_0, \ldots, c_9, \mathbf{d}, \mathbf{e}$, are estimated out of sample from 60-month rolling windows. Within each rolling window, we run 12 separate panel regressions, each panel populated by firms with the same number of months (k) since their last 10K earnings announcement: $k \leq 1, k = 2, k = 3, ..., k = 11, k \geq 12$. We skip a year between the rolling regressions and the analyst bias forecast, which is obtained by multiplying the rolling-window-estimated coefficients by the latest available regressors.[14] Firm-months are aligned, both in the out-of-sample regression and the prediction equation so that the prior-year *ex post* bias reflects the same delay, k, from the 10K earnings announcement as the current month t bias of AB_i in eq. (5).

To illustrate, consider the prediction of firm i's May 1996 analyst bias. Assume that firm i's May 1996 consensus earnings forecast is for a fiscal year ending in December 1996. Also, assume that firm i always reports its annual earnings in February. Then, firm i's $PastAB_i$ regressor would be fiscal 1995's actual analyst bias for May 1995's forecast, made 3 months past fiscal 1994's earnings

[12]These indicate prior-month membership in one of 15 notched S&P rating groups. Ratings AAA and AA+ are grouped together, and the six omitted ratings, CCC+, CCC, CCC−, CC, C, and D, embedded in the constant, are grouped together because they contain fewer observations. Further details on all variables are found in the Appendix.

[13]We have verified that our results are largely invariant to minor changes in the specification used to predict analyst bias. For example, including idiosyncratic volatility, or excluding credit risk dummies and dispersion as predictor variables does not qualitatively change our results.

[14]Due to the out-of-sample analyst bias prediction, our first predicted analyst bias is for December 1991.

announcement. Some firms may report annual earnings in January one year and in March the next, in which case the $PastAB_i$ regressor would be 14 rather than 12 months prior to the month in which $\widehat{AB}_i$ is measured.[15] Our regression coefficients for the May 1996 forecast example would come from a panel of data points where firms' I/B/E/S forecasts in the June 1990-May 1995 dependent variable were 3 months after the announcement date of their most recently reported earnings. We skip a year between the rolling window and the prediction month to ensure that the May 1995 *ex post* analyst bias used in the rolling regression is known by April 1996.

Relating *ex post* biases at the same point in consecutive annual earnings forecast cycles—usually 12 months apart—accounts for the fact that analyst optimism bias predictably diminishes over each cycle, as documented by Richardson, Teoh, and Wysocki (2004). In part, this is because analysts cannot maintain the same degree of optimism for the portion of annual earnings fully disclosed by the release of quarterly earnings in corporate 10Q statements. Firms also offer earnings guidance as the fiscal year evolves. Figure I Plot A documents forecast bias cyclicality for our sample. It graphs average *ex post* bias in 48 event-time months centered around the most recent 10K announcement at the graph's midpoint. The three lines correspond to average *ex post* bias for firms with credit ratings, as well as for investment-grade and non-investment-grade (NIG) firms. Credit rating is one important indicator of whether earnings are hard to forecast. All three lines show a similar 12-month pattern: analyst bias is largest at the beginning of the forecast cycle, just after earnings are announced. It diminishes monotonically as the next 10K earnings announcement approaches; then, the bias pops up again as the next earnings cycle begins. Analyst bias and its cyclical pattern is more exaggerated for NIG firms. In light of the high degree of cyclicality in forecast bias, forecasting the *ex post* bias with cycle-specific regressions is appropriate.

Table I reports the average of eq. (5)'s coefficients and average firm-clustered test statistics across all 5-year rolling regression windows using firms sorted by forecast cycle k. In addition to calculating $\widehat{AB}$ within each month, we also create a cycle-adjusted measure of predicted analyst forecast bias, denoted $\widehat{AB}^{CA}$. For each cohort k, we calculate the average predicted analyst bias across all firm-months in cohort k. We adjust the *ex ante* bias, $\widehat{AB}$, for its cycle k by multiplying it with the ratio of the average predicted bias for cycle 1 to that for k.

[15] We exclude observations for which the $PastAB_i$ precedes AB_i by more than 15 months (indicating an announcement delay of more than 3 months). Our results are robust to changing the maximum difference to 20 months.

The significant coefficients reported in Table I are fairly consistent in sign and magnitude across most of the forecast cycle months, weakening in magnitude as we near the earnings announcement month. Past analyst bias and analyst forecast dispersion are positively related to *ex post* analyst bias; earnings surprises and past returns (particularly negative ones) are inversely related to *ex post* analyst bias. These inverse relationships could be due to the infrequency of analysts earnings forecast updates: true expectations of earnings update almost continuously. Past returns and earnings surprises would rationally update earnings expectations. Credit risk is also related to analyst bias at the margin. One reason may be that firms in financial distress tend to have "knife-edge" earnings numbers. A small degree of unwarranted optimism about sales can generate a huge percentage increase in the earnings forecast and vice versa. Later parts of the paper discuss the role of credit risk and other proxies for hard-to-forecast earnings in great detail.

Table I's regressions have average adjusted R-squareds ranging from 7% to 11% across forecast cycle months. These R-squareds represent the degree to which a relatively crude attempt to improve upon the consensus forecast of supposed experts succeeds. A 10% R-squared says we could have revised the consensus forecast at the time to explain 10% of the *ex post* forecast error variation realized later in the announcement month. The R-squareds are not affected by the general tendency towards analyst optimism, only by predictable differences in the optimism bias *across* firms in the same forecast cycle month. By contrast, most quantitative attempts by researchers to directly forecast earnings—rather than improve earnings forecasts by directly estimating the bias—have less accuracy than the consensus earnings forecast.

Figure I Plot B's *ex ante* bias, $\widehat{AB}$, exhibits the same event-time cyclicality as Plot A's *ex post* bias. As in Plot A, the zeniths of Plot B's lines are larger for NIG firms. The same cyclicality cannot be seen in Figure I Plot C, which graphs the same three lines for cycle-adjusted analyst bias, $\widehat{AB}^{CA}$. However, Plot C still shows far greater unwarranted optimism for the NIG firms' forecasts.

Summary Statistics. Table II Panel A presents the time-series average of the monthly cross-sectional means of various characteristics of firms sorted into quintiles $\widehat{AB}1$ to $\widehat{AB}5$ (left half) or $\widehat{AB}1^{CA}$ to $\widehat{AB}5^{CA}$ (right half) based on month t predicted and cycle-adjusted bias, respectively. Panel A shows that predicted analyst bias, like the actual bias realized at the future earnings announcement, tends to reflect an overall bias towards optimism, but the bias widely varies across firms. Forecasts for the most optimistically biased quintile—$\widehat{AB}5$ and $\widehat{AB}5^{CA}$—tend to overshoot actual earnings by about 49% and 46%, respectively; forecasts for the least optimistic quintile overshoot by less than 0.6% and 0.5%, respectively. These most and least optimistic quintiles differ in many firm attributes. The most optimistic quintile consists of smaller firms with larger book-to-market ratios, lower analyst coverage, and lower past-month and current-month returns. At the same time, the most optimistically forecasted firms tend to have higher idiosyncratic volatility and market risk in both the CAPM (1-factor) and Fama-French 5-factor models. For example, left half CAPM betas average 1.50 for $\widehat{AB}5$ firms and 0.87 for $\widehat{AB}1$ firms, while 5-factor market betas average 1.41 in $\widehat{AB}5$ and 1.01 in $\widehat{AB}1$. These high-optimism firms also are relatively more sensitive to SMB and HML. These factor exposures argue for higher rather than the lower returns the high bias firms exhibit. The RMW and CMA factor exposures are the only ones consistent with the most optimistically forecasted firms experiencing lower current-month returns than other firms. The bias sort shows a nearly monotonic pattern in all risk attributes and 5-factor alphas.

High optimism bias tends to concentrate in firms with harder-to-forecast earnings. Extreme quintiles' MSE comparisons indicates mean squared errors of forecasted vs. actual earnings that are 18 to 22 times larger for the most optimistic quintile (0.07 vs. 1.28 or 1.57). These high-optimism firms also have over seven times more forecast dispersion across analysts (0.23 vs. 0.03), almost twice the idiosyncratic volatility (2.27 vs. 1.34 or 2.32 vs. 1.33), and the most negative earnings surprises (SUE of -0.55 or -0.65 versus 1.89). Importantly, firms with the greatest unwarranted optimism contains the highest-credit-risk firms. The least optimistic quintile's average S&P credit rating is A+, while the most optimistic quintile averages BB. In fact, 70% (left half) and 71% (right half) of the most optimistically biased firms are rated non-investment grade (BB+ or worse) while 33% (left half) and 35% (right half) of them are highly speculative (B+ or worse). Almost all of the distressed firms (CCC+ or worse) are in the most optimistically biased quintile.

The relatively low returns and alphas of firms with high forecast optimism or high credit risk may be a difficult puzzle to disentangle. The earnings forecasts of high-credit-risk firms tend to have a high degree of analyst optimism. Punctuating this argument is Table II Panel B, which lists the average number of firms in 25 cells sorted independently each month on $\widehat{AB}$ and credit risk. In the lowest-credit-risk quintile, CR1, there are almost seven times more firms in the lowest bias quintile than in the highest bias quintile. Likewise, in the highest-credit-risk quintile, CR5, the numbers are virtually the reverse: seven times more firms exist in the highest optimism quintile. The apparent correlation between analyst forecast optimism and credit risk suggests that each attribute could account for the cross-sectional return pattern associated with the other. Only careful study of both attributes simultaneously can help distinguish the true effect of each on returns and alphas.

Relating Ex Ante Forecast Bias to the Cross-Section of Returns. To isolate the separate return implications of analyst bias and credit risk, we sort stocks into 25 portfolios based on 5×5 independent sorts on month $t-1$ credit risk and *ex ante* analyst bias or cycle-adjusted bias. We then compute average month t returns and alphas benchmarked against five risk-adjustment models: the 5-factor model of Fama and French (2015), the 3-factor model of Fama and French (1993), the 4-factor model of Carhart (1997), the characteristic adjustment of Daniel, Grinblatt, Titman, and Wermers (1997), and the q-factor model of Hou, Xue, and Zhang (2015).

We also run monthly cross-sectional regressions of stock returns, $r_{i,t}$, on one-month lagged *ex ante* analyst bias, $\widehat{AB}_{i,t-1}$, (or the analogous cycle-adjusted bias) and various combinations of lagged firm-level variables known to predict the cross-section of returns. The full specification is:

$$\begin{aligned} r_{i,t} \;&=\; c_{0,t} + c_{1,t}\,\widehat{AB}_{i,t-1} + c_{2,t}\,(\widehat{AB}_{i,t-1} \times D_{CR5(i),t-1}) + c_{3,t}\,D_{CR5(i),t-1} \\ &\quad + c_{4,t}\,log(Size_{i,t-2}) + c_{5,t}\,log(BM_{i,t-lag}) + c_{6,t}\,r_{i,t-7:t-2} \\ &\quad + c_{7,t}\,SUE_{i,t-1} + c_{8,t}\,Disp_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{6}$$

where $D_{CR5,t-1}$ is a credit risk dummy variable that takes the value of 1 if the firm is among the 20% worst-rated stocks in month $t-1$, $log(Size)_{i,t-2}$ is the natural logarithm of the firm's market capitalization, $log(BM)_{i,t-lag}$ is the log of the firm's book-to-market ratio computed and lagged relative to returns as in Fama and French (1992), $r_{i,t-7:t-2}$ is the cumulative return over months $[t-7:t-2]$, $Disp_{i,t-1}$ is the dispersion in analyst forecasts in month $t-1$, and $SUE_{i,t-1}$ is the last reported quarterly earnings surprise as benchmarked by the random walk model.

Lagging the predicted bias regressor, $\widehat{AB}_{i,t-1}$, by one month ensures that all regressors are known prior to the start of the return month, including $PastAB_i$. Recall the paper's prior example of the May 1996 bias computation. The prediction of bias at the end of this month is derived, in part, from a past *ex post* bias computed for May 1995's forecast that becomes known only in February 1996. It is the June 1996 risk-adjusted return that we correlate with the May 1996 predicted bias, but May 1996's predicted bias uses past bias information known in February 1996, as well as other predictor variables, like coverage, known at the end of April 1996.

Analyst bias is not only correlated with credit risk, but also a number of other characteristics associated with return anomalies. Table II shows that analyst bias is correlated with idiosyncratic volatility, dispersion, past 6-month return, earnings surprises (SUE), and profitability (RMW). These attributes predict returns, as do a number of characteristics not listed in Table II. Moreover, a large number of return anomalies, such as the dispersion anomaly, exist only within high-credit-risk firms (as documented in Avramov, Chordia, Jostova, and Philipov 2013). These facts warrant study of other anomalies with methodologies that mirror the analysis of credit risk described above.

II. Anomaly Characteristics, Analyst Bias, and Returns

To separate the return effects of analyst bias and various firm characteristics, Table III shows average returns, spreads, and associated risk-adjusted returns along with t-statistics for groups of 25 equal-weighted portfolios. Panel A reports results on analyst bias and credit risk, Panel B on cycle-adjusted analyst bias and credit risk, while Panels C studies the interaction of analyst bias and 12 other attributes: idiosyncratic volatility, dispersion, momentum (past 6-month return), gross profitability, return on assets, net operating assets, net stock issuance, composite equity issues, investments, asset growth, accruals, and earnings surprises. The firm attributes in Panel C cover all non-distress anomalies studied in Stambaugh, Yu, and Yuan (2012, 2015) and Avramov, Chordia, Jostova, and Philipov (2013).[16] Distress anomalies are studied in more detail in Table VII. We form each group of 25 portfolios from an independent 5×5 sort on lagged analyst bias, $\widehat{AB}$, and the lagged characteristic. For each characteristic, we report time-series averages of raw returns and spreads with alphas benchmarked against the Fama and French (2015) 5-factor model.

Returns and Risk-Adjusted Returns Sorted by Credit Rating and Analyst Forecast Bias. The top half of Panels A (predicted bias) and B (cycle-adjusted bias) shows average returns, while the

[16] All anomaly variables are described in the Appendix. Variables using annual accounting data are lagged as in Fama and French (1992, 2008): sorting in June of year t uses accounting data as of fiscal year end $t-1$.

bottom half shows 5-factor risk-adjusted returns along with sample t-statistics. The panels also report the corresponding extreme quintile spreads (and sample t-statistics) along their border rows. The standout numbers all occur in the CR5 rows. In these two rows, raw return spreads are about 150 bpm; the alpha spreads are even larger, with the long and short sides contributing about equally.

While the 79 bpm alpha for the most conservatively forecasted firms in Panel A's CR5 row is significant only at the 10% level ($t = 1.86$), its magnitude is almost identical to the much more significant -80 bpm alpha of the most optimistically forecasted firms in the same row ($t = -2.88$). The former alpha's 5% insignificance is attributable to the small number of high-credit-risk firms with conservative earnings forecasts. By contrast, Panel B's opposite-signed alphas of the CR5 row's two extreme quintiles are both extremely significant and of similar magnitude—whether compared to each other to their non-cycle-adjusted counterparts in Panel A. Thus, whether one is long high-credit-risk firms with the most conservative forecasts, or short high-credit-risk firms with the most optimistic forecasts, alphas are on the order of 10% per year. The associated long-short strategy's alpha is close to 20% per year. Given that all of the firms have S&P credit ratings, which tend to be available only for larger firms, an anomaly of this economic magnitude is quite rare.[17]

The double sorts of Panels A and B lead to three conclusions. First, except for firms with the most credit risk, risk-adjusted returns across analyst bias groups do not significantly differ from zero. Among more creditworthy firms (rows CR1-CR4), virtually no relationship exists between *ex ante* analyst bias and the cross-section of expected returns (as implied by their statistical nearness to zero). Second, the least-creditworthy firms (row CR5) exhibit a monotonic relationship between predicted analyst bias and returns, whether risk-adjusted or not. Third, the anomalous inverse relationship between a stock's credit risk and its expected return (the 'credit risk puzzle' documented in prior research) could be an artifact of the correlation between credit risk and analyst bias. We earlier noted that the greatest number of firms are in the top-left and bottom-right corners of the 5×5 panels. Thus, return and risk-adjusted return differences between firms in these corner cells

[17] The abnormally low returns from the AB5/CR5 portfolio persist for up to six more months. For example, delaying the signal of optimism and credit risk by q months leads to significant 5-factor risk-adjusted returns of -80, -87, -100, -73, -72, and -75 bpm for $q = 1, \ldots, 6$, respectively. (By contrast, the alpha spread of 135 bpm is significant at the 5% level with delays of only one month, and significant at the 10% level with a delay of two months, but is never less than 63 bpm with delays of up to six months.) Thus, holding a short position in the least-creditworthy stocks with the greatest analyst optimism for an additional six months beyond the Table III trading month adds 487 bpm to the 80 bpm captured in Panel A's short strategy (tabulated results are available upon request).

could be due to differences in credit risk or to differences in analyst bias. One cannot infer a negative premium for credit risk simply from the negative correlation between credit risk and return: the negative correlation could easily be due to a negative return premium for analyst bias.

When controlling for both credit risk and analyst bias, as in Panels A and B of Table III, the data pattern of the entire matrix of risk-adjusted returns complicates conclusions about the separate roles played by credit risk and analyst bias. One explanation for the observed data pattern is that increases in analyst optimism bias reduce returns, *but only for the highest-credit-risk firms.* A competing explanation is that extreme credit risk has a depressing effect on the returns of high-bias ($\widehat{AB}5$) firms and an enhancing effect for low-bias ($\widehat{AB}1$) firms. The first explanation is more parsimonious and hence more plausible: Occam's razor suggests that the returns in the CR5 rows are the sum of a premium for credit risk (which could be zero, positive, or negative and is fixed since all stocks are in the same credit group) and a negative premium for analyst optimism in CR5.

The magnitude and sign of the fixed credit-risk premium is particularly difficult to flesh out. That premium depends on the analyst bias column against which credit risk is benchmarked. As an illustration, consider the bottom half of Panel A. Here, the risk-adjusted return of 79 bpm in cell $\widehat{AB}1$/CR5 is the sum of the top-left (cell $\widehat{AB}1$/CR1) risk-adjusted return of -14 bpm plus a positive credit-risk premium of about 92 bpm (bottom row). Moving rightward along the CR5 row reduces returns because analyst bias increases, but the credit-risk premium should stay the same, as we are still in the same credit-risk group (CR5). However, when starting from the middle categories of analyst bias (column $\widehat{AB}3$), the CR5$-$CR1 credit-risk premium is -18 bpm; and when starting from the column of greatest analyst bias, the CR5$-$CR1 credit-risk premium is -40 bpm and of the same magnitude as the one obtained from the $\widehat{AB}1$ column.

The appropriate analyst bias column for identifying a bias-independent credit-risk premium depends on which degree of predicted analyst bias has no effect on returns. In part, one's view of markets determines this benchmark. If investors understand that analysts tend to be optimistic overall, and shift their beliefs so that the degree of analyst bias does not tend to generate inflated or deflated share prices for the average firm, then column $\widehat{AB}3$, which contains stocks with the median degrees of bias, is the benchmark for calculating the credit-risk premium. With this benchmark, the CR5$-$CR1 difference estimates (negative) credit risk premia of -18 (Panel A) and -31 (Panel B) bpm, both insignificant. However, predicted analyst bias is closest to zero in the $\widehat{AB}1$ quintile of firms, which carries larger positive credit risk premia (CR5−CR1) of 92 and 104 bpm in Panels A and B, respectively. Regardless of one's belief about the correct column to focus on for a credit-risk premium, it is the relatively greater concentration of firms in the CR5/$\widehat{AB}5$ and CR1/$\widehat{AB}1$ cells that appears to generate the odd negative correlation between credit risk and return.

Returns and Risk-Adjusted Returns Sorted by Other Characteristics and Analyst Forecast Bias. Panel C of Table III studies the role of analyst bias for 12 other anomalies. The 12 groups of 25 portfolios report the average of the time series of equal-weighted portfolio returns as well as extreme-quintile raw and 5-factor alpha spreads. The spreads in the bottom border row are based on either row 1 less row 5 if the anomaly (unconditionally) has row 1 earning a higher return than row 5, and on row 5 less row 1 if the anomaly tends to produce a higher return for row 5. Hence, these bottom border row spreads should be positive if the anomaly has an independent effect from analyst bias.

A large fraction of Panel C's 5×5 groupings express patterns resembling those seen in Panels A and B. First, analyst bias plays a significant return-influencing role primarily in the row for which the paired anomaly tends to produce the lowest returns. With idiosyncratic volatility, for example, only the IVOL5 row has both a significant return and alpha spread.[18] The same pattern of dual significance for the anomaly's poorest-performing quintile applies to momentum, gross profitability, return on assets, net operating assets, net stock issuance, composite equity issuance, and asset growth. In all cases, except for earnings surprises, the row with the anomaly's short position produces the largest raw and risk-adjusted spread from an analyst bias strategy.

Second, when controlling for analyst bias, the anomaly rarely produces a significant return spread and only rarely produces consistent positive spreads across the analyst bias quintiles. Consider idiosyncratic volatility. None of the spreads in the border row at the bottom are significant and only two of the five spreads exhibit the same positive sign seen in prior research on idiosyncratic volatility. The low returns seen for high-idiosyncratic-volatility stocks occur primarily for stocks in the highest analyst bias quintiles. Thus, as with credit risk, we have trouble separating an analyst bias effect from an idiosyncratic volatility effect, particularly since Table II Panel A shows that analyst optimism and idiosyncratic volatility are highly correlated. The poor and inconsistent anomaly spread in the

[18] McLean and Pontiff (2016), who document that anomalies tend to attenuate post-publication, also find anomaly profitability to be higher among high-idiosyncratic-risk stocks.

bottom border row applies, not just to credit and idiosyncratic volatility, but to most anomalies we study in Panel C. Only one of 12 anomalies (Accruals) shows a significant positive return spread for firms in the least optimistic analyst bias quintile. And all but two anomalies, Investments and Composite equity issues, show their largest spread within the highest-analyst-bias quintile.

The question remains: "Why does the analyst bias anomaly exist only for firms with certain types of attributes, like high-credit-risk firms?" Clearly, high-credit-risk firms are those for which getting the earnings right is most important. Being wrong in one's forecast can mean the difference between a doubling in stock price or the holding of worthless equity in a bankruptcy proceeding. It is also hard to forecast the earnings of high-credit-risk firms. Firms with low past returns, high idiosyncratic volatility, and a host of other attributes also seem like firms where forecasting uncertainty is large. A pure Bayesian is more likely to severely update a high variance prior than a low variance one. In the case of dispersion, the fact that the signal comes from analysts who disagree makes the consensus forecast a relatively more appealing signal for updating than signals from any single source—including one's favorite analyst. The surprise here is market participants' failing to recognize which firms have biased earnings forecasts and accordingly, alter demand and share prices to eliminate the efficient markets anomaly. True Bayesian investors would not make this mistake!

Regressions' Marginal Effect of Analyst Bias and Anomalies on Risk-Adjusted Returns. To verify that key findings remain unaltered with additional controls, Table IV regresses returns on predicted analyst bias (or its cycle-adjusted cousin), a dummy variable for the firm attribute associated with one of 13 anomalies, interactions between the two, and control variables. The controls include industry fixed effects, as well as firm characteristics known to predict returns, including logged size, logged book-to-market, past returns, earnings surprises, and dispersion in analyst forecasts. These controls also correlate with analyst bias. For example, negative past-earnings surprises predict analyst optimism, and earnings surprises are positively correlated with future returns (see Ball and Brown 1968; Foster, Olsen, and Shevlin 1984).[19] Similarly, dispersion in analyst forecasts,[20] size, book-to-market, and past returns correlate both with analyst bias and future returns.[21]

[19] In part, the earnings surprise-return correlation stems from the ability of past surprises to predict future "surprises," despite the unfortunate choice of terminology. See Freeman and Tse (1989) and Bernard and Thomas (1990).

[20] See for example, Table II as well as Ackert and Athanassakos (1997) and Diether, Malloy, and Scherbina (2002).

[21] Doukas, Kim, and Pantzalis (2005) find that excessive analyst optimism (driven by banking incentives and self-interest) is associated with overvaluation and low future returns.

To better understand how all of these variables interact, Table IV reports the time-series average of monthly coefficients and their Fama and MacBeth (1973) t-statistics from five specifications of monthly cross-sectional regressions of returns on lagged regressors, described above. Industry dummies appear in all specifications.[22] The analyst bias variable in the three interaction specifications—3, 4a, and 4b—is the deviation of predicted analyst bias from the sample's median bias (3 and 4a) and mean bias (4b). The deviation forces the interaction term to be zero for a typical firm, allowing us to quantify a credit-risk effect that is independent from analyst bias.

The sequencing of anomalies is identical to Table III. Panel A focuses on the credit risk anomaly, using CR5 as the anomaly dummy, and measures bias as the predicted analyst bias, $\widehat{AB}$; Panel B focuses on credit risk and measures bias with its cycle-adjusted cousin, $\widehat{AB}^{CA}$. Panel C focuses on the remaining 12 anomalies, measuring bias as predicted analyst bias. Panels A and B report coefficients on all regressors (except for industry fixed effects), while Panel C's regressions omit the coefficients on the controls for brevity, but are the same specifications used in Panels A and B with the relevant anomaly dummy replacing the latter panels' CR5 dummy. Each of Panel C's anomaly dummies takes on the value of 1 if the firm belongs to the extreme quintile (1 or 5) associated with the lowest returns for that anomaly. Hence, the coefficient on the dummy alone represents the incremental effect of belonging to that anomaly quintile versus all other quintiles.

Panel A and B's specifications (with specification 1 identical across the two panels) yield several insights about the return premia effects of analyst bias, credit risk, and their interaction. Some of these insights are similar to those discussed for Tables II and III. For example, estimates of regression specification 0 indicate that returns are inversely related to both predicted analyst bias (Panel A) and cycle-adjusted bias (Panel B), even with controls for industry, size, book-to-market, and momentum. Moreover, from specification 1, the credit-risk effect survives these same controls, but becomes insignificant once we include analyst bias (specification 2) and disappears entirely (specifications 3, 4a, and 4b) when we have controls that recognize their interaction. Specifications 3, 4a, and 4b thus indicate that extreme credit risk enhances the return-depressing effects of analyst optimism, but credit risk has no consistent effect on its own. To fit the regression model, credit risk would have to have a positive, zero, or negative premium, of any size, depending on the value for

[22]The results are highly similar without industry controls and are omitted from the table for brevity.

analyst bias. This is no premium at all, but rather an indication that analyst bias, rather than credit risk, carries a significant (negative) premium for CR5 stocks. The only fixed credit-risk premium that fits this regression model is the coefficient on the CR5 regressor itself. While this positive coefficient is insignificant, it is clearly not the negative number touted in the literature.

By contrast, analyst bias carries only one of two quantifiable premia. For the 80% of firms that are not in CR5, the premium per unit of analyst bias is given by the coefficient on $\widehat{AB}$ (or $\widehat{AB}^{CA}$ for Panel B). This coefficient is negative but statistically indistinguishable from zero. For the 20% of firms in the CR5 category, the premium for analyst bias is the premium for firms not in CR5 category plus the coefficient on the interaction term. Thus, specifications 3 and 4 allow us to properly quantify the effect of credit risk after parsing out the effect of analyst bias.

To illustrate how the least squares criterion quantifies both the credit risk and analyst bias premia, consider specification 4a's "all-controls" regression. Here, the credit-risk premium is positive but insignificant (9 bpm in specification 4a of Panel A, 22 bpm in Panel B). This is in sharp contrast to the negative credit risk-return relation (-48 bpm, specification 1) when the return depressing effect of analyst bias is not controlled for. Moreover, consistent with Table III, the analyst bias coefficient (-23 and -14 bpm in specification 4a of Panels A and B, respectively) show that analyst optimism bias predicts lower returns, albeit insignificantly, for stocks outside the greatest-credit-risk quintile. The significant interaction coefficients in Panels A and B quantify the relatively greater return-depressing effect of analyst bias in the highest-credit-risk category. For both specifications in the panels, the sum of the analyst bias coefficient and the interaction coefficient represents the effect of analyst bias in the CR5 category. This sum is of larger magnitude and more significant than the interaction coefficient alone, revealing an impressive economic magnitude for the analyst bias anomaly among CR5 stocks.

Consider, for example, specification 4a of Panel A, with a -1.19 coefficient sum ($= -0.23 - 0.96$). This sum indicates that for every 100% increase in the earnings forecast due to analyst bias, a CR5 firm subsequently earns 119 bp less per month. The (heretofore unreported) difference in bias between CR5 firms in the top and bottom-bias quintiles is about 55% for Panel A. Thus, even accounting for the effect of control variables like momentum, book-to-market, earnings, dispersion, and earnings surprises, a diversified long-short strategy of quintile extremes could earn abnormal returns of about 65 bpm (= $119 \times 55/100$). Given the (unreported) bias range of 108.2%, the comparable abnormal return for Panel B is almost 87 bpm (= $80 \times 108.2/100$).

Returns of these magnitudes far exceed transaction costs. As noted in footnote 17, the return depressing effect of optimism tends to persist for up to seven months. Thus, the transaction costs of trading strategies that hope to profit from the analyst bias strategy could be relatively small compared to the other similarly profitable strategies like momentum or industry momentum.[23] Note also that Panels A and B of Table IV do not exhibit a significant momentum effect on returns in any of the specifications that control for analyst bias. This is a common feature of more than the momentum anomaly, and one we explore in the remainder of Table IV.

Panel C of Table IV reports coefficients and test statistics for the 12 remaining anomalies, replacing the CR5 dummy with a quintile dummy for the corresponding anomaly attribute.[24] For Panel C's anomalies, 100% have no significant effect when controlling for analyst bias in specifications 3 and 4a; 75% have no separate effect from analyst bias in specification 4b. Moreover, for 10 of the 12 anomalies, including the 25% with significant separate effects in 4b, Panel C shows a strong and significant negative coefficient on the interaction term. In all cases, the interaction term diminishes the anomaly's effect observed without controls.

All anomalies exhibit a significant return depressing effect from predicted analyst bias in the anomaly quintile associated with the lowest returns (as judged by the sum of the coefficients of analyst bias and the interaction term). In the case of SUE, where the interaction term's coefficient is positive, analyst optimism has even greater return depressing effects on the 80% of firms that are not in the lowest earnings surprise category. This may mean that firms belonging to other earnings surprise quintiles are just as hard to value.

Robustness to risk adjustment, sort methodology, value weighting, and firm size. To assess the robustness of our findings, Table V studies how four alternative risk-adjustment techniques (Panel A), sequential sorts (Panel B), value weighting (Panel C), and restrictions on firm size (Panel D) alter the returns and risk-adjusted returns in Table III Panel A. Panel A reports alphas from 5×5 inde-

[23] See, for example, Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999).

[24] While the control variables coefficients of the four specifications are not reported for brevity, note that three of the anomalies—dispersion, past 6-month return, and earnings surprise—necessarily omit one of the controls, (the one associated with the anomaly), to avoid artificial dampening of the anomaly effect on returns. For example, the four momentum specifications do not have a momentum control variable.

pendent sorts on credit risk and predicted analyst bias using the Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the matching portfolio procedure of Daniel, Grinblatt, Titman, and Wermers (1997). With all four risk adjustments, alpha spreads from the analyst bias anomaly are only significant for the CR5 row. In CR5, alpha spreads range from 102 bpm (the q-factor model) to 183 bpm (the 3-factor model). The row's 5-factor alpha spread of 159 bpm fits comfortably in the middle of the range.

Panel B studies returns and alpha spreads from sequential sorts—first on credit risk and then on predicted analyst bias (top half), as well as the reverse sequence (bottom half). The 120 and 117 bpm 5-factor alpha spreads in the CR5 row of Panel B's top and bottom arrays, respectively, are smaller than the 159 bpm alpha spread from the independent sort in Table III Panel A, but still quite significant. We expect spread shrinkage with sequential sorts because of either lower variation in analyst bias (top half) or less extreme credit risk (bottom half, making them easier to value) than independently sorted firms across the cell-pairs being differenced.

Table V Panel C reinforces our conclusions from Table III that our results are not driven by microcaps, like other anomalies, as suggested in Hou, Xue, and Zhang (2015). When value-weighting stocks within each of the 25 cells, the CR5 row's significant 129 bpm return spread and 136 bpm alpha spread are modestly smaller than their corresponding 150 and 159 bpm spreads in Table III.

Panel D's 3-way independent sorts further confirm that our results are not driven by small firms. In lieu of value weighting, Panel D sorts firms into groups of above-median market cap (top half) and below-median market cap firms (bottom half). The size-sorted pair of 5×5 arrays report returns and extreme quintile spreads (at the borders). For both top- and bottom-half arrays, the far right column's difference between the CR5 row's bias-driven alpha spreads and those in other rows is large. However, when comparing corresponding cells across the two arrays, virtually no difference exist between the bias spreads of small and large firms in the same credit risk quintile. While large-firm spreads hurdle significance only at the 10% level, they exceed the corresponding (5% significant) spreads of smaller firms, which tend to populate the CR5 row. The associated difference in spreads between large and small firms is insignificant at all standard significance thresholds.

Strategic analysts and institutional ownership. Our findings to this point are consistent with an omitted variable bias as the source of many low-return anomalies. First, including analyst bias as a control greatly reduces and typically eliminates many anomalies. Second, the (opposite) return-altering effects of conservative and optimistic analyst earnings forecasts are largely witnessed in hard-to-value firms. Finally, hard-to-value firms and analyst optimism tend to concentrate in the low-return quintile of anomaly characteristics. We interpret these findings as suggesting that investors in hard-to-value firms rely more on overly optimistic analyst opinions. The opinions studied are earnings forecasts, but analyst offer other communication that could lead to stock price deviations from fair value. If analyst earnings forecasts cause investors to misprice stocks—as opposed to both investors and analysts independently making the same valuation-relevant mistakes—alternative sources of analyst communication should also influence prices. One alternative to earnings forecasts is the communication implicit in analysts' buy, sell, and hold recommendations. However, we need a metric that indicates when a recommendation is relatively more optimistic than an earnings forecast.

Strategic analysts, or "two-tongued" analysts as Malmendier and Shanthikumar (2014) call them, are those whose stock recommendations are relatively more optimistic than their earnings forecasts when benchmarked against their analyst peers. When a firm's investors' reliance on analysts distorts its price, artificially inflated recommendations will reinforce an upwardly biased consensus forecast, but offset an overly conservative consensus forecast. About 1/3 more strategic analysts exist in the $\widehat{AB}5$ category, so the category's price-inflating influence of overly optimistic analysts earnings forecasts—seen only for hard-to-value categories of firms—is likely to be largest for $\widehat{AB}5$ firms.

Table VI Panel A sorts firms into those with zero (top half) and one or more (bottom half) strategic analysts[25] (the median firm has zero strategic analysts). The pair of 5×5 arrays, each with independent sorts on credit risk and analyst bias, reports returns and spreads in the format seen with the firm-size split (Panel D of Table V). Both arrays exhibit the same pattern seen throughout the paper: there is no significant effect in the CR1 to CR4 rows, but a significant alpha spread between returns in the extreme bias quintiles in the CR5 row (due to missing observations in some months, return spreads do not exactly match the difference of the row's corresponding extreme quintile cells). Compared to the CR5/$\widehat{AB}5$ cells' 60 and -80 bpm return and alpha from Table III Panel A, the comparable return and (unreported) alpha for firms with zero strategic analyst are higher: 95 and -41 bpm, respectively. By contrast, for firms with at least one strategic analyst,

[25]The authors are grateful to an anonymous referee for suggesting this line of inquiry.

the comparable returns and alphas are lower: -16 and -117 bpm, respectively. The (unreported) differences between these returns and alphas across the split of firms with and without strategic analysts are highly statistically significant. In the CR5/$\widehat{AB}$1 cell, Table VI Panel A's two arrays show virtually no change in returns. However, the (unreported) alphas are 125 bpm with and 77 bpm without strategic analysts. The alpha difference here, which are consistent with our theory, is not statistically different from zero, probably because the cells being differenced have few firms.

Panel B of Table VI looks at the same sorts of credit risk and analyst bias, but stratified by institutional holdings. It reports the 5×5 array pairs for stock with above- and below-median institutional holdings. The array with above-median institutional holdings exhibits no analyst bias anomaly; the array with below-median institutional holdings shows the now familiar pattern: a strong analyst bias anomaly in the CR5 row, but no similar anomaly for the better-credit-risk firms. This result is consistent with our thesis of the analyst bias anomaly being driven by investor over-reliance on biased analyst forecasts. Because institutions rely less on analysts, and often do their own independent research, the consensus forecast carries less weight in their trading decisions. By contrast, when retail investors are relatively more likely to be the firm's shareholders, reliance on analyst forecasts is much larger.

Failure probability and a larger stock sample. Previously, we measured credit risk with the firm's S&P rating, which limits the sample to mostly larger firms. To expand the universe, Table VII employs a metric of credit risk with a wider coverage, failure probability (FP), computed as in Campbell, Hilscher, and Szilagyi (2008). For all stocks, we first estimate predicted analyst bias as in Table I, but using quintile failure probability dummies in lieu of credit rating dummies. We then use the breakpoints from this alternative specification of predicted bias to study the expanded universe of stocks (Panel A), as well as stocks that are unrated (Panel B) and rated (Panel C) with 5×5 independent sorts on FP and predicted analyst bias. Using failure probability instead of credit rating to calculate $\widehat{AB}$ increases the sample size from 245,763 firm-month observations in Table III to 531,413 firm-months here, or from a monthly average of 816 stocks to 1,741 stocks.

Panels A-C show a familiar pattern: analyst bias's greatest spreads are in the high-credit-risk category (FP5). Panel A and B's returns and spreads are largely identical because there are far more unrated (1,048 per month) than rated stocks with FP (693 per month) in our sample. Among FP5 firms, their significant return and alpha spreads differ by at most 3 bpm. In turn, this pair of alpha spreads, 156 and 158 bpm, are largely identical to the 159 bpm seen in Table III Panel A. The alpha spreads that differ from Table III Panel A are those from the rows of the more creditworthy firms. Despite being smaller than the FP5 rows' alpha spreads, these FP1 to FP4 analyst bias spreads are larger and more significant than the corresponding alpha spreads for the least creditworthy rated stocks, irrespective of whether rated stocks' credit risk (CR quintile) breakpoints are taken from a first stage regression using only rated stocks and credit rating fixed effects (as in Table III) or from FP breakpoints using all stocks and failure-probability-quintile fixed effects (as seen here in Table VII Panel C. The unrated-stock sample accounts for the larger and sometimes significant spreads of more creditworthy firms, as none of Panel C's FP1 to FP4 analyst bias spreads are large or statistically significant. This finding fits comfortably within the paper's hypothesis that analyst bias distorts the share prices of hard-to-value stocks. Unrated stocks, even with lower failure probabilities, are generally harder to value than rated stocks, other things equal.

III. Conclusion

Analyst forecast bias profoundly affects the stock prices of firms with hard-to-forecast earnings. These firms tend to display extreme values of firm characteristics associated with poor future returns. When such firms have greater degrees of analyst optimism, they tend to become overpriced, and subsequently earn lower returns. This finding is consistent with the intuitive belief that analyst bias distorts share prices away from their fair values.

Direct measurement of the price distortion is a tall order, as it requires a proper model of fair value. Rather than commit to any particular model of fair value, we simply show that when analyst bias is extreme, risk-adjusted returns are consistent with share price inflation (or deflation) that reverts to zero. This conclusion follows from the plausible assumption that fair value—adjusted for risk and the time value of money—follows a random walk.

There are several contributors to the convergence of distorted prices to fair prices that drive the observed abnormal returns. The first is the mean reversion in analyst bias itself. One expects such mean reversion as a matter of statistical principal. Statistical forecast errors, being less than fully persistent, necessarily regress to zero. We have depicted such regression to the mean in Figure II. The second source is the partial revelation of truth which makes the market pay less attention to the analysts' consensus forecast. As the fiscal year evolves, the market obtains more accurate information about fiscal year earnings—from companies' quarterly-earnings disclosures and guidance, among other sources. Firms with high degrees of analyst optimism bias lose their price inflation when investor reliance on analyst forecasts diminishes. Likewise, the deflated prices of firms with conservative analyst forecasts lose their deflation when that reliance diminishes as well.

The analyst-bias anomaly not only leads to highly profitable trading strategies, but explains many popular anomalies, including the credit risk, idiosyncratic volatility, dispersion, momentum (past 6-month return), gross profitability, return on assets, and investments, among others. Firms within one tail of the extreme values of these characteristics tend to earn lower returns, despite being riskier on a variety of metrics. The inferior returns of these stocks disappear once analyst bias is controlled for. While our story of prices being driven by analyst bias is ultimately a behavioral explanation of anomalous stock price movements, it is a plausible one. And it is far more appealing to have one parsimonious explanation of many return anomalies than separate and unconnected behavioral explanation for each return anomaly. Irrespective of whether one accepts analyst bias as the root cause of many anomalies, it is an important omitted variable in assessing many cross-sectional anomalies. In may also explain why many cross-sectional anomalies are evident only among high-credit-risk firms, as documented in Avramov, Chordia, Jostova, and Philipov (2013).

In further robustness checks, we examined the profitability of the credit risk and idiosyncratic volatility anomalies among rated firms without analyst coverage. We found no significant return-altering effects from these attributes. This finding supports the argument that analyst bias causes the wedge between prices and fair values, rather than investors and analysts making correlated mistakes. Admittedly, anomaly effects may exist for microcap firms that are unrated and we may find that those effects are explained by biases in guidance and forecasts by those firms or other sources. However, due to lacking data on information sources other than analysts, we cannot address the issue of whether our key result—that biases in the information flow to investors distorts stock prices—applies only to rated stocks with analyst forecasts or generalizes to all stocks. We also examined whether the analyst bias effect is stronger for firms in multiple industries or firms with multiple business segments, which may be more complex firms. The implicit assumption here is that these firms are harder to value. However, the size of the analyst bias anomaly in the highest-credit-risk quintile is statistically the same in complex and non-complex firms.

There are several promising avenues for future research. We have yet to study how variation in aggregate analyst bias over time affects the market risk premium. The causes of analyst bias and its cross-sectional variation also remains a mystery, despite promising forays into this area by Easterwood and Nutt (1999) and Lim (2001) and our attempts to sort analyst bias's effect by size, the number of strategic analysts, and the proportion of retail ownership. We attempted rudimentary investigation of whether analyst optimism is correlated with future debt issuance but found no differences in debt issuance across the analyst bias quintiles.

The finding that analyst optimism is so salient among stocks with hard-to-forecast earnings may shed light on the viability of previously proposed explanations for analyst optimism in general. These include overconfidence (Hilary and Menzly, 2006), under/overreaction to bad/good news (Easterwood and Nutt, 1999), underwriter affiliation and investment banking relationships (Lin and McNichols, 1998), bolstering trading commissions (Hayes, 1998), and access to firm managers (Francis and Philbrick, 1993). The first two explanations are plausible, but hard to test. They are part of a debate on the role that psychological research should play in the field of asset pricing. The remaining hypotheses also seem plausible. Hard-to-value stocks may be more important to the career success of an analyst. However, these agency-related explanations face a counterargument: hard-to-value stocks tend to be smaller and thus less likely to generate large trading revenues or investment banking fees.

Finally, one of the most appealing aspects of being able to predict analyst bias is that it may lead to better estimates of stock price inflation and deflation compared to fair values. Models that directly measure stock price distortions exist. However, the risk-adjusted returns that we predict are likely to stem from stock-price distortions with a known behavioral cause. These risk-adjusted returns may offer a promising alternative for measuring inflation or deflation and ultimately resolve a debate about the degree to which markets are efficient.

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Appendix

Variable	Description
Return (%)	Monthly return from CRSP, adjusted for dividend distributions and delistings.
Price	Monthly price from CRSP.
Shares	Number of share outstanding from CRSP (variable SHROUT).
Market cap	Total market value of equity computed as the product of shares outstanding and price.
BM	Book-to-market ratio. The ratio of the book value of equity to the market value of equity, computed and lagged as in Daniel, Grinblatt, Titman, and Wermers (1997).
Idiosyncratic volatility	Sum of squared residuals from regressions of daily returns on Carhart's (1997) four factors.
Analyst coverage	The number of individual analyst estimates used for computing the consensus forecasts in I/B/E/S.
Analyst dispersion	The standard deviation of analysts earnings forecasts divided by the absolute value of mean earnings forecast, subject to at least 2 analysts covering the firm (as in Diether, Malloy, and Scherbina 2002).
Analyst bias	The difference between the average consensus earnings per share (EPS) forecast minus the EPS realized at the end of the fiscal year, scaled by the absolute value of the realized EPS.
Amihud illiquidity	Monthly average of the ratio of absolute daily returns and the product of daily price and volume (see Amihud 2002).
S&P Rating	S&P long term issuer credit rating from Compustat or from Credit Ratings in WRDS.
Failure probability	The fitted value of the logistic regression model of Campbell, Hilscher, and Szilagyi (2008) (see Model 1 in Table III on p.2910).
Institutional holdings	The percent of shares outstanding held by institutions from Thomson Financial.
SUE	Standardized unexpected earnings, computed as the difference between current quarter EPS and EPS four quarters prior, divided by the standard deviation of EPS changes over eight prior quarters (see Chordia and Shivakumar 2006).
Accruals	Net income minus net cash flow from operating activities, scaled by total assets (see Teoh and Wong 2002).
Asset growth	Rate of growth in total assets over the previous fiscal year (see Cooper, Gulen, and Schill 2008).
Gross profitability	Income before extraordinary items minus dividends on preferred stock, divided by the book value of equity.
Investments	The annual change in property plant and equipment and inventories, divided by lagged assets (see Titman, Wei, and Xie 2004).
Net operating assets	Difference of all operating assets and all operating liabilities scaled by total assets (see Hirshleifer, Hou, Teoh, and Zhang 2004).
Net stock issuance	Percent change in split-adjusted shares outstanding over the previous fiscal year (as in Stambaugh, Yu, and Yuan 2012).
Composite equity issuance	An alternative issuance measure by Daniel and Titman (2006) defined as the amount of equity a firm issues (or retires) in exchange for cash or services. It is the net issuance measure adjusted for stock option plans, share-based acquisitions, repurchases, dividends, or other cash distributions.
Return on assets	Operating income before depreciation as a fraction of average total assets based on most recent two periods (see WRDS Financial Ratios Manual).

Table I. Prediction of analyst bias

Using 1986-2016 monthly data on all U.S. exchange-listed non-penny stocks with the necessary data, this table reports average coefficient estimates, average firm-clustered t-statistics (in parentheses), average R-squared, and average number of observations for eq. (5)'s 60-month rolling panel regressions. These regressions are run separately for groups of firms sorted by the number of months (k) since the last 10K earnings announcement. Observations when the new forecast appears in the same month as the prior earnings announcement ($k = 0$) are included in the regression for month $k = 1$.

	$k \leq 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$	$k = 7$	$k = 8$	$k = 9$	$k = 10$	$k = 11$	$k \geq 12$
Constant	0.087	0.081	0.098	0.075	−0.060	−0.092	−0.049	−0.047	−0.028	−0.053	−0.008	−0.006
	(0.05)	(−0.00)	(0.21)	(0.12)	(−0.45)	(−0.66)	(−0.57)	(−0.48)	(−0.37)	(−0.71)	(−0.39)	(−0.07)
$PastAB$	0.099	0.098	0.090	0.087	0.070	0.074	0.080	0.060	0.060	0.043	0.046	0.056
	(**2.91**)	(**3.21**)	(**2.97**)	(**2.99**)	(**2.35**)	(**2.35**)	(**2.75**)	(**2.12**)	(1.89)	(1.32)	(1.53)	(1.18)
$Dispersion$	0.262	0.248	0.213	0.291	0.398	0.378	0.433	0.446	0.367	0.386	0.411	0.438
	(1.80)	(**2.17**)	(1.77)	(**2.64**)	(**3.56**)	(**3.82**)	(**4.34**)	(**4.16**)	(**3.65**)	(**3.60**)	(**3.35**)	(**2.39**)
$Coverage$	−0.002	−0.001	−0.001	−0.001	−0.000	−0.001	−0.001	−0.001	−0.001	−0.002	−0.002	−0.002
	(−0.85)	(−0.58)	(−0.82)	(−0.94)	(−0.44)	(−0.90)	(−0.95)	(−0.83)	(−1.11)	(−1.78)	(−1.90)	(−1.36)
$PastRet^{-}$	−0.927	−0.871	−0.866	−0.844	−0.909	−0.731	−0.696	−0.548	−0.434	−0.341	−0.263	−0.223
	(**−4.24**)	(**−4.15**)	(**−4.16**)	(**−4.27**)	(**−4.38**)	(**−4.39**)	(**−4.65**)	(**−4.14**)	(**−3.99**)	(**−3.75**)	(**−2.98**)	(−1.65)
$PastRet^{+}$	−0.361	−0.295	−0.254	−0.243	−0.263	−0.254	−0.187	−0.163	−0.097	−0.032	−0.041	−0.078
	(**−4.38**)	(**−3.88**)	(**−3.33**)	(**−3.60**)	(**−3.94**)	(**−4.33**)	(**−3.23**)	(**−3.46**)	(**−2.10**)	(−0.76)	(−0.90)	(−1.27)
SUE^{-}	−0.040	−0.045	−0.056	−0.084	−0.063	−0.042	−0.036	−0.037	−0.035	−0.042	−0.029	−0.019
	(−1.80)	(**−1.96**)	(**−2.70**)	(**−3.68**)	(**−2.92**)	(**−2.29**)	(**−2.54**)	(**−2.82**)	(**−2.69**)	(**−2.84**)	(**−2.43**)	(−1.27)
SUE^{+}	−0.018	−0.022	−0.027	−0.029	−0.025	−0.022	−0.018	−0.015	−0.009	−0.006	−0.005	−0.002
	(**−2.22**)	(**−2.63**)	(**−3.58**)	(**−3.83**)	(**−3.34**)	(**−3.46**)	(**−3.59**)	(**−2.96**)	(**−2.00**)	(−1.39)	(−1.15)	(−0.44)
D_{Small}	0.043	0.060	0.058	0.057	0.064	0.048	0.044	0.043	0.024	0.019	0.011	0.005
	(0.91)	(1.40)	(1.30)	(1.39)	(1.64)	(1.15)	(1.13)	(1.26)	(0.70)	(0.90)	(0.71)	(0.23)
D_{Value}	0.021	0.019	0.016	0.021	0.026	0.027	0.020	0.019	0.011	0.009	0.004	−0.001
	(0.70)	(0.67)	(0.53)	(0.71)	(0.89)	(0.96)	(0.80)	(0.79)	(0.43)	(0.39)	(0.11)	(−0.06)
Rating dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.108	0.104	0.099	0.110	0.108	0.099	0.102	0.090	0.075	0.071	0.068	0.080
Observations	5,296	3,903	3,949	3,985	4,006	3,996	3,939	3,943	3,989	4,022	3,958	1,597

Table II. Descriptive Statistics

Each month t, we sort all stocks in our sample into quintiles based on predicted analyst bias, $\widehat{AB}_t$, and cycle-adjusted predicted analyst bias, $\widehat{AB}_t^{CA}$. The table reports, for each quintile, the time-series average of the month t cross-sectional means of various firm characteristics. The exception are the reported alphas and betas, which are obtained from first sorting returns into the $\widehat{AB}$ and rating quintiles, and regressing the time-series of quintile portfolio returns on the MKT (CAPM) or Fama and French (2015) factors. Variables are defined in the paper or in the data appendix. The last two rows report the mean squared error of the consensus forecast's deviation from actual earnings (standardized by the absolute value of actual EPS), without and with (i.e., demeaned) forecast adjustments for each column's ex-post bias that month. MSE averages errors first by month within each quintile, then across months. Panel B reports the average number of observations in 5×5 independent sorts on $\widehat{AB}$ and credit rating, CR. The sample includes 245,763 firm-month observations of a total of 2,640 firms or an average of 816.5 firms per month for the December 1991 to December 2016 period.

Panel A: Characteristics across quintiles

	Analyst Bias Quintile ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)					Cycle-Adjusted Bias Quintile ($\widehat{AB}1^{CA}$=Low, $\widehat{AB}5^{CA}$=High)				
Characteristic	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1^{CA}$	$\widehat{AB}2^{CA}$	$\widehat{AB}3^{CA}$	$\widehat{AB}4^{CA}$	$\widehat{AB}5^{CA}$
AB (%)	0.59	3.22	7.24	17.30	48.85	0.49	3.90	8.53	18.57	45.54
$\widehat{AB}$ (%)	−5.19	4.62	12.80	24.40	57.38	−4.92	5.28	14.24	25.98	53.42
$\widehat{AB}^{CA}$ (%)	−13.96	9.27	26.35	47.19	94.91	−14.77	7.60	23.26	44.07	103.61
Market capitalization ($bln)	19.75	14.13	10.51	7.07	3.54	19.81	14.39	10.73	6.65	3.43
Book-to-market ratio	0.55	0.65	0.71	0.77	0.85	0.56	0.64	0.71	0.76	0.87
Coverage (# of analysts))	16.49	14.23	12.78	11.38	9.78	16.51	14.42	12.90	11.22	9.61
Past six-month return (%)	19.32	10.80	6.97	2.19	−8.23	19.30	11.66	7.65	2.29	−9.87
Month $t+1$ return (%)	0.97	1.02	1.12	1.02	0.85	0.97	0.99	1.09	1.06	0.86
Month $t+1$ CAPM alpha (%)	0.21	0.26	0.31	0.08	−0.30	0.22	0.25	0.27	0.13	−0.31
CAPM beta	0.87	0.89	0.97	1.17	1.50	0.86	0.86	0.98	1.16	1.53
Month $t+1$ 5-factor alpha (%)	−0.12	−0.16	−0.07	−0.27	−0.56	−0.11	−0.15	−0.12	−0.24	−0.56
MKT beta	1.01	1.04	1.06	1.20	1.41	1.00	1.00	1.09	1.20	1.43
SMB beta	0.17	0.23	0.32	0.47	0.72	0.16	0.22	0.33	0.50	0.70
HML beta	0.04	0.23	0.39	0.58	0.81	0.04	0.21	0.39	0.55	0.86
RMW beta	0.37	0.39	0.28	0.21	−0.03	0.37	0.37	0.33	0.23	−0.08
CMA beta	0.26	0.21	0.06	−0.16	−0.36	0.25	0.22	0.03	−0.11	−0.37
S&P letter rating	A−	BBB+	BBB	BBB−	BB	A−	BBB+	BBB	BBB−	BB
S&P numeric rating	7.85	8.29	9.00	10.10	11.85	7.82	8.19	8.99	10.18	11.92
Fraction NIG firms ($\leq BB+$)	0.17	0.22	0.30	0.45	0.70	0.17	0.20	0.30	0.46	0.71
Fraction rated B+ or worse	0.05	0.04	0.07	0.14	0.33	0.04	0.04	0.07	0.14	0.35
Fraction rated CCC+ or worse	0.01	0.00	0.00	0.01	0.02	0.01	0.00	0.00	0.00	0.02
Idiosyncratic volatility (×100)	1.34	1.33	1.45	1.69	2.27	1.33	1.31	1.44	1.68	2.32
Dispersion in analyst forecasts	0.03	0.04	0.05	0.08	0.23	0.03	0.04	0.05	0.08	0.23
SUE	1.89	1.00	0.54	0.13	−0.55	1.89	1.06	0.58	0.13	−0.65
MSE	0.07	0.11	0.23	0.53	1.57	0.07	0.14	0.27	0.58	1.45
MSE (demeaned)	0.07	0.11	0.22	0.48	1.28	0.07	0.13	0.26	0.53	1.20

Panel B: Number of firms in sorts on $\widehat{AB}$ and credit rating, CR

	Analyst Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)				
Rating Quintiles	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$
CR1	66.57	54.58	41.55	24.75	9.84
CR2	47.49	45.80	40.62	31.70	15.75
CR3	23.45	30.25	33.95	33.81	24.00
CR4	16.59	23.10	31.78	44.28	50.53
CR5	9.00	9.37	15.21	28.57	62.93

Table III. Returns Sorted on Analyst Bias and Anomaly Variables

Stocks are sorted into portfolios based on a 5×5 independent sort on month $t-1$ S&P credit rating and either predicted analyst bias $\widehat{AB}$ (Panels A), or cycle-adjusted analyst bias$\widehat{AB}$ (Panels B). The table reports, for each portfolio, the time-series average of equally weighted monthly portfolio returns or Fama and French (2015) 5-factor risk-adjusted returns (in percentages). Panel C sorts on $\widehat{AB}$ and alternative anomaly variables used in Stambaugh, Yu, and Yuan (2012, 2015) or Avramov, Chordia, Jostova, and Philipov (2013).

Panel A: Sort on $\widehat{AB}_{t-1}$ and credit rating, CR_{t-1}

Rating Groups	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)					
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
Raw returns						
CR1	0.85	0.92	1.11	1.00	0.79	0.05
	(**4.03**)	(**4.24**)	(**4.56**)	(**3.46**)	(**2.02**)	(0.17)
CR2	0.95	1.00	1.09	1.01	1.06	−0.12
	(**4.09**)	(**4.33**)	(**4.23**)	(**3.42**)	(**2.82**)	(−0.39)
CR3	0.93	1.01	1.10	1.11	0.98	−0.05
	(**3.27**)	(**3.68**)	(**4.07**)	(**3.42**)	(**2.41**)	(−0.16)
CR4	1.12	1.03	1.27	0.97	1.09	0.03
	(**2.96**)	(**3.13**)	(**3.79**)	(**2.67**)	(**2.28**)	(0.20)
CR5	2.10	1.51	1.08	0.81	0.60	1.50
	(**3.65**)	(**2.94**)	(**2.31**)	(1.80)	(1.10)	(**2.77**)
CR1−CR5	−1.26	−0.58	0.04	0.19	0.19	
	(−**2.41**)	(−1.45)	(0.11)	(0.63)	(0.49)	
Fama and French (2015) 5-factor-adjusted portfolio returns						
CR1	−0.14	−0.15	0.02	−0.14	−0.40	0.26
	(−1.74)	(−**1.96**)	(0.20)	(−1.12)	(−1.63)	(0.94)
CR2	−0.08	−0.10	−0.08	−0.10	−0.10	0.01
	(−0.78)	(−1.03)	(−0.71)	(−0.75)	(−0.45)	(0.05)
CR3	−0.26	−0.20	−0.14	−0.26	−0.47	0.22
	(−1.78)	(−1.67)	(−1.32)	(−1.88)	(−**2.17**)	(0.77)
CR4	−0.23	−0.40	−0.04	−0.42	−0.37	0.15
	(−1.03)	(−**2.53**)	(−0.27)	(−**2.90**)	(−1.58)	(0.43)
CR5	0.79	0.08	−0.16	−0.50	−0.80	1.59
	(1.86)	(0.25)	(−0.58)	(−**2.35**)	(−**2.88**)	(**3.13**)
CR1−CR5	−0.92	−0.23	0.18	0.36	0.40	
	(−**2.23**)	(−0.73)	(0.60)	(1.67)	(1.36)	

Panel B: Sort on $\widehat{AB}^{CA}_{t-1}$ and credit rating, CR_{t-1}

	$\widehat{AB}1^{CA}$	$\widehat{AB}2^{CA}$	$\widehat{AB}3^{CA}$	$\widehat{AB}4^{CA}$	$\widehat{AB}5^{CA}$	$\widehat{AB}1^{CA}-\widehat{AB}5^{CA}$
Raw returns						
CR1	0.85	0.94	1.14	1.08	0.52	0.32
	(**4.05**)	(**4.38**)	(**4.53**)	(**3.84**)	(1.26)	(0.90)
CR2	0.98	0.98	1.09	1.07	1.17	−0.19
	(**4.27**)	(**4.28**)	(**4.25**)	(**3.61**)	(**2.90**)	(−0.58)
CR3	0.85	1.00	1.06	1.14	1.08	−0.23
	(**2.98**)	(**3.80**)	(**3.71**)	(**3.60**)	(**2.54**)	(−0.69)
CR4	1.20	0.95	1.08	1.08	1.09	0.11
	(**3.14**)	(**2.95**)	(**3.36**)	(**2.90**)	(**2.22**)	(0.39)
CR5	2.07	1.25	1.10	0.79	0.61	1.45
	(**3.59**)	(**2.42**)	(**2.43**)	(1.77)	(1.12)	(**2.65**)
CR1−CR5	−1.22	−0.31	0.04	0.29	−0.09	
	(−**2.35**)	(−0.76)	(0.11)	(0.92)	(−0.26)	
Fama and French (2015) 5-factor-adjusted portfolio returns						
CR1	−0.13	−0.13	0.04	−0.03	−0.68	0.56
	(−1.60)	(−1.74)	(0.41)	(−0.22)	(−**2.78**)	(**1.99**)
CR2	−0.05	−0.10	−0.07	−0.09	−0.02	−0.02
	(−0.44)	(−1.07)	(−0.75)	(−0.68)	(−0.10)	(−0.09)
CR3	−0.32	−0.20	−0.22	−0.19	−0.41	0.09
	(−**2.09**)	(−1.82)	(−**2.01**)	(−1.41)	(−1.78)	(0.29)
CR4	−0.16	−0.42	−0.20	−0.36	−0.41	0.25
	(−0.72)	(−**2.47**)	(−1.51)	(−**2.53**)	(−1.72)	(0.72)
CR5	0.91	−0.03	−0.27	−0.50	−0.80	1.71
	(**2.11**)	(−0.09)	(−1.05)	(−**2.35**)	(−**2.82**)	(**3.23**)
CR1−CR5	−1.04	−0.10	0.31	0.47	0.12	
	(−**2.44**)	(−0.31)	(1.13)	(**2.12**)	(0.27)	

Table III. (continued)

Panel C: Sort on $\widehat{AB}_{t-1}$ and Anomaly Variables

Uncertainty Groups	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)						FF 5-factor
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
Idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006)							
IVOL1	0.88	0.94	1.14	1.07	1.11	−0.23	0.01
	(**4.33**)	(**4.76**)	(**5.07**)	(**4.23**)	(**3.32**)	(−0.86)	(0.05)
IVOL2	0.91	0.99	1.16	1.08	1.20	−0.29	−0.02
	(**4.04**)	(**4.04**)	(**4.56**)	(**3.86**)	(**3.40**)	(−1.12)	(−0.09)
IVOL3	0.91	1.04	1.09	0.96	1.14	−0.23	0.01
	(**3.48**)	(**3.69**)	(**3.86**)	(**2.95**)	(**3.08**)	(−0.92)	(0.03)
IVOL4	1.02	1.19	1.23	1.07	0.85	0.17	0.34
	(**3.13**)	(**3.96**)	(**3.75**)	(**2.96**)	(1.93)	(0.57)	(1.23)
IVOL5	1.28	1.10	0.90	0.75	0.48	0.80	0.92
	(**3.05**)	(**2.78**)	(**2.29**)	(1.71)	(0.90)	(**2.03**)	(**2.53**)
IVOL1−IVOL5	−0.40	−0.16	0.24	0.31	0.63		
	(−1.22)	(−0.57)	(0.84)	(1.09)	(1.69)		
Dispersion (Diether, Malloy, and Scherbina, 2002)							
DISP1	0.92	0.99	1.17	1.00	1.03	−0.11	0.42
	(**4.35**)	(**4.46**)	(**4.65**)	(**3.27**)	(**2.47**)	(−0.23)	(1.55)
DISP2	0.96	0.94	1.06	0.93	0.94	0.02	0.36
	(**4.04**)	(**3.94**)	(**4.22**)	(**2.81**)	(**2.20**)	(0.08)	(1.36)
DISP3	0.73	0.98	1.01	0.89	0.41	0.32	0.49
	(**2.71**)	(**3.74**)	(**3.72**)	(**2.79**)	(1.00)	(1.24)	(1.73)
DISP4	0.88	0.88	1.17	0.82	0.48	0.40	0.48
	(**2.60**)	(**2.98**)	(**3.91**)	(**2.43**)	(1.19)	(1.34)	(1.70)
DISP5	0.75	0.81	0.69	0.79	0.11	0.64	0.79
	(1.46)	(**2.06**)	(1.92)	(**2.16**)	(0.25)	(1.89)	(1.71)
DISP1−DISP5	0.18	0.18	0.49	0.21	0.92		
	(0.41)	(0.71)	(1.60)	(0.93)	(**2.97**)		
Momentum (Jegadeesh and Titman, 1993, past 6-month returns)							
R6(loser)	1.30	1.66	1.11	0.90	0.33	0.96	1.17
	(**2.61**)	(**3.80**)	(**2.83**)	(**2.05**)	(0.64)	(**2.08**)	(**2.47**)
R6(2)	1.15	1.08	1.25	1.04	0.89	0.26	0.51
	(**3.75**)	(**3.68**)	(**4.29**)	(**3.13**)	(**2.30**)	(1.04)	(**2.32**)
R6(3)	0.90	1.03	1.10	1.08	0.95	−0.05	0.11
	(**3.52**)	(**4.36**)	(**4.23**)	(**3.71**)	(**2.60**)	(−0.22)	(0.56)
R6(4)	0.87	0.86	0.99	0.94	0.80	0.07	0.40
	(**3.71**)	(**3.53**)	(**3.85**)	(**3.36**)	(**2.05**)	(0.23)	(1.68)
R6(winner)	0.96	0.91	1.06	0.93	1.16	−0.20	−0.05
	(**3.46**)	(**3.32**)	(**3.58**)	(**2.86**)	(**2.88**)	(−0.75)	(−0.16)
Winner−Loser	−0.34	−0.75	−0.06	0.03	0.83		
	(−0.81)	(−**2.02**)	(−0.19)	(0.10)	(**2.69**)		
Gross Profitability (Novy-Marx, 2013)							
GP1	0.97	0.88	1.08	0.79	−0.05	1.03	1.33
	(**3.62**)	(**3.78**)	(**4.25**)	(**2.24**)	(−0.11)	(**2.62**)	(**4.32**)
GP2	0.85	0.97	0.96	0.77	0.70	0.14	0.50
	(**2.92**)	(**3.40**)	(**3.18**)	(**2.10**)	(1.48)	(0.39)	(1.64)
GP3	0.86	1.05	1.08	1.14	0.93	−0.07	0.23
	(**3.01**)	(**3.52**)	(**3.50**)	(**3.16**)	(1.94)	(−0.21)	(0.79)
GP4	0.98	1.08	1.31	0.90	1.15	−0.17	0.18
	(**3.69**)	(**3.96**)	(**4.31**)	(**2.45**)	(**2.54**)	(−0.57)	(0.73)
GP5	1.00	1.13	1.05	0.98	0.83	0.17	0.67
	(**4.29**)	(**4.66**)	(**3.54**)	(**2.95**)	(1.73)	(0.46)	(**2.27**)
GP5−GP1	0.03	0.25	−0.03	0.19	0.88		
	(0.12)	(1.22)	(−0.15)	(0.88)	(**2.88**)		

Table III. (continued)

Panel C: Sort on $\widehat{AB}_{t-1}$ and Anomaly Variables

Uncertainty Groups	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)						FF 5-factor
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
Return on Assets							
ROA1	0.80	0.89	1.10	0.85	0.16	0.64	0.89
	(**2.49**)	(**2.95**)	(**3.68**)	(**2.24**)	(0.34)	(**1.99**)	(**2.95**)
ROA2	1.01	1.06	1.14	0.84	0.67	0.34	0.81
	(**4.00**)	(**4.31**)	(**4.24**)	(**2.51**)	(1.53)	(1.03)	(**3.05**)
ROA3	1.02	1.02	1.09	0.88	0.48	0.54	0.81
	(**4.09**)	(**3.97**)	(**3.99**)	(**2.52**)	(1.14)	(1.79)	(**3.15**)
ROA4	0.88	1.06	1.13	1.02	0.80	0.08	0.44
	(**3.51**)	(**4.07**)	(**3.81**)	(**3.00**)	(1.79)	(0.25)	(1.76)
ROA5	0.88	0.88	0.93	0.79	0.46	0.42	0.73
	(**3.82**)	(**3.68**)	(**3.24**)	(**2.33**)	(0.99)	(1.17)	(**2.43**)
ROA5−ROA1	0.08	−0.00	−0.17	−0.06	0.30		
	(0.34)	(−0.02)	(−0.92)	(−0.29)	(1.04)		
Net Operating Assets (Hirshleifer, Hou, Teoh, and Zhang, 2004)							
NOA1	1.00	1.13	1.29	1.27	1.22	−0.21	0.13
	(**3.60**)	(**4.01**)	(**4.29**)	(**3.56**)	(**2.34**)	(−0.57)	(0.43)
NOA2	1.03	0.96	1.15	1.22	1.26	−0.23	0.25
	(**4.40**)	(**3.88**)	(**4.05**)	(**3.62**)	(**2.70**)	(−0.66)	(0.89)
NOA3	0.80	1.09	1.16	1.00	0.82	−0.02	0.47
	(**3.56**)	(**4.64**)	(**4.28**)	(**3.07**)	(1.89)	(−0.07)	(1.88)
NOA4	0.86	1.01	1.06	0.99	0.85	0.01	0.41
	(**3.37**)	(**4.03**)	(**4.06**)	(**2.94**)	(1.85)	(0.02)	(1.44)
NOA5	1.01	0.84	0.91	0.41	−0.08	1.09	1.29
	(**3.39**)	(**2.85**)	(**2.92**)	(1.03)	(−0.17)	(**2.93**)	(**3.99**)
NOA1−NOA5	−0.01	0.29	0.38	0.87	1.30		
	(−0.05)	(1.59)	(**2.02**)	(**4.55**)	(**4.66**)		
Net Stock Issues (Ritter, 1991; Loughran and Ritter, 1995)							
NSI1	1.04	1.00	1.16	1.20	1.39	−0.35	0.05
	(**4.47**)	(**3.97**)	(**4.29**)	(**4.03**)	(**3.39**)	(−1.16)	(0.19)
NSI2	0.92	0.98	1.15	1.20	1.01	−0.09	0.38
	(**4.04**)	(**4.21**)	(**4.44**)	(**3.68**)	(**2.40**)	(−0.29)	(1.51)
NSI3	0.86	1.16	1.22	1.07	0.81	0.04	0.48
	(**3.42**)	(**4.51**)	(**4.30**)	(**3.10**)	(1.82)	(0.13)	(1.90)
NSI4	0.94	0.98	1.06	0.98	0.76	0.17	0.35
	(**3.34**)	(**3.61**)	(**3.67**)	(**2.76**)	(1.62)	(0.51)	(1.22)
NSI5	0.92	0.95	0.94	0.59	0.16	0.76	0.90
	(**3.16**)	(**3.30**)	(**3.13**)	(1.56)	(0.33)	(**2.01**)	(**2.86**)
NSI1−NSI5	0.12	0.05	0.22	0.62	1.23		
	(0.67)	(0.34)	(1.33)	(**3.12**)	(**4.52**)		
Composite Equity Issues (Daniel and Titman, 2006)							
CEI1	1.06	1.15	1.11	0.81	0.48	0.58	0.45
	(**3.53**)	(**3.76**)	(**3.41**)	(**2.05**)	(0.98)	(1.73)	(1.51)
CEI2	1.09	1.22	1.18	1.09	0.86	0.23	0.34
	(**4.03**)	(**4.67**)	(**4.10**)	(**3.35**)	(**2.00**)	(0.71)	(1.12)
CEI3	0.91	1.01	1.16	1.07	0.95	−0.03	0.03
	(**3.91**)	(**4.22**)	(**4.37**)	(**3.40**)	(**2.36**)	(−0.12)	(0.13)
CEI4	0.83	0.87	1.08	1.10	0.75	0.08	0.23
	(**3.65**)	(**3.62**)	(**4.09**)	(**3.67**)	(1.86)	(0.27)	(0.91)
CEI5	0.85	0.83	0.94	0.74	0.22	0.63	0.73
	(**3.33**)	(**3.21**)	(**3.50**)	(**2.23**)	(0.53)	(**2.08**)	(**2.53**)
CEI1−CEI5	0.21	0.32	0.17	0.07	0.26		
	(1.21)	(1.87)	(0.99)	(0.35)	(1.13)		

Table III. (continued)

Panel C: Sort on $\widehat{AB}_{t-1}$ and Anomaly Variables

Uncertainty Groups	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High) $\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	FF 5-factor $\widehat{AB}1-\widehat{AB}5$
Investments (Titman, Wei, and Xie, 2004)							
INV1	1.02	1.10	1.18	1.04	0.60	0.42	0.54
	(**3.72**)	(**3.71**)	(**4.02**)	(**2.77**)	(1.23)	(1.18)	(1.76)
INV2	0.84	0.96	1.21	0.93	1.17	−0.32	0.12
	(**3.40**)	(**3.74**)	(**4.08**)	(**2.64**)	(**2.51**)	(−0.96)	(0.39)
INV3	0.95	0.87	1.02	0.96	0.85	0.09	0.37
	(**3.90**)	(**3.42**)	(**3.73**)	(**2.71**)	(1.90)	(0.30)	(1.41)
INV4	0.83	1.06	1.07	1.02	0.70	0.13	0.45
	(**3.62**)	(**4.63**)	(**4.02**)	(**3.19**)	(1.50)	(0.34)	(1.44)
INV5	1.02	0.98	0.95	0.77	0.44	0.58	0.82
	(**3.36**)	(**3.43**)	(**3.01**)	(**1.99**)	(0.87)	(1.77)	(**2.27**)
INV1−INV5	0.00	0.12	0.24	0.27	0.16		
	(0.00)	(0.58)	(1.20)	(1.13)	(0.48)		
Asset growth (Cooper, Gulen, and Schill, 2008)							
AG1	1.10	1.18	1.15	1.29	1.33	−0.22	0.37
	(**3.89**)	(**4.21**)	(**3.78**)	(**3.51**)	(**2.79**)	(−0.67)	(1.40)
AG2	1.12	1.04	1.19	1.08	0.84	0.29	0.41
	(**4.93**)	(**4.23**)	(**4.48**)	(**3.45**)	(1.86)	(0.87)	(1.90)
AG3	1.02	1.06	1.19	1.03	0.61	0.41	0.29
	(**4.42**)	(**4.53**)	(**4.60**)	(**3.27**)	(1.50)	(1.33)	(1.11)
AG4	0.84	0.96	1.04	1.00	1.01	−0.17	0.29
	(**3.36**)	(**3.72**)	(**3.93**)	(**3.09**)	(**2.28**)	(−0.48)	(1.07)
AG5	0.88	0.84	0.92	0.61	0.12	0.76	0.83
	(**3.04**)	(**2.83**)	(**2.89**)	(1.57)	(0.25)	(**2.19**)	(**2.64**)
AG1−AG5	0.22	0.35	0.23	0.68	1.21		
	(1.20)	(1.86)	(1.26)	(**3.09**)	(**5.02**)		
Accruals (Teoh and Wong, 2002)							
ACC1	1.04	1.10	1.17	0.93	0.60	0.44	0.52
	(**3.34**)	(**3.61**)	(**3.49**)	(**2.42**)	(1.23)	(1.23)	(1.52)
ACC2	1.14	1.16	1.26	1.01	0.96	0.19	0.32
	(**4.85**)	(**4.74**)	(**4.39**)	(**2.99**)	(**2.17**)	(0.57)	(1.15)
ACC3	0.86	0.88	1.19	0.91	0.42	0.45	0.52
	(**3.76**)	(**3.69**)	(**4.51**)	(**2.89**)	(0.94)	(1.37)	(1.70)
ACC4	0.83	0.92	0.99	0.97	0.39	0.44	0.64
	(**3.52**)	(**4.01**)	(**3.89**)	(**2.89**)	(0.89)	(1.37)	(**2.27**)
ACC5	0.66	0.93	0.81	0.71	0.17	0.49	0.66
	(**2.45**)	(**3.28**)	(**2.74**)	(**1.98**)	(0.38)	(1.79)	(**2.24**)
ACC1−ACC5	0.38	0.17	0.36	0.22	0.43		
	(**2.01**)	(0.89)	(1.75)	(1.00)	(1.63)		
SUE							
SUE1	0.53	1.07	0.92	0.76	0.49	0.04	0.52
	(1.47)	(**3.49**)	(**3.31**)	(**2.31**)	(1.11)	(−0.06)	(1.36)
SUE2	0.93	0.97	1.05	1.00	0.45	0.48	0.87
	(**3.22**)	(**3.86**)	(**3.87**)	(**2.98**)	(1.02)	(1.54)	(**3.36**)
SUE3	0.97	1.15	1.21	1.18	0.73	0.23	0.47
	(**3.83**)	(**4.59**)	(**4.29**)	(**3.56**)	(1.64)	(0.73)	(1.89)
SUE4	0.87	1.05	1.03	1.04	0.83	0.04	0.26
	(**3.34**)	(**4.04**)	(**3.60**)	(**2.91**)	(1.90)	(0.13)	(1.04)
SUE5	0.99	0.90	1.32	0.81	1.23	−0.24	0.04
	(**4.25**)	(**3.60**)	(**4.49**)	(**2.19**)	(**2.41**)	(−0.58)	(0.12)
SUE5−SUE1	0.46	−0.17	0.40	0.05	0.74		
	(1.59)	(−0.89)	(**2.32**)	(0.22)	(**2.15**)		

Table IV. Cross-Sectional Regressions of Returns on Firm Characteristics

The table reports average coefficients and Fama-MacBeth t-statistics from monthly cross-sectional regressions of returns (in percentages), $r_{i,t}$, on firm-level characteristics:

$$\begin{aligned} r_{i,t} \quad = \quad & c_{0,t} + c_{1,t}\, D_{CR5(i),t-1} + c_{2,t}\, \widehat{AB}_{i,t-1} + c_{3,t}\, (\widehat{AB}^{*}_{i,t-1} \times\ D_{CR5(i),t-1}) \\ & + c_{4,t}\, log(Size_{i,t-2}) + c_{5,t}\, log(BM_{i,t-lag}) + c_{6,t}\, r_{i,t-7:t-2} + c_{7,t}\, SUE_{i,t-1} + c_{8,t}\, Disp_{i,t-1} \end{aligned} \tag{7}$$

where $D_{CR5(i),t-1}$ is a dummy variable indicating whether the firm belongs to the worst-rated quintile of firms, $log(Size_{i,t-2})$ is the natural log of the firm's market capitalization, $log(BM_{i,t-lag})$ is the natural log of the firm's book-to-market ratio, computed and lagged as in Daniel, Grinblatt, Titman, and Wermers (1997), $r_{i,t-7:t-2}$ is the past 6-month cumulative return, $SUE_{i,t-1}$ is the quarterly earnings surprise, and $Disp_{t-1}$ is the dispersion in analyst earnings forecasts. All regressions have fixed effect dummies for 19 of the 20 industries of Moskowitz and Grinblatt (1999). Panel A uses predicted analyst bias ($\widehat{AB}$) and Panel B uses cycle-adjusted predicted analyst bias ($\widehat{AB}^{CA}$). $\widehat{AB}^{*}_{it}$ in specifications 0-4a (4b) demeans each $\widehat{AB}_{it}$ with the sample median (mean) analyst bias. $\widehat{AB}^{*CA}_{it}$ removes the sample median (mean) $\widehat{AB}^{CA}$ from each $\widehat{AB}^{CA}_{it}$. Panel C replaces the credit rating dummy in Panel A with dummies indicating the quintile of firms to be shorted based on alternative anomaly variables used in Stambaugh, Yu, and Yuan (2012, 2015) and Avramov, Chordia, Jostova, and Philipov (2013).

Panel A: Using predicted analyst bias, $\widehat{AB}$, CR5 = quintile with highest credit risk

Regression Specification	0	1	2	3	4a	4b
Constant	1.12	0.95	1.42	1.21	1.15	1.15
	(1.38)	(1.36)	(1.92)	(1.67)	(1.56)	(1.56)
$D_{CR5,t-1}$		−0.48	−0.30	0.03	0.09	−0.06
		(−**2.90**)	(−1.79)	(0.14)	(0.39)	(−0.32)
$\widehat{AB}_{i,t-1}$	−0.70		−0.62	−0.40	−0.23	−0.23
	(−**2.78**)		(−**2.66**)	(−1.59)	(−0.89)	(−0.89)
$\widehat{AB}^{*}_{i,t-1} \times D_{CR5,t-1}$				−0.76	−0.96	−0.96
				(−**2.09**)	(−**2.54**)	(−**2.54**)
$log(Size_{t-2})$	−0.02	−0.01	−0.04	−0.03	−0.03	−0.03
	(−0.45)	(−0.29)	(−0.94)	(−0.72)	(−0.70)	(−0.70)
$log(BM_{t-1})$	0.13	0.11	0.11	0.11	0.10	0.10
	(**2.23**)	(**2.09**)	(**1.98**)	(**1.96**)	(1.81)	(1.81)
$r_{t-7:t-2}$	0.28	0.92	0.24	0.22	0.20	0.20
	(0.74)	(**2.42**)	(0.64)	(0.58)	(0.52)	(0.52)
SUE_{t-1}					0.02	0.02
					(1.11)	(1.11)
$Disp_{t-1}$					−0.07	−0.07
					(−0.27)	(−0.27)
Adjusted R^2 (%)	11.98	10.29	12.44	12.66	13.10	13.10

Panel B: Using cycle-adjusted analyst bias, $\widehat{AB}^{CA}$, CR5 = quintile with highest credit risk

Constant	1.21	0.95	1.50	1.25	1.21	1.21
	(1.52)	(1.36)	(**2.06**)	(1.74)	(1.67)	(1.67)
$D_{CR5,t-1}$		−0.48	−0.28	0.22	0.22	0.01
		(−**2.90**)	(−1.69)	(1.04)	(1.06)	(0.06)
$\widehat{AB}^{CA}_{i,t-1}$	−0.42		−0.38	−0.21	−0.14	−0.14
	(−**2.79**)		(−**2.75**)	(−1.37)	(−0.88)	(−0.88)
$\widehat{AB}^{*CA}_{i,t-1} \times D_{CR5,t-1}$				−0.64	−0.66	−0.66
				(−**3.07**)	(−**3.04**)	(−**3.04**)
$log(Size_{t-2})$	−0.02	−0.01	−0.04	−0.03	−0.03	−0.03
	(−0.57)	(−0.29)	(−1.05)	(−0.75)	(−0.76)	(−0.76)
$log(BM_{t-1})$	0.13	0.11	0.11	0.11	0.10	0.10
	(**2.26**)	(**2.09**)	(**2.01**)	(1.95)	(1.81)	(1.81)
$r_{t-7:t-2}$	0.20	0.92	0.16	0.14	0.11	0.11
	(0.53)	(**2.42**)	(0.44)	(0.38)	(0.31)	(0.31)
SUE_{t-1}					0.02	0.02
					(0.91)	(0.91)
$Disp_{t-1}$					−0.02	−0.02
					(−0.08)	(−0.08)
Adjusted R^2 (%)	12.00	10.29	12.46	12.72	13.15	13.15

Table IV. (continued)

Panel C: Using predicted analyst bias, $\widehat{AB}$

Regression Specification	1	2	3	4a	4b
Idiosyncratic volatility: $IVOL5$ = quintile with highest volatility					
$D_{IVOL5,t-1}$	−0.29	−0.26	−0.02	−0.02	−0.14
	(−**2.11**)	(−**2.02**)	(−0.11)	(−0.13)	(−0.86)
$\widehat{AB}_{i,t-1}$		−0.56	−0.24	0.11	0.11
		(−**2.40**)	(−1.01)	(0.44)	(0.44)
$\widehat{AB}^{*}_{i,t-1} \times D_{IVOL5,t-1}$			−0.80	−0.82	−0.82
			(−**2.41**)	(−**2.29**)	(−**2.29**)
Dispersion: $DISP5$ = quintile with highest dispersion					
$D_{DISP5,t-1}$	−0.36	−0.24	0.01	0.02	−0.08
	(−**3.37**)	(−**2.59**)	(0.04)	(0.16)	(−0.59)
$\widehat{AB}_{i,t-1}$		−0.61	−0.38	−0.20	−0.20
		(−**2.65**)	(−1.53)	(−0.73)	(−0.73)
$\widehat{AB}^{*}_{i,t-1} \times D_{DISP5,t-1}$			−0.56	−0.67	−0.67
			(−**1.96**)	(−**2.24**)	(−**2.24**)
Momentum: $LOSER$ = quintile with lowest past six-month returns					
D_{LOSER}	−0.37	−0.25	0.23	0.21	−0.02
	(−**2.03**)	(−1.61)	(1.06)	(0.98)	(−0.12)
$\widehat{AB}_{i,t-1}$		−0.70	−0.04	0.09	0.09
		(−**2.74**)	(−0.14)	(0.33)	(0.33)
$\widehat{AB}^{*}_{i,t-1} \times D_{LOSER}$			−1.56	−1.51	−1.51
			(−**4.63**)	(−**4.32**)	(−**4.32**)
Gross Profitability: $GP1$ = quintile with lowest profitability					
$D_{GP1,t-1}$	−0.32	−0.30	0.10	0.14	−0.13
	(−**3.03**)	(−**2.86**)	(0.82)	(1.19)	(−0.95)
$\widehat{AB}_{i,t-1}$		−0.59	−0.30	−0.16	−0.16
		(−**2.33**)	(−1.19)	(−0.60)	(−0.60)
$\widehat{AB}^{*}_{i,t-1} \times D_{GP1,t-1}$			−1.50	−1.82	−1.82
			(−**4.43**)	(−**5.26**)	(−**5.26**)
Return on Assets: ROA1 = lowest return on assets (calculated as in WRDS)					
D_{ROA1}	−0.27	−0.17	0.13	0.12	−0.02
	(−**2.01**)	(−1.35)	(0.87)	(0.84)	(−0.13)
$\widehat{AB}_{i,t-1}$		−0.61	−0.38	−0.27	−0.27
		(−**2.44**)	(−1.51)	(−1.01)	(−1.01)
$\widehat{AB}^{*}_{i,t-1} \times D_{ROA1}$			−0.91	−0.91	−0.91
			(−**2.65**)	(−**2.56**)	(−**2.56**)
Net Operating Assets: $NOA5$ = quintile with highest net operating assets					
$D_{NOA5,t-1}$	−0.44	−0.36	−0.15	−0.13	−0.29
	(−**4.99**)	(−**4.18**)	(−1.75)	(−1.54)	(−**2.65**)
$\widehat{AB}_{i,t-1}$		−0.57	−0.35	−0.20	−0.20
		(−**2.26**)	(−1.35)	(−0.72)	(−0.72)
$\widehat{AB}^{*}_{i,t-1} \times D_{NOA5,t-1}$			−0.98	−1.02	−1.02
			(−**3.00**)	(−**3.10**)	(−**3.10**)

Table IV. (continued)

Panel C: Using predicted analyst bias, $\widehat{AB}$

Regression Specification	1	2	3	4a	4b
Net Stock Issues: NSI5=quintile with highest net stock issuance					
$D_{NSI5,t-1}$	−0.48	−0.38	−0.15	−0.14	−0.30
	(**−5.27**)	(**−4.58**)	(−1.64)	(−1.51)	(**−2.82**)
$\widehat{AB}_{i,t-1}$		−0.64	−0.47	−0.32	−0.32
		(**−2.61**)	(−1.91)	(−1.26)	(−1.26)
$\widehat{AB}^{*}_{i,t-1} \times D_{NSI5,t-1}$			−0.97	−1.03	−1.03
			(**−2.85**)	(**−2.94**)	(**−2.94**)
Composite Equity Issues: CEI5=quintile with highest issuance					
$D_{CEI5,t-1}$	−0.38	−0.37	−0.09	−0.09	−0.28
	(**−4.62**)	(**−4.60**)	(−0.97)	(−0.97)	(**−2.64**)
$\widehat{AB}_{i,t-1}$		−0.63	−0.33	−0.18	−0.18
		(**−2.54**)	(−1.31)	(−0.70)	(−0.70)
$\widehat{AB}^{*}_{i,t-1} \times D_{CEI5,t-1}$			−1.22	−1.26	−1.26
			(**−3.82**)	(**−3.85**)	(**−3.85**)
Investments: INV5 = highest investments to assets					
D_{INV5}	−0.21	−0.10	0.03	0.04	−0.08
	(**−2.41**)	(−1.26)	(0.33)	(0.50)	(−0.74)
$\widehat{AB}_{i,t-1}$		−0.61	−0.41	−0.32	−0.32
		(**−2.39**)	(−1.44)	(−1.08)	(−1.08)
$\widehat{AB}^{*}_{i,t-1} \times D_{INV5}$			−0.81	−0.81	−0.81
			(**−2.23**)	(**−2.17**)	(**−2.17**)
Asset Growth: AG5 = quintile with highest asset growth					
$D_{AG5,t-1}$	−0.30	−0.29	−0.16	−0.13	−0.24
	(**−3.31**)	(**−3.27**)	(−1.66)	(−1.39)	(**−2.16**)
$\widehat{AB}_{i,t-1}$		−0.64	−0.49	−0.29	−0.29
		(**−2.61**)	(−1.93)	(−1.12)	(−1.12)
$\widehat{AB}^{*}_{i,t-1} \times D_{AG5,t-1}$			−0.71	−0.73	−0.73
			(**−2.30**)	(**−2.35**)	(**−2.35**)
Accruals: ACC5 = highest accruals					
$D_{ACC5,t-1}$	−0.26	−0.22	−0.08	−0.08	−0.14
	(**−2.76**)	(**−2.18**)	(−0.61)	(−0.62)	(−0.96)
$\widehat{AB}_{i,t-1}$		−0.62	−0.57	−0.52	−0.52
		(**−2.44**)	(**−2.23**)	(**−2.09**)	(**−2.09**)
$\widehat{AB}^{*}_{i,t-1} \times D_{ACC5,t-1}$			−0.58	−0.38	−0.38
			(−1.41)	(−0.90)	(−0.90)
SUE: SUE1 = quintile with lowest earnings surprises					
$D_{SUE1,t-1}$	−0.17	−0.06	−0.11	−0.11	−0.07
	(**−2.24**)	(−0.81)	(−1.18)	(−1.12)	(−0.69)
$\widehat{AB}_{i,t-1}$		−0.75	−0.87	−0.75	−0.75
		(**−3.02**)	(**−3.22**)	(**−2.84**)	(**−2.84**)
$\widehat{AB}^{*}_{i,t-1} \times D_{SUE1,t-1}$			0.28	0.25	0.25
			(0.96)	(0.79)	(0.79)

Table V. Robustness Tests

This table repeats the 5×5 independent sorts on credit rating and predicted analyst bias from Table III. Panel A reports portfolio returns adjusted for the Fama and French (1993), Carhart (1997), Hou, Xue, and Zhang (2015) factors, as well as returns characteristics-adjusted for size, book-to-market, and past-returns as in Daniel, Grinblatt, Titman, and Wermers (1997). Panel B sequentially sorts on credit rating and $\widehat{AB}$ (in both orders), before reporting equally weighted raw (first 6 columns) and Fama and French (2015)-adjusted portfolio returns (last column). Panel C reports raw (first 6 columns) and Fama and French (2015)-adjusted value-weighted portfolio returns (last column). Panel E reports equally weighted portfolio returns from triple independent sorts on market capitalization (below and above median), $\widehat{AB}$ (quintiles), and credit rating (quintiles). All returns are in percentages.

Panel A: Risk-adjusted portfolio returns

Rating Group	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)					
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1 - \widehat{AB}5$
Fama and French (1993) 3-factor adjusted portfolio returns						
CR1	0.11	0.09	0.18	−0.05	−0.44	0.55
	(1.21)	(1.02)	(1.71)	(−0.40)	(−1.80)	(1.95)
CR2	0.13	0.11	0.11	−0.10	−0.19	0.32
	(1.09)	(1.02)	(0.99)	(−0.73)	(−0.84)	(1.15)
CR3	−0.01	0.01	0.06	−0.08	−0.40	0.39
	(−0.05)	(0.04)	(0.53)	(−0.56)	(−1.80)	(1.38)
CR4	0.02	−0.08	0.08	−0.33	−0.48	0.50
	(0.07)	(−0.43)	(0.52)	(**−2.13**)	(**−2.00**)	(1.45)
CR5	0.75	0.11	−0.23	−0.64	−1.08	1.83
	(1.75)	(0.36)	(−0.85)	(**−2.93**)	(**−3.80**)	(**3.61**)
CR1−CR5	−0.63	−0.02	0.41	0.59	0.64	
	(−1.49)	(−0.08)	(1.38)	(**2.68**)	(**2.12**)	
Carhart (1997) 4-factor adjusted portfolio returns						
CR1	0.02	0.11	0.30	0.13	−0.06	0.08
	(0.23)	(1.19)	(**3.05**)	(1.12)	(−0.29)	(0.35)
CR2	−0.03	0.11	0.19	0.08	0.20	−0.23
	(−0.25)	(0.99)	(1.68)	(0.70)	(1.11)	(−1.11)
CR3	−0.13	−0.01	0.10	0.10	0.03	−0.16
	(−0.88)	(−0.09)	(0.83)	(0.76)	(0.18)	(−0.77)
CR4	−0.16	−0.11	0.14	−0.13	0.01	−0.17
	(−0.71)	(−0.63)	(0.96)	(−0.92)	(0.06)	(−0.66)
CR5	0.63	0.17	−0.15	−0.29	−0.47	1.10
	(1.49)	(0.53)	(−0.57)	(−1.59)	(**−2.41**)	(**2.44**)
CR1−CR5	−0.61	−0.06	0.45	0.42	0.41	
	(−1.46)	(−0.20)	(1.53)	(**1.99**)	(1.39)	
Hou, Xue, and Zhang (2015) q-factor adjusted portfolio returns						
CR1	−0.16	−0.13	0.12	−0.09	−0.27	0.11
	(−1.95)	(−1.52)	(0.98)	(−0.62)	(−1.00)	(0.38)
CR2	−0.15	−0.09	−0.02	−0.02	0.16	−0.31
	(−1.41)	(−0.81)	(−0.18)	(−0.10)	(0.68)	(−1.17)
CR3	−0.25	−0.18	−0.07	−0.10	−0.08	−0.17
	(−1.66)	(−1.34)	(−0.53)	(−0.63)	(−0.35)	(−0.64)
CR4	−0.33	−0.39	−0.01	−0.24	0.05	−0.38
	(−1.51)	(**−2.26**)	(−0.06)	(−1.44)	(0.23)	(−1.22)
CR5	0.75	0.20	−0.11	−0.25	−0.27	1.02
	(1.77)	(0.61)	(−0.41)	(−1.12)	(−1.06)	(**2.15**)
CR1−CR5	−0.91	−0.33	0.23	0.15	0.00	
	(**−2.19**)	(−1.03)	(0.78)	(0.73)	(0.01)	

Table V. (continued)

Rating Group	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)					
Daniel, Grinblatt, Titman, and Wermers (1997) characteristics-adjusted returns						
CR1	−0.03	0.03	0.13	0.09	−0.13	0.10
	(−0.30)	(0.31)	(1.39)	(0.73)	(−0.60)	(0.40)
CR2	0.00	−0.02	0.03	0.03	0.07	−0.07
	(0.03)	(−0.14)	(0.32)	(0.30)	(0.39)	(−0.28)
CR3	−0.12	−0.03	0.02	0.03	−0.05	−0.07
	(−0.88)	(−0.25)	(0.15)	(0.29)	(−0.32)	(−0.28)
CR4	0.09	−0.15	0.13	−0.15	0.02	0.08
	(0.45)	(−0.90)	(1.01)	(−1.21)	(0.08)	(0.28)
CR5	0.90	0.36	−0.08	−0.22	−0.46	1.36
	(**2.14**)	(1.18)	(−0.35)	(−1.32)	(**−2.11**)	(**2.88**)
CR1−CR5	−0.93	−0.33	0.21	0.30	0.33	
	(**−2.20**)	(−1.04)	(0.80)	(1.55)	(1.23)	

Rating Group	Raw Returns: $\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	FF (2015) portf. alpha $\widehat{AB}1-\widehat{AB}5$
	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)						
Panel B: Sequential sort on credit rating, CR, and $\widehat{AB}_{t-1}$							
Sequential sort on credit rating, CR, and then on $\widehat{AB}_{t-1}$							
CR1	0.85	0.85	0.99	1.03	1.02	−0.17	−0.00
	(**3.86**)	(**4.05**)	(**4.41**)	(**4.21**)	(**3.39**)	(−0.81)	(−0.00)
CR2	0.93	0.98	1.10	1.11	1.16	−0.23	−0.17
	(**3.90**)	(**4.38**)	(**4.52**)	(**4.14**)	(**3.53**)	(−0.95)	(−0.77)
CR3	0.93	1.02	1.10	1.20	1.07	−0.15	0.06
	(**3.34**)	(**3.74**)	(**3.94**)	(**3.84**)	(**2.76**)	(−0.55)	(0.26)
CR4	1.02	1.19	1.01	1.12	0.99	0.03	0.14
	(**3.08**)	(**3.69**)	(**2.87**)	(**2.82**)	(**1.99**)	(0.09)	(0.48)
CR5	1.47	0.95	0.85	0.49	0.43	1.04	1.20
	(**3.31**)	(**2.13**)	(1.72)	(0.91)	(0.69)	(**2.34**)	(**2.89**)
CR1−CR5	−0.62	−0.10	0.14	0.53	0.59		
	(−1.78)	(−0.29)	(0.36)	(1.28)	(1.31)		
Sequential sort on $\widehat{AB}_{t-1}$ *and then on credit rating, CR*							
CR1	0.76	0.88	1.12	1.00	1.06	−0.29	−0.04
	(**3.64**)	(**4.00**)	(**4.57**)	(**3.57**)	(**2.94**)	(−1.06)	(−0.18)
CR2	1.04	0.91	1.03	1.16	1.08	−0.15	0.41
	(**4.62**)	(**3.83**)	(**3.83**)	(**3.68**)	(**2.44**)	(−0.46)	(1.55)
CR3	0.80	1.12	1.15	1.11	0.83	0.26	0.51
	(**3.11**)	(**4.47**)	(**4.24**)	(**3.10**)	(1.70)	(0.64)	(1.66)
CR4	0.94	1.06	1.33	1.08	0.81	0.14	0.39
	(**3.28**)	(**3.67**)	(**4.27**)	(**2.80**)	(1.42)	(0.31)	(1.26)
CR5	1.24	1.15	1.06	0.81	0.24	1.00	1.17
	(**3.24**)	(**3.22**)	(**2.61**)	(1.72)	(0.35)	(**2.05**)	(**2.44**)
CR1−CR5	−0.48	−0.28	0.06	0.20	0.82		
	(−1.67)	(−1.15)	(0.19)	(0.63)	(1.70)		

Table V. (continued)

Rating Group	Raw Returns: Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High) $\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	FF (2015) portf. alpha $\widehat{AB}1-\widehat{AB}5$
Panel C: Value-weighted portfolio returns (independent sort on $\widehat{AB}$ and CR)							
CR1	0.69	0.85	0.98	0.93	0.84	−0.15	−0.06
	(**3.13**)	(**3.87**)	(**3.74**)	(**2.96**)	(**2.08**)	(−0.45)	(−0.21)
CR2	0.89	0.78	0.94	0.91	0.91	−0.02	0.07
	(**3.49**)	(**2.94**)	(**3.31**)	(**2.78**)	(**2.22**)	(−0.07)	(0.22)
CR3	0.89	0.96	0.97	1.00	0.68	0.21	0.59
	(**2.66**)	(**3.65**)	(**3.38**)	(**3.03**)	(1.68)	(0.59)	(1.67)
CR4	1.21	0.96	1.30	0.74	0.96	0.25	0.33
	(**2.57**)	(**2.68**)	(**3.43**)	(1.86)	(**2.07**)	(0.66)	(0.80)
CR5	1.70	1.18	0.93	0.25	0.41	1.29	1.36
	(**2.78**)	(**2.06**)	(1.70)	(0.48)	(0.72)	(**2.28**)	(**2.57**)
CR1−CR5	−1.01	−0.32	0.05	0.68	0.43		
	(−1.82)	(−0.68)	(0.11)	(1.73)	(0.97)		
Panel D: Raw returns by market capitalization							
Small firms							
CR1	0.56	1.20	1.11	1.20	0.67	−0.12	0.20
	(1.69)	(**5.02**)	(**4.07**)	(**3.28**)	(0.98)	(−0.09)	(0.41)
CR2	0.82	1.06	1.12	1.01	1.05	−0.23	−0.16
	(**3.00**)	(**4.23**)	(**4.12**)	(**3.12**)	(**2.60**)	(−0.59)	(−0.44)
CR3	0.76	0.96	1.16	1.09	1.20	−0.44	−0.25
	(**2.30**)	(**3.15**)	(**3.98**)	(**3.23**)	(**2.79**)	(−1.41)	(−0.94)
CR4	1.16	0.89	1.30	1.05	1.18	−0.01	0.08
	(**2.87**)	(**2.60**)	(**3.75**)	(**2.86**)	(**2.41**)	(0.03)	(0.12)
CR5	2.21	1.40	1.13	1.04	0.97	1.24	1.25
	(**3.46**)	(**2.65**)	(**2.40**)	(**2.31**)	(1.80)	(1.92)	(**2.13**)
CR1−CR5	−1.65	−0.20	−0.02	0.15	−0.30		
	(−**2.05**)	(−0.55)	(−0.04)	(0.49)	(−0.07)		
Big firms							
CR1	0.84	0.91	1.07	0.98	0.96	−0.12	0.03
	(**3.94**)	(**4.04**)	(**4.24**)	(**3.24**)	(**2.39**)	(−0.33)	(0.11)
CR2	0.99	1.00	1.00	1.04	1.01	−0.02	0.12
	(**4.18**)	(**4.21**)	(**3.70**)	(**3.30**)	(**2.32**)	(0.02)	(0.40)
CR3	0.89	0.93	0.98	0.99	0.61	0.28	0.39
	(**3.01**)	(**3.44**)	(**3.34**)	(**2.78**)	(1.39)	(0.81)	(1.15)
CR4	0.95	1.11	0.83	0.59	0.95	0.01	−0.05
	(**2.19**)	(**2.93**)	(**2.02**)	(1.36)	(1.67)	(0.19)	(−0.08)
CR5	2.15	−0.04	1.42	−0.36	0.37	1.78	1.56
	(**2.30**)	(−0.04)	(1.66)	(−0.46)	(0.46)	(1.75)	(1.74)
CR1−CR5	−1.32	0.95	−0.35	1.34	0.59		
	(−1.35)	(1.19)	(−0.35)	(**2.25**)	(1.02)		

Table VI. Impact of Retail Investors and Strategic Analysts on the Analyst Bias-Return Relation
Panel A presents returns (%) from triple independent sorts on the number of strategic analysts covering the firm (zero or at least one), $\widehat{AB}$ (quintiles), and credit rating (quintiles). A strategic analyst is one who provides a relatively optimistic recommendation (i.e. above consensus) and a relatively pessimistic EPS forecast (below consensus). The analysis is restricted to firms with at least two analysts. The strategic variable, calculated from daily I/B/E/S data, is lagged one month relative to returns. Panel B presents returns (%) from triple independent sorts on institutional ownership (below and above median), $\widehat{AB}$, and credit rating. Institutional ownership, measured as the fraction of shares outstanding held by institutions, is lagged 4 to 6 months relative to returns, to account for the quarterly 13F SEC filings.

Rating Group	Raw Returns: Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High) $\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	FF (2015) portf. alpha $\widehat{AB}1-\widehat{AB}5$
Panel A: Raw returns by relative weight of strategic analysts							
Firms with zero strategic analysts							
CR1	0.89	0.82	0.77	1.00	0.45	0.53	0.64
	(**3.96**)	(**3.55**)	(**2.70**)	(**2.89**)	(0.95)	(1.29)	(1.63)
CR2	0.88	1.01	1.06	0.94	0.56	0.33	0.45
	(**3.43**)	(**4.08**)	(**3.75**)	(**2.90**)	(1.17)	(0.82)	(1.27)
CR3	0.96	1.20	0.81	1.09	0.89	0.03	0.40
	(**2.78**)	(**3.69**)	(**2.59**)	(**2.85**)	(1.85)	(0.06)	(0.93)
CR4	1.40	1.03	1.43	1.19	0.90	0.50	0.46
	(**3.14**)	(**2.62**)	(**3.96**)	(**3.03**)	(1.71)	(1.07)	(1.03)
CR5	2.20	1.42	0.84	1.03	0.95	1.50	1.81
	(**2.81**)	(**2.21**)	(1.36)	(1.86)	(1.50)	(1.78)	(**2.23**)
CR1−CR5	−1.33	−0.59	−0.02	0.00	−0.73		
	(−1.78)	(−1.04)	(−0.04)	(0.01)	(−1.25)		
Firms with at least one strategic analyst							
CR1	0.79	0.88	1.17	1.00	1.04	−0.23	−0.22
	(**3.25**)	(**3.38**)	(**4.01**)	(**2.85**)	(**2.05**)	(−0.51)	(−0.53)
CR2	1.09	0.96	1.23	0.86	1.09	0.02	−0.08
	(**3.78**)	(**3.48**)	(**3.79**)	(**2.39**)	(**2.27**)	(0.04)	(−0.20)
CR3	0.72	0.93	1.27	1.04	1.19	−0.45	−0.41
	(1.87)	(**2.75**)	(**3.88**)	(**2.75**)	(**2.43**)	(−1.03)	(−1.00)
CR4	0.47	1.36	1.05	0.49	1.17	−0.54	−0.44
	(0.92)	(**3.18**)	(**2.50**)	(1.06)	(**2.10**)	(−1.04)	(−0.90)
CR5	2.19	1.12	1.29	0.15	−0.16	1.99	1.88
	(**2.59**)	(1.29)	(1.76)	(0.26)	(−0.26)	(**2.43**)	(**2.35**)
CR1−CR5	−1.17	−0.12	−0.08	0.84	1.14		
	(−1.50)	(−0.16)	(−0.12)	(**1.96**)	(**2.11**)		
Panel B: Raw returns by level of institutional ownership							
Firms with higher retail ownership							
CR1	0.92	0.87	1.06	1.01	1.21	−0.28	−0.26
	(**4.44**)	(**4.09**)	(**4.31**)	(**3.36**)	(**2.84**)	(−0.76)	(−0.72)
CR2	0.86	1.02	0.95	0.92	1.11	−0.25	−0.54
	(**3.67**)	(**4.45**)	(**3.78**)	(**2.86**)	(**2.62**)	(−0.59)	(−1.47)
CR3	0.66	1.15	1.20	0.95	0.81	−0.15	0.06
	(**1.97**)	(**4.24**)	(**4.76**)	(**3.05**)	(1.84)	(−0.34)	(0.17)
CR4	1.18	1.25	1.05	0.88	1.26	−0.08	−0.26
	(**2.21**)	(**3.20**)	(**2.76**)	(**2.25**)	(**2.33**)	(0.14)	(−0.49)
CR5	2.17	2.16	1.49	1.06	0.76	1.41	1.29
	(**3.33**)	(**3.21**)	(**2.87**)	(**2.15**)	(1.35)	(**2.08**)	(**2.33**)
CR1−CR5	−1.24	−1.29	−0.43	−0.05	0.45		
	(−1.89)	(**−2.18**)	(−0.84)	(−0.15)	(0.88)		
Firms with higher institutional ownership							
CR1	0.69	1.00	1.14	0.77	0.57	0.12	0.65
	(**2.85**)	(**3.91**)	(**4.11**)	(**2.30**)	(0.88)	(0.19)	(1.18)
CR2	0.98	0.95	1.20	1.05	1.12	−0.14	0.32
	(**3.75**)	(**3.55**)	(**3.96**)	(**3.10**)	(**2.51**)	(−0.38)	(1.03)
CR3	1.09	0.80	0.98	1.09	1.08	0.02	0.31
	(**3.57**)	(**2.67**)	(**3.09**)	(**3.04**)	(**2.50**)	(0.05)	(1.04)
CR4	0.98	0.78	1.18	0.87	1.03	−0.05	0.17
	(**2.54**)	(**2.24**)	(**3.47**)	(**2.28**)	(**2.13**)	(−0.09)	(0.40)
CR5	1.52	0.93	0.83	0.67	0.85	0.67	0.35
	(**2.20**)	(1.57)	(1.48)	(1.36)	(1.45)	(0.59)	(0.40)
CR1−CR5	−0.83	0.07	0.31	0.11	−0.28		
	(−1.32)	(0.15)	(0.64)	(0.23)	(−0.38)		

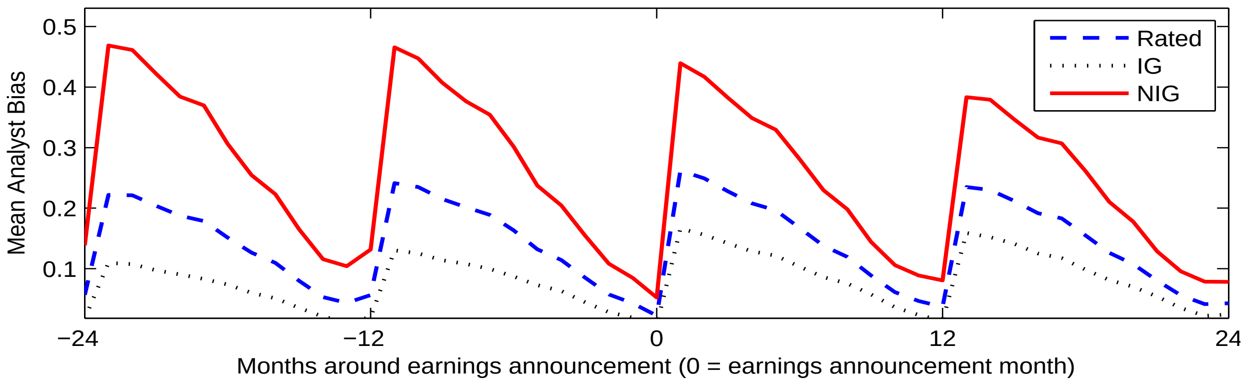
Table VII. Robustness Tests: Alternative Credit Risk Proxy

We sort all stocks (rated and unrated) into 5 × 5 portfolios independently sorted on lagged $\widehat{AB}$ and failure probability, FP, calculated as in Campbell, Hilscher, and Szilagyi (2008). $\widehat{AB}$ is computed for all stocks with each month's FP quintile dummies (omitting FP5 included in the constant), instead of credit rating dummies. The failure probability and $\widehat{AB}$ breakpoints in Panels A, B, and C are the same and based on all firms (rated and unrated). FP1 (FP5) is the quintile with the lowest (highest) failure probability. The table report the time-series average equally weighted portfolio returns (%), return spreads, and 5-factor alpha spreads, along with sample t-statistics in parentheses.

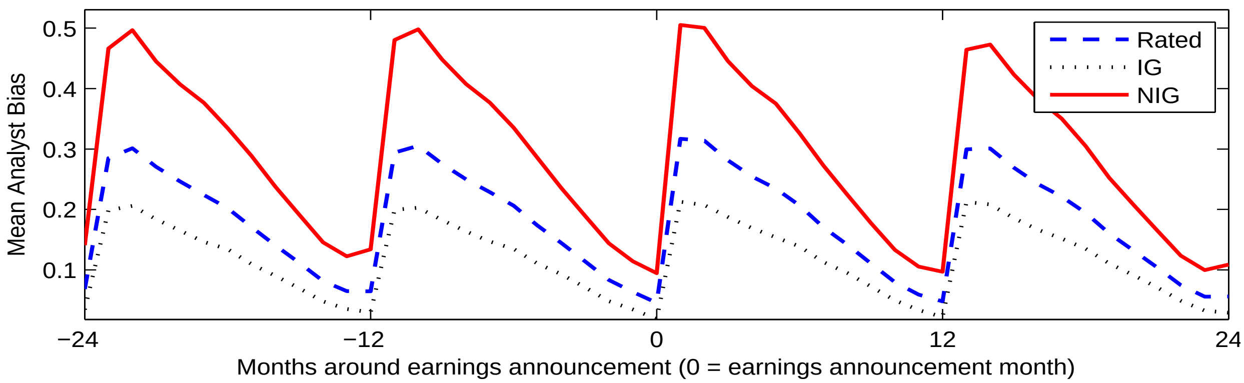
Uncertainty Groups	Bias Quintiles ($\widehat{AB}1$=Low, $\widehat{AB}5$=High)						FF 5-factor
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
Panel A: All stocks							
FP1	0.91	0.84	0.93	0.86	0.48	0.43	0.61
	(**3.88**)	(**3.40**)	(**3.18**)	(**2.69**)	(1.19)	(1.54)	(**2.46**)
FP2	0.95	0.97	1.03	0.96	0.69	0.25	0.45
	(**3.91**)	(**3.80**)	(**3.66**)	(**2.95**)	(1.71)	(0.90)	(1.83)
FP3	1.14	1.11	1.06	0.87	0.79	0.35	0.55
	(**4.26**)	(**4.31**)	(**3.64**)	(**2.72**)	(**2.04**)	(1.38)	(**2.43**)
FP4	1.24	1.34	1.28	0.98	0.85	0.39	0.30
	(**3.41**)	(**4.28**)	(**3.84**)	(**2.69**)	(**2.06**)	(1.45)	(1.19)
FP5	1.76	0.98	0.89	0.87	0.51	1.25	1.56
	(**3.58**)	(**2.16**)	(1.89)	(1.77)	(0.94)	(**3.18**)	(**4.13**)
FP1−FP5	−0.84	−0.13	0.04	−0.01	−0.02		
	(−**2.44**)	(−0.45)	(0.14)	(−0.05)	(−0.08)		
Panel B: Unrated stocks							
FP1	0.98	0.80	0.91	0.79	0.42	0.56	0.75
	(**3.53**)	(**2.94**)	(**2.92**)	(**2.36**)	(0.99)	(1.93)	(**2.78**)
FP2	1.13	1.03	1.00	0.94	0.74	0.39	0.58
	(**3.70**)	(**3.46**)	(**3.20**)	(**2.78**)	(1.74)	(1.35)	(**2.09**)
FP3	1.24	1.27	1.09	0.79	0.69	0.55	0.75
	(**3.83**)	(**4.16**)	(**3.35**)	(**2.34**)	(1.72)	(1.95)	(**2.84**)
FP4	1.49	1.47	1.42	0.98	0.82	0.67	0.50
	(**3.54**)	(**4.17**)	(**3.96**)	(**2.61**)	(**2.00**)	(**2.15**)	(1.66)
FP5	1.82	0.84	1.02	0.85	0.54	1.28	1.58
	(**3.27**)	(1.72)	(**2.07**)	(1.71)	(1.02)	(**2.91**)	(**3.65**)
FP1−FP5	−0.84	−0.04	−0.11	−0.06	−0.12		
	(−**2.10**)	(−0.10)	(−0.34)	(−0.20)	(−0.39)		
Panel C: Rated stocks							
FP1	0.82	0.94	0.99	0.89	0.69	0.14	0.19
	(**3.97**)	(**4.04**)	(**3.40**)	(**2.55**)	(1.30)	(0.36)	(0.46)
FP2	0.78	0.92	1.05	0.98	0.50	0.28	0.59
	(**3.52**)	(**3.82**)	(**3.91**)	(**2.84**)	(1.13)	(0.78)	(1.87)
FP3	1.07	0.96	1.08	0.94	0.97	0.11	0.39
	(**4.12**)	(**3.90**)	(**3.83**)	(**2.91**)	(**2.39**)	(0.35)	(1.41)
FP4	0.98	1.21	1.12	1.01	0.81	0.17	0.23
	(**2.71**)	(**3.87**)	(**3.41**)	(**2.66**)	(1.79)	(0.52)	(0.75)
FP5	1.65	1.38	0.69	0.93	0.36	1.29	1.43
	(**2.96**)	(**2.72**)	(1.39)	(1.70)	(0.61)	(**2.55**)	(**2.78**)
FP1−FP5	−0.83	−0.45	0.30	−0.04	0.32		
	(−1.74)	(−1.12)	(0.88)	(−0.09)	(0.89)		

Figure I. Analyst bias around 10K earnings announcements
The figure presents the average analyst bias in 48 event-time months centered around the most recent 10K announcement at the graph's midpoint. The three lines correspond to average analyst bias for firms with credit ratings, as well as for investment-grade (IG) and non-investment-grade (NIG) firms. Panel A reports *ex post* analyst bias, AB, Panel B presents predicted analyst bias, $\widehat{AB}$, and Panel C reports cycle-adjusted analyst bias, $\widehat{AB}^{CA}$.

Plot A: *Ex post* analyst bias: AB



Plot B: Predicted analyst bias: $\widehat{AB}$



Plot C: Cycle-adjusted analyst bias: $\widehat{AB}^{CA}$

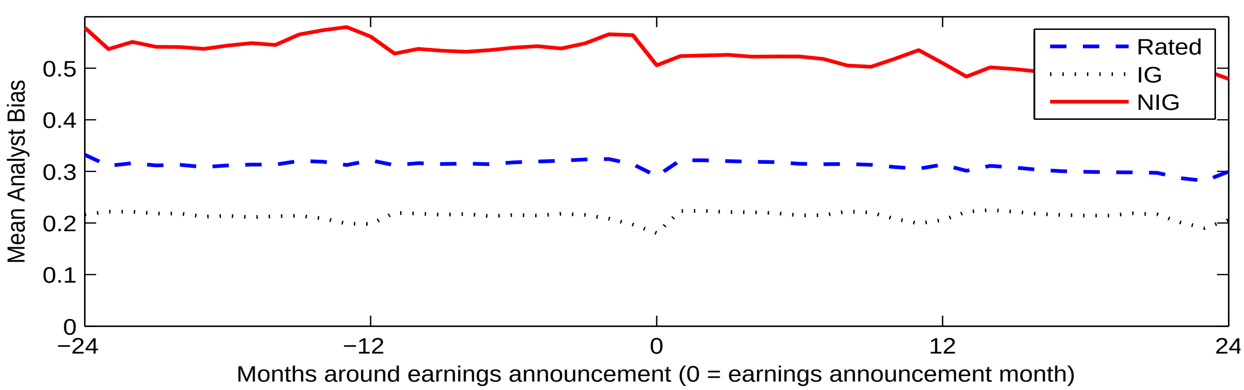
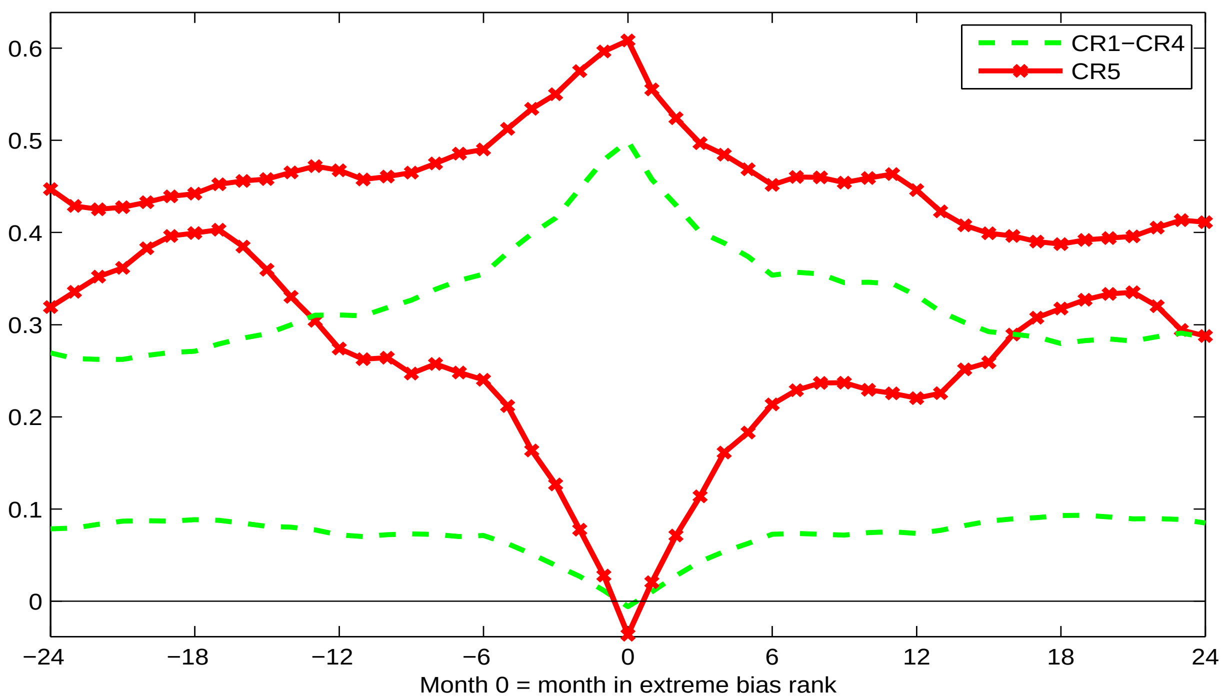


Figure II. Analyst bias around extreme bias ranks.
The figure presents, in event time, mean predicted analyst bias (Plot A), or cycle-adjusted analyst bias (Plot B), around month 0 in which a firm is in the lowest (two bottom lines) or highest (two top lines) analyst bias quintile.

Plot A: Predicted analyst bias ($\widehat{AB}$)



Plot B: Cycle-adjusted analyst bias (cycle-specific $\widehat{AB}$)