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ABSTRACT

Cross-sectional forecasts of conservative and optimistic biases in analyst earnings estimates predict a stock's future returns, especially for firms that are hard to value. Trading strategies—whether based on the component of analyst bias that is correlated with major return anomalies or the component that is orthogonal to these anomalies—earn abnormal profits. The prevalence of optimistic analyst earnings estimates and rarity of conservative estimates emerges as a common link between anomaly-generating firm characteristics and subsequent negative alphas. For the vast majority of anomaly strategies, profitability disappears once we control for analyst bias.

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A large body of research ties cross-sectional stock return differences to characteristics for which high uncertainty, and often high risk, signals low returns. These characteristic-based return signals are used to generate long-short "anomaly investment strategies." The characteristics include credit risk (Dichev 1998), past returns (Jegadeesh and Titman 1993), earnings surprises (Ball and Brown 1968), asset growth (Cooper, Gulen, and Schill 2008), analyst forecast dispersion (Diether, Malloy, and Scherbina 2002), gross profitability (Novy-Marx 2013), and a whole zoo of other characteristics summarized in Hou, Xue, and Zhang (2020).

Heterogeneity in analyst forecast bias across stocks facilitates understanding of the puzzling links between average returns and these characteristics. Prior research documents that analyst earnings forecasts tend to be optimistic and their errors are predictable.[1] It also shows that forecast optimism increases with uncertainty (De Bondt and Thaler 1990; Das, Levine, and Sivaramakrishnan 1998). Considering that anomaly strategies profit mostly from stocks with low earnings predictability and high valuation complexity (Avramov, Chordia, Jostova, and Philipov 2013), we investigate the extent to which anomalies "disappear" once we control for the analyst biases associated with these stocks.

For almost all of the attributes listed above, predictable analyst forecast bias among hard-to-value ("HTV") stocks accounts for the anomaly strategy returns. In 5×5 sorts, the low returns of stocks identified as overvalued by each attribute occur primarily in the most optimistically forecasted quintiles. In less optimistically forecasted quintiles almost no anomaly yields significant profits; and, with most anomalies, the long-short strategy "backfires," producing negative payoffs for stock quintiles with the most predictably conservative earnings estimates. Moreover, in cross-sectional regressions of future returns on the anomaly attribute or, separately, on our analyst bias regressors, the anomaly variable and analyst bias are statistically significant. However, when the anomaly and analyst bias regressors are included together in the regression, the anomaly variable is insignificant in all but one cases, while the interaction between a hard-to-value dummy and analyst bias is always significant.

[1] See De Bondt and Thaler (1990), Frankel and Lee (1998), Linnainmaa, Torous, and Yae (2016), and Abarbanell and Lehavy (2003), among others.

We decompose analyst bias into two components, both with similar efficacy at return prediction. The first component is orthogonal to the major anomaly characteristics. The second is correlated with anomalies. By construction, the orthogonal component of analyst bias cannot explain return anomalies generated by firm characteristics. Conversely, anomaly characteristics cannot explain the return prediction success of analyst bias's orthogonal component. By contrast, the anomaly-correlated component of analyst bias tends to be "the winning horse" in races between the analyst bias of hard-to-value stocks and anomalies as return predictors. For example, of the six aforementioned anomalies, only one significantly predicts returns once the correlated component of analyst bias is controlled for. In all cases, however, the anomaly-correlated component of analyst bias, like its orthogonal sibling, significantly predicts returns despite controls for the characteristic-based anomalies.

For the 20% hardest-to-value stocks, the persuasion of analysts, even when biased, is likely to be more salient. Accordingly, alpha spreads within this stock category, which most likely arise from convergence to fair value, stand out for the size of the economic effect. Here, 5-factor Fama and French (2015) alpha spreads between the least and most optimistically forecasted quintiles of HTV stocks are between 1.1% and 1.2% per month. These magnitudes are not a small-stock phenomenon as the quintiles are value weighted. Finally, the spread is about the same, irrespective of whether bias quintiles are formed from the correlated or orthogonal components of analyst bias.

These results offer a parsimonious and nuanced view of characteristic-based stock return anomalies. Prior research documents that anomaly strategy profits derive mostly from the strategy's short leg (Stambaugh, Yu, and Yuan 2012; Avramov, Chordia, Jostova, and Philipov 2013). Such findings motivate short sales frictions that deter arbitrageurs from correcting inflated prices as an explanation for the anomaly and the asymmetry between the profitability of its long and short legs. However, analyst bias also accounts for additional return variation that is separate from its correlation with the anomaly characteristic. In particular, when analysts are relatively conservative, stocks in the anomaly's short leg tend to earn high returns, even though the anomaly characteristic predicts a low return. Thus, analyst bias contains a previously undiscovered "buy" signal within the short leg of anomaly strategies.[2] The most likely explanation for these findings is that analyst opinions about hard-to-value stocks persuade investors to make positive valuation mistakes when analyst consensus is optimistic and negative valuation mistakes when analyst consensus is conservative. Persuasion does not occur with stocks that are simpler to value.

For most anomalies, analyst optimism is vastly more prevalent among stocks in the strategy's short leg. Typically, these stocks are also more difficult to value than the stocks in the long leg. Thus, when the anomaly characteristic signals a short sale, it is relatively more likely to be a stock with analyst optimism that can persuade investors to overvalue the stock. This dual and correlated abundance—of both optimism bias and valuation complexity—explains why abnormal returns tend to concentrate in the short leg of characteristic-based strategies.

Take the credit rating anomaly, for which worse-rated stocks earn lower returns. The mean 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. Within the short leg of the anomaly strategy, firms with the most optimistic analyst bias significantly underperform other companies of similar risk, including other stocks in the strategy's short leg. Here, 5×5 independent portfolio sorts indicate that all of credit rating's explanatory power for returns is found in the relatively optimistic analyst earnings forecasts of the stocks the anomaly strategy sells short rather than credit risk *per se*. This result generalizes to 5×5 sorts of analyst bias with many other anomaly characteristics. Indeed, for all the major anomalies studied with 5×5 sorts, the 20% most optimistically forecasted stocks in the short leg stands out as the worst-performing portfolio or ranks very close to the worst performing portfolio among all 25 portfolios in the double sort. By contrast, again within the *short side*, relatively conservative analyst forecasts tend to earn superior returns. For 2/3 of the anomalies studied with 5×5 sorts, firms in the short leg (e.g., the highest-credit-risk, lowest momentum, highest dispersion, most negative earnings surprise) with the most conservative earnings forecasts outperform each of the remaining 24 portfolios in the 5×5 sort.

[2] Veenman and Verwijmeren (2018) study conservative forecasts just prior to earnings announcements.

While no correlational study can demonstrate causality, our findings are consistent with the plausible hypothesis that stock prices are distorted by investors who rely on predictably inaccurate forecasts by "experts." There is extensive empirical evidence that investors follow analysts' reports and overweight incorrect analyst opinions (rather than analysts and investors making correlated mistakes).[3] A simple model of this phenomenon can generate our empirical results. In the paper's model, investors fail to de-bias earnings forecasts until confronted with contradictory information. When uncertainty is high and earnings are hard to predict, the lack of alternative information signals makes investors receptive to (biased) analyst forecasts. As earnings are reported and news about the firm arrives, investors reduce their reliance on analysts, thereby decreasing the stock price distortion arising from the biased forecasts.

Our paper also offers several econometric insights. First, it explains why analyst bias must be predicted *ex ante*, as the *ex post* bias spuriously correlates inversely with returns. Second, we prove that *ex ante* direct estimation of the bias generates asymptotically consistent estimates of the return-predicting coefficients of true bias. This econometric contribution highlights potential pitfalls to indirect estimation of bias—e.g., using accounting variables to predict earnings and subtracting the prediction from the analyst EPS forecast to compute bias. We also prove that analyst bias computed with indirect estimation generates inconsistent estimates of the return-predicting coefficients of bias.

Despite extensive research on analyst bias and a few findings that link analyst forecasts to equity returns, the negative analyst bias-return relation is not promoted as a prominent asset pricing anomaly, nor regarded as a potential explanation for many anomalies. La Porta (1996) and Dechow and Sloan (1997) find that half of the value strategy's profitability derives from investors' naive reliance on analysts' extreme long-term growth forecasts. Abarbanell and Bernard (1992) show that analysts' underreaction to prior earnings contributes to the post earnings announcement drift. Teoh and Wong (2002) conjecture that analyst forecast

[3] Michaely and Womack (1999), Lim (2001), Chen and Jiang (2006), and Cowen, Groysberg, and Healy (2006) show analyst optimism is driven by their job-specific incentives, which investors do not share, rather than behavioral biases. Hence, investors and analysts are unlikely to make correlated mistakes from common signals. This is supported by La Porta (1996), Dechow and Sloan (1997), Jackson (2005), Mikhail, Walther, and Willis (2007), and So (2013), who find that investors naively benchmark to analyst forecasts.

errors predicted from accruals might explain the long-term underperformance of new issuers, but the conjecture is not tested empirically.

Perhaps most related to our work is research by Guo, Li, and Wei (2020) and Engelberg, McLean, and Pontiff (2020) who find that analysts' buy-sell recommendations tend to concur with trade signals from one anomaly group, while disagreeing with signals from the other. Guo, Li, and Wei (2020) also show that anomaly profits remain significant when controlling for analyst recommendations, and that disagreements between recommendations and anomaly signals enhance anomaly spreads in one of the groups. Engelberg, McLean, and Pontiff (2020) document that target-price signals are most inflated, as measured by *ex post* price forecast errors, among anomaly shorts and often contradict the buy-sell recommendation signal for the same stock. As one key difference, we derive a component of analyst bias that is orthogonal to anomalies and show that it negatively correlates with future returns. More importantly, our study offers a unifying theme that ties consensus *ex ante* EPS forecast bias to anomaly strategy profitability—for almost all anomalies.

Specifically, controlling for analyst bias's effect on *HTV* firms' returns erases the joint significance of five of the six aforementioned anomalies, with asset growth the exception. In addition to the six anomalies, the paper's cross-sectional regressions investigate the role of analyst bias in 60 anomalies studied by Hou, Xue, and Zhang (2020). Many of these anomalies—10 for each of their broad categories of Momentum, Value vs. Growth, Profitability, Investment, Intangibles, and Trading Frictions—are highly correlated with the former six. Analyst bias is almost universally a significant predictor of returns when controlling for each of the 60 anomaly characteristics. However, the reverse is not true. About 80% of the 60 anomalies have no significant ability to predict returns after controlling for the analyst bias of hard-to-value stocks. Similar to asset growth, 6 of the 13 exceptions are investment anomalies. These findings are robust to alternative specifications.

To summarize our contribution, we show that (1) predictable biases in earnings forecasts, both conservative and optimistic, and whether correlated or uncorrelated with anomalies, signal abnormal returns, but only for firms that are hard to value, (2) the profitability of most anomaly strategies largely disappears once we account for analyst bias, (3) the prevalence of analyst optimism (and rarity of analyst pessimism) among firms in the short leg of anomalies underlies (most) anomaly profitability, (4) a simple stylized behavioral model can rationalize the data pattern observed, and (5) there are econometric pitfalls when estimating the role of analyst bias in return anomalies and we offer methods to overcome them.

I. Data and Methodology

Each month t includes stock i in a trading strategy based on portfolio sorts or cross-sectional regressions. Trades employ month $t-1$ signals from bias estimates for stock i's I/B/E/S consensus earnings forecast and other firm characteristics.

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.[4] We exclude stocks that lack a month $t-1$ share price at or above $1, a month t CRSP return,[5] 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,[6] and the Compustat and I/B/E/S variables needed to calculate the predicted analyst biases described below. These requirements generate a sample of 245,310 firm-month observations with an average of 815 firms per month and a total of 2,634 firms over the sample period. The need for both an S&P credit rating and an I/B/E/S forecast skews our sample towards larger firms. For example, market capitalization averages $1.23 billion in the lowest credit rating quintile, which contains the smallest firms.

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

[5]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).

[6]A firm's credit rating is S&P's long-term issuer credit rating as listed in Compustat or WRDS Credit Ratings when missing from Compustat. S&P states "long-term issuer credit rating is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations." When we average credit ratings across firms, the 22 S&P letter ratings convert 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; BB+ to D are non-investment grade.

Calculation of anomaly-based characteristics The six major anomalies we study: credit risk (S&P credit rating, Dichev 1998), past six-month returns (Jegadeesh and Titman 1993), earnings surprises (SUE, Ball and Brown 1968), asset growth (Cooper, Gulen, and Schill 2008), analyst forecast dispersion (Diether, Malloy, and Scherbina 2002), and gross profitability (Novy-Marx 2013), are calculated as per their original paper. The labels and calculations for the 60 additional anomalies follow directly from Hou, Xue, and Zhang (2020).

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:

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

where EPS_i^T is firm i's actual EPS for the fiscal year FY1 (ultimately announced in month T)[7] and $ConForecastEPS_{i,t}^T$ is the month t analyst consensus forecast of that annual EPS.[8] Assuming rational expectations, the prediction from this regression, or *ex ante* bias, is an appropriate substitute for the unmeasurable true bias (see Appendix). By contrast, *ex post* bias cannot be used to asses whether bias influences stock prices. An *ex post* bias measure that looks ahead at a firm's future earnings to compute bias could inversely correlate with future returns for reasons that have nothing to do with the analysts' optimism for a stock—but

[7]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. To prevent small positive and negative values of actual EPS from unduly affecting our inferences, we also exclude *ex post* bias observations that are outside the 1st and 99th percentiles for the sample. We similarly censor other variables with obvious outliers.

[8]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.

rather, because future returns are leading indicators of future realized earnings.

Predicted analyst bias comes in two flavors. The first, referred to as *anomaly-correlated analyst bias*, will be denoted as $\widehat{AB}$. This component estimates next period's analyst forecast error from a regression of historical analyst forecast errors on firm characteristics (with values known at the time of trade initiation), including many that generate return anomalies. The second, referred to as *anomaly-free* or *orthogonal analyst bias*, is denoted as $\widehat{AB}^{\perp Z}$. This second component is constructed to be perfectly orthogonal to the set of major characteristics $\mathbf{Z}$, outlined in the paper's opening paragraph, that generate return anomalies. It comes from regressing historical analyst forecast errors on variables that are orthogonal to $\mathbf{Z}$.

The second bias prediction, $\widehat{AB}^{\perp Z}$, cannot assess whether analyst bias explains anomalies. An $\widehat{AB}^{\perp Z}$ that is orthogonal to anomaly vector $\mathbf{Z}$ does not alter the anomaly variables' coefficients when included in the same regression. However, this bias component can help assess whether anomaly-free bias distorts returns. We will learn that both the anomaly-correlated and anomaly-free analyst bias components predict future returns similarly, and that the former subsumes the return predictability of most anomalies. This suggests that analyst bias, and not the anomaly, is the root source of the anomaly's return predictability.

Anomaly-Correlated Analyst Bias Dropping time subscripts for notational simplicity, the regression that estimates the anomaly-correlated component of predicted analyst bias,

$$\begin{aligned}\widehat{AB}_i \;=\; & c_0 + c_1\, PastAB_i + c_2\, Dispersion_i + c_3\, Coverage_i \\ & + c_4\, PastRet_i^- + c_5\, PastRet_i^+ + c_6\, SUE_i^- + c_7\, SUE_i^+ \\ & + c_8\, D_{Small,i} + c_9\, D_{Value,i} + \mathbf{d}\, \mathbf{D}_{Rating,i} + \mathbf{e}\, \mathbf{D}_{Industry,i},\end{aligned} \tag{2}$$

employs regressors, some tied to return anomalies, 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 credit rating dummies ($\mathbf{D}_{Rating,i}$),[9] and industry dummies ($\mathbf{D}_{Industry,i}$) for 19 of the 20 industries in Moskowitz and Grinblatt (1999).[10] Extensive evidence of autocorrelation in analyst forecast errors justifies past analyst bias as a regressor;[11] prior research on bias prediction motivates the remaining variables.[12]

Eq. (2)'s prediction coefficients, $c_0, \ldots, c_9, \mathbf{d}, \mathbf{e}$, are estimated out of sample from 60-month rolling windows. Within each window, we run 12 separate panel regressions, each 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 bias forecast, obtained by multiplying the rolling-window-estimated coefficients by the latest available regressors.[13] 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. (2).

To illustrate, consider firm i's May 1996 analyst bias prediction. 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 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

[9]These indicate prior-month membership in one of 15 notched 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.

[10]Our conclusions are 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 the results.

[11]See Linnainmaa, Torous, and Yae (2016), Markov and Tamayo (2006), Abarbanell and Bernard (1992) and Ali, Klein, and Rosenfeld (1992), among others.

[12]See Das, Levine, and Sivaramakrishnan (1998), Larocque (2013), Ali, Klein, and Rosenfeld (1992), and Hughes, Liu, and Su (2008).

[13]Out-of-sample bias prediction requires that the first predicted analyst bias month be December 1991.

12 months prior to the month in which $\widehat{AB}_i$ is measured.[14] Our regression coefficients for the May 1996 forecast example would come from a data panel where firms' I/B/E/S forecast errors—used as the June 1990-May 1995 estimation period's dependent variable—are all 3 months after the announcement date of each firms' 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 diminishing analyst optimism bias 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, AB, 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 (IG) 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 are 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.

Figure I Plot B's *ex ante* anomaly-correlated bias, $\widehat{AB}$, exhibits event-time cyclicality that is similar to Plot A's *ex post* bias. Like Plot A, Plot B's NIG zeniths exceed those of IG firms.

Anomaly-Free Analyst Bias Anomaly-free analyst bias is constructed to be orthogonal to six major anomalies: credit risk, momentum, earnings surprise (SUE), dispersion, asset

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

growth, and gross profitability, which constitute **Z**. While far more than six anomalies exist, all that we study are largely spanned by the six used for orthogonalization. As with anomaly-correlated bias, anomaly-free analyst bias is computed from information available prior to month t and linked to returns in month $t+1$.

$\widehat{AB}_{it}^{\perp Z}$ is a linear combination of six predictor variables:

$$\widehat{AB}_{it}^{\perp Z} = \widehat{\gamma}_{0,t-12} + \sum_{j=1}^{6} \widehat{\gamma}_{t-12}^{j} * \widehat{\delta}_{it}^{j}. \tag{3}$$

Predictors δ^1, ..., δ^6 are constructed to be orthogonal to the six anomaly variables with projection. Coefficients $\gamma^1, \ldots, \gamma^6$, estimated by regressing 12-month lagged *ex post* bias on 12-month lags of the six orthogonalized variables are applied to the most recent orthogonalized variables at the time of strategy implementation. Firm i's δ_i^j is the residual from one of six cross-sectional regressions indexed by j, each with the six major anomaly regressors:

$$Y_{i,t}^{j} = b_t^j(0) + \sum_{m=1}^{6} b_t^j(m) Z_{i,t}^{m} + \delta_{i,t}^{j}, \tag{4}$$

where Y_i is one of six variables: firm i's *size-adjusted year-to-year change in the consensus forecast* [$(ConForecastEPS_y - ConForecastEPS_{y-1})$/AT per share], *accounts payable* [AP/AT], *cash* [CHE/AT], *current liabilities* [LCT/AT], and *net income* [NI/AT], each with book asset scaling AT in the denominator, as well as the *number of institutional owners* from Thomson Reuters.[15]

Figure I Plot C's *ex ante* anomaly-free bias, $\widehat{AB}^{\perp Z}$, exhibits event-time cyclicality that is similar to Plot A's *ex post* bias and Plot B's anomaly-correlated bias. Unlike Plots A and B, the zeniths of Plot C's NIG lines are about the same as those for IG firms. That is because, by construction, anomaly-free bias is orthogonal to credit risk, so any vertical deviations between the bias plots based on credit risk are likely to be small and due to random noise.

[15] Abbreviations reflect Compustat variable names, where applicable. Results are similar if instead of *net income*, we use *sales* [SALE], or *dividends* [DV], or *cost of goods sold* [COGS], or *property plant and equipment* [PPENT], as conditioning variables. All variables are winsorized at the 1st and 99th percentile.

Direct vs. Indirect Bias Estimation As an alternative to direct estimation of analyst bias, So (2013) indirectly measures bias as the consensus earnings forecast less an unbiased earnings estimate from observables that exclude the consensus forecast. However, if consensus forecasts offer incremental information for earnings estimation, So's (2013) earnings estimates will deviate from unbiased earnings estimated more precisely from a larger set—one containing both the econometrician's information and the consensus forecast's incremental information (Loudis 2019). Subtracting the less precise earnings estimate from the consensus forecast maintains the same deviation from indirect bias estimated with the better earnings forecast. The deviation appears as residual error in regressions of returns on the less precise indirect bias estimates. As the appendix proves, the residual correlates with the indirect bias regressor, as well as future returns generated by analyst bias—implying inconsistent estimation of the regression slope coefficient. Eq. (2) and (3)'s direct bias estimates lack this flaw.

Hard-to-Value Firms The paper's introduction argued that it is the joint prevalence of both analyst optimism and valuation complexity in one tail of each anomaly characteristic's distribution that explains many anomalies. For example, high credit risk firms tend to also have both high degrees of analyst optimism and valuation complexity. If analyst opinions, however biased, are persuasive when firms have high credit risk, their unwarranted optimism may temporarily inflate these firms' stock prices. Credit risk *per se* would then inversely correlate with subsequent returns as the inflation diminishes over time. This plausible hypothesis for what has been referred to as "the credit risk puzzle" arises only because high credit risk firms are harder to value and have overly optimistic earnings forecasts. This phenomenon extends to other proxies for valuation complexity, many anomaly-related.

In a given month, we define a firm as hard-to-value (HTV) if its stock belongs to the anomaly strategy's short leg tercile for at least 4 of 6 major anomaly attributes we focus on. This would be the highest tercile for credit risk, dispersion, and asset growth, but the lowest tercile for momentum, earning surprise (SUE), and gross profitability. On average, almost 20% of firms are in the tercile's short leg for at least 4 of the 6 anomaly attributes. This HTV

percentage matches the quintile categorization of extremes that is common in the literature. All other firms are referred to as easy-to-value (ETV).

Summary Statistics For five anomaly-correlated analyst bias quintiles $\widehat{AB}1$ to $\widehat{AB}5$ (left half) or five anomaly-free bias quintiles $\widehat{AB}_1^{\perp Z}$ to $\widehat{AB}_5^{\perp Z}$ (right half), Table I Panel A presents time-series averages of the monthly cross-sectional means of various firm characteristics.

Panel A's top row shows that the quintiles assigned by both bias predictions reflect overall optimism. $\widehat{AB}$'s most conservative quintile, $\widehat{AB}1$, has I/B/E/S earnings estimates overshooting actual earnings by an average of 0.59%; at the opposite extreme, $\widehat{AB}5$, I/B/E/S overshoots by a substantially larger 48.85%. The unreported *ex post* mean of 15.17% confirms the overall optimism. The top row's extreme quintile spread is also smaller in Panel A's right half, making average bias larger for its most conservative quintile (12.95%) and smaller for its most optimistic quintile (18.24%), compared to their left half counterparts. *Ex post* bias quintiles, not shown, exhibit a wider spread than row 1 shows for either bias prediction model. In its most conservative quintile, I/B/E/S under-predicts future earnings by an average 19%; its most optimistic over-predicts by 90%.

So which extreme quintile spread best reflects true bias's spread? And do the 20% most conservatively forecasted firms have biases that truly under-predict future earnings, as we contend? The true (i.e., best *ex ante*) bias's extreme quintile averages are unknown because (i) quintiles from bias prediction models rely on incomplete information and (ii) the distribution of *ex post* bias depends on more than bias heterogeneity. However, statistics principles suggest the true bias's quintile spread lies between the (*ex post*) spreads of quintiles formed from model-based *ex ante* bias predictions and quintiles formed from the *ex post* bias. For one, analysts make forecast errors even when bias is perfectly removed. Large errors show up in the extreme quintiles, artificially exaggerating the bias's spread. On the other hand, large sample bias estimates from imperfect bias models compress spreads compared to the best model. At one extreme, the poorest bias-prediction model cannot discriminate: it predicts the same mean-like or median bias for all firms to maximize fit. A less than perfect bias model discriminates, but like the poorest model, tilts estimates for firms with deservedly extreme bias towards interior values, compared to a superior model.

Another factor, *ex post* bias's positive skewness, also influences perceptions of overall optimism. The *ex post* bias's median of 0.23%, almost zero, is far less than its mean. Skewness shifts the *ex ante* models' relatively conservative quintiles toward optimism—more for anomaly-free than anomaly-correlated bias. This is because positive skewness makes the fit of right tail observations relatively more important than fits of other observations. Conservative quintiles exhibit greater shifts towards optimism with anomaly-free bias because its more constrained predictors lead to larger spread compression, as the prior paragraph noted.

In Panel A, the left half's extreme quintiles differ in attributes besides bias. The most optimistic quintile consists of smaller firms with larger book-to-market ratios, and lower past-6-month and next-month returns. At the same time, the most optimistically forecasted firms tend to have higher market risk in both the CAPM and Fama and French (2015) 5-factor models. Left-half CAPM betas average 1.50 for $\widehat{AB}5$ and 0.87 for $\widehat{AB}1$, while 5-factor market betas average 1.41 in $\widehat{AB}5$ and 1.01 in $\widehat{AB}1$. High-optimism firms also are relatively more sensitive to SMB and HML, warranting higher future returns. The RMW and CMA factor exposures are the only ones consistent with the most optimistically forecasted firms experiencing the lower next-month returns that they actually realize compared to other firms. Overall, the left half's risk factor pattern implies that raw return spreads understate risk-adjusted spreads, both with CAPM and 5-factor risk adjustment. Alpha rows confirm this.

High anomaly-correlated optimism bias also tends to concentrate in firms with difficult-to-forecast earnings. Compared to the most conservatively forecasted quintile, these high-optimism firms also have 40% less analyst coverage, over seven times more analyst forecast dispersion (0.23 vs. 0.03), and the most negative earnings surprises (SUE of −0.55). The most optimistic anomaly-correlated bias quintile also contains the highest-credit-risk firms. The left half's least optimistic quintile's average S&P credit rating is A+, while the most optimistic quintile averages BB with 70% being non-investment grade. The earnings of credit-distressed and highly leveraged firms can improve or deteriorate quickly, which makes analyst forecasts and valuation targets precarious compared to those for more creditworthy firms.

The fraction of firms that are hard to value—the average of the HTV dummy variable—also increases as anomaly-correlated bias moves from the lowest to highest quintile. A mere 2% of the most conservatively forecasted firms are hard to value by our definition; 43% are hard to value in the most optimistically forecasted quintile. This difference is not a mechanical consequence of the construction of HTV and anomaly-correlated bias. The columns of Panel A's left half, determined by linear functions of anomaly variables, are based on equation 2's coefficients. These coefficients need not generate the tercile membership required for HTV firms to be far more frequent in the left half's fifth column compared to its first column.

Buttressing this argument is the spread in average HTV across quintiles of the *ex post* bias, AB (omitted from the table). The latter spread depends, not on anomaly-based predictors, but only on the analyst forecast and realized future earnings. For *ex post* bias quintiles, 34% are hard-to-value in quintile 5, but only 16% are hard-to-value in quintile 1. The similar HTV pattern between the *ex post* and anomaly-correlated analyst biases largely reflects that the latter is credibly estimating its *ex post* cousin.

A variable in Panel A's left half that shows no great pattern across quintiles is anomaly-free analyst bias $\widehat{AB}^{\perp Z}$. Indeed, the time-series average of the cross-sectional correlations between anomaly-correlated and anomaly-free bias is just 0.035. This negligible, albeit non-zero, correlation reflects the small differences between $\mathbf{Z}$, which the anomaly-free bias predictors in eq. (3) are orthogonalized to, and eq. (2)'s more elaborate versions of the regressors.

The relatively low returns and alphas of firms with high anomaly-correlated analyst optimism may be difficult to distinguish from anomaly effects *per se*. For example, the earnings forecasts of high-credit-risk firms tend to have a high degree of analyst optimism. Punctuating this argument is the left half of Table I Panel B. Panel B's left half 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 reversed: seven times more firms exist in the highest-optimism quintile. While not reported in a table, these patterns also hold for *ex post* analyst bias, AB.

The apparent correlation between analyst forecast optimism and anomaly characteristics in the left half of Panel A suggests that each attribute could account for the cross-sectional return pattern associated with the other. Facilitating separation of analyst bias from anomaly characteristics is Table I Panel A's right half, which presents summary statistics for anomaly-free bias quintiles. The right half displays much less variation across quintiles than the left half. Naturally, any variable that is a function of anomalies should exhibit low variation across anomaly-free bias quintiles. As one example, HTV for quintile 5 is more than twenty times larger than for quintile 1 in Panel A's left half, but the two corresponding HTV averages are virtually identical in Panel A's right half.

A notable exception to the left-half-vs-right-half pattern for Q5 vs. Q1 is the month $t+1$ return row, for which the anomaly-free bias exhibits a greater return spread than the anomaly-correlated bias quintiles. The return spread is modest, however. Analyst bias's economically significant role in asset pricing only becomes apparent once we focus on HTV firms. Alas, summary tables study one association at a time. To unmask analyst bias's extraordinary return predictive power, one must study its role in conjunction with other variables.

II. Anomaly Characteristics, Analyst Bias, and Returns

Two approaches now distinguish analyst bias's return effects from those of firm attributes.

Portfolio Sorts Each of Panels A-F of Table II reports time-series averages of 25 value-weighted portfolio returns, expressed as percent per month, along with extreme-quintile return spreads and 5-factor Fama and French (2015) alpha spreads. T-statistics in parentheses are bold when 5% significant. The portfolios are stratified by 5×5 independent sorts of month t anomaly-correlated analyst bias, $\widehat{AB}_{i,t}$, and an anomaly variable[16] known as of month t. Each panel corresponds to one of six major anomaly characteristics: credit risk (from S&P rating),

[16]Variables employing annual accounting data are lagged as in Fama and French (1992, 2008): items from fiscal year $y-1$ link to returns in the 12 months starting July of calendar year y.

momentum, earnings surprise (SUE), dispersion, asset growth, and gross profitability.

Several observations are common to all six panels. First, in the two columns on the right, which report extreme quintile return and alphas spreads, one row of each panel stands out for its size and significance. For example, Panel A's standout is the CR5 row. Within this least creditworthy quintile of firms, the return and alpha difference between the most and least optimistically forecasted firms is 157 and 151 bp per month, respectively. The two spreads are enormous by research standards, particularly for value-weighted portfolios. They also demonstrate a high degree of significance with t-statistics of 2.78 and 2.86. The same standout row occurs in the other five panels. The lowest momentum, most negative earnings surprise, highest dispersion, largest asset growth, and lowest gross profitability rows all show the largest effect from anomaly-correlated analyst bias, even though the row itself controls for the anomaly by limiting its variation to be within a quintile. All 12 return spreads and alpha spreads in these standout rows are two-tailed significant at the 10% level; only a couple miss the 5% significance threshold, but barely. The lowest raw return spreads, SUE1 (58 bp per month), still represents a value-weighted annualized return spread of about 7% per year, and its associated 5-factor annualized alpha spread is an enviable 107 bp per month.

The remaining four rows of each panel are unremarkable with what seem to be one random exception. AG2 has a significant alpha spread of 65 bp per month, but an insignificant raw return spread. While DISP4 also has a large and more significant alphas spread than dispersion's standout row, DISP5, the difference between them is negligible. Moreover, dispersion's fourth quintile still contains earnings forecasts with substantial analyst disagreement.

Compared to the other four rows, each panel's standout row arguably represents firms with the greatest valuation complexity. Thus, Table II's rightmost column pairs document an analyst bias return anomaly, but one tied largely to the complexity of valuing a firm and forecasting its future earnings. By contrast, each panel's bottom spread row, which controls for the analyst bias quintile, indicates that the anomaly disappears or backfires, often reversing the sign of its return spread from what prior anomaly research predicts.

For example, the literature suggests that high credit risk leads to low returns. However, the only significant credit risk effects are in the two most optimistic quintiles of analyst bias; in the three less optimistic quintiles, there is no credit risk anomaly. Indeed, the credit risk anomaly reverses in the least optimistic quintile with significance at the 10% level and the largest magnitude of all five credit risk spreads.

Theories purporting to "explain" the credit risk anomaly must consider such contradictory findings. We explain the odd return pattern by the abundance of high credit risk firms in cells with the most optimistically forecasted firms and of low credit risk firms in conservatively forecasted cells (Table I Panel B). Similar concentrations of firms across the 25 independently-sorted cells occur for most of the other anomalies. Thus, Table II suggests that the literature's anomaly effects are largely return spreads between each panel's top left and bottom right cell. These two corners of the 5×5 independent sort maximize variation in the anomaly characteristic, just as the top and bottom cells of any column do. However, unlike the column-fixed spreads, the corner spread allows analyst bias to vary. The anomaly characteristic's effect on returns is remarkably different if we limit variation in analyst bias—e.g., when focusing on anomaly-based return spreads within any column.

With the exception of asset growth and gross profitability, the most conservatively forecasted firms in the standout rows tend to have the largest (in 3 panels) or second largest (in 1 panel) returns of any portfolio in its respective 5×5 matrix. This is the opposite of what the anomaly itself would predict. However, it is consistent with conservatively forecasted HTV firms being undervalued and earning superior returns as they converge to fair value.

To further analyze the analyst bias anomaly, Table III presents time-series averages of value-weighted month $t+1$ portfolio returns based on the hard-to-value dummy variable, HTV, for both anomaly-correlated (Panel A) and anomaly-free (Panel B) analyst bias. Recall that the HTV dummy indicates whether the stock is in the short tercile of at least four of the six anomalies; otherwise, the firm is easy-to-value, ETV. Panel A shows that anomaly-correlated analyst bias, $\widehat{AB}$, has no ability to predict returns among ETV stocks. However, with HTV stocks, the monthly return and alphas spread (133 and 115 bp per month, respectively) between the extreme bias quintiles are large and statistically significant.

Could the linear combination of return predictive variables that best predicts bias simply be creating some super anomaly characteristic—an anomaly combination that predicts returns better than any characteristic by itself. It seems unlikely that ex-post bias, eq. (2)'s dependent variable, could generate coefficients that coincidentally create such a super anomaly. Panel B's anomaly-free bias, which is orthogonal to the six anomaly characteristics, helps refute the super-anomaly hypothesis. For one, the 5-factor alpha spreads of HTV firms in Panels A and B are virtually identical and the latter's significance is much larger. And while the raw return extreme quintile spreads are modestly larger for Panel A's anomaly-correlated bias, both panels' return spreads are large and equally significant. Lastly, Panel B, like Panel A, shows that the corresponding spreads for ETV stocks insignificantly differ from zero. Without bias itself playing a role, the chance that two such disparate bias prediction approaches would predict returns in such similar ways is rather remote. By contrast, believing investors are more easily influenced by analysts for HTV firms seems reasonable.

The only aspect of Table III Panel B that does not add support to our thesis is the similar return between the conservatively forecasted HTV and ETV firms. The five-factor (unreported) alpha of HTV firms in that conservatively forecasted quintile is the largest of all 10 alphas, but it is small and not statistically significant. According to our persuasion story, HTV firms that are conservatively forecasted should be undervalued and earn higher returns—just as they do for the anomaly-correlated bias estimates in Panel A.

Our best explanation for the similar HTV and ETV quintile 1 returns in Panel B is that the anomaly-free bias estimates conservative quintile 1's membership with less precision than quintile 5 membership. Recall Table I's discussion of why the anomaly-free bias estimate may misclassify the true bias quintiles of firms that are forecast conservatively. If Panel B's $2{\times}5$ sorts generate conservative quintiles that lack firms that are truly estimated conservatively, being HTV or ETV is irrelevant. There is no price distortion to begin with. The compression of anomaly-free bias estimates between conservative and median quintiles is less relevant for the return and alpha spreads across the extreme bias quintiles. These spreads obtain statistical power from each row's most optimistically biased cells. As noted earlier, analyst bias is highly skewed towards extreme optimism. This allows Table III's bias-related spreads within the HTV and ETV rows to identify themselves as significant or not.

Skewness's greater compression of conservative anomaly-free bias estimates is also unlikely to mitigate the power of cross-sectional regression coefficients. These coefficients, constructed from regressions of returns on anomaly-free bias, detect bias's return-predictive ability. As Fama and MacBeth (1973) noted, such coefficients also measure returns from zero-cost spread portfolios. The latter have particularly large portfolio weights when anomaly-free bias's distribution is highly skewed towards optimism. Again, optimistically forecasted firms generate the power to detect spreads attached to differences in bias.

Cross-Sectional Regression Analysis Table IV reports average coefficients and their Fama and MacBeth (1973) test statistics. Coefficients come from monthly cross-sectional regressions of returns on one-month lagged anomaly-correlated bias, one-month lagged anomaly-free bias, interactions of the two bias components with HTV, and our six major anomaly variables. Fifteen specifications employ various regressor subsets of

$$
\begin{aligned}
r_{t+1} \;=\; & c_t + \underbrace{\sum_{k=1}^{6} \zeta_t^k Z_{it}^k}_{6\ key\ anomalies} \\
& + \underbrace{\omega_{0t}\left(\widehat{AB}_{it}\right) + \omega_{1t}\left(\widehat{AB}_{it} \times HTV_{it}\right)}_{anomaly-correlated\ analyst\ bias} \\
& + \underbrace{\theta_{0t}\left(\widehat{AB}_{it}^{\perp Z_t}\right) + \theta_{1t}\left(\widehat{AB}_{it}^{\perp Z_t} \times HTV_{it}\right)}_{anomaly-free\ analyst\ bias} + e_{it}.
\end{aligned} \tag{5}
$$

Z_{it}^k is the k^{th} of six major anomaly characteristics: credit rating [$Rating_t$], momentum [MOM_t, past six-month returns], earnings surprise [SUE_t], forecast dispersion [$DISP_t$], asset growth [AG_t], and gross profitability [GP_t], each measured as of month t and thus known prior to the start of the return month $t+1$. Specification 15's full control specification omits anomaly-correlated bias, $\widehat{AB}$, due to multicollinearity with the six anomaly controls. Here, all regressors but one are parametric variables, with HTV the lone dummy variable.

Table IV's Specification 1 indicates that returns inversely relate to both anomaly-correlated and (with about 10% significance) anomaly-free analyst bias. Specification 2 shows that the prediction power of both analyst bias components stems entirely from HTV firms. Specifications 3 to 8 demonstrate that each of the six anomaly characteristics predict cross-sectional differences in future returns. However, all but one anomaly—asset growth—lose significant predictive power (as seen in Specifications 9-15) when we control for analyst bias among HTV stocks. These findings are consistent with Table II's 5×5 sorts as well as Table III.

Asset growth's return predictive ability is slightly weaker when included alongside the remaining anomalies and controlling for analyst bias. This anomaly accounts for the 6-anomaly size of Hotelling's T-squared statistic[17] and its p-value of 0.02 (controlling for analyst biases). Table IV's Hotelling test of the joint significance of the five remaining anomalies excluding asset growth is insignificant (p-value = 0.45). Thus, anomaly-correlated bias captures the joint explanatory power of these five anomaly controls. Results not in the table find a p-value of 0.01 for the joint significance of the five when omitting bias regressors.

Using Table IV's key specification prototypes, Table V studies analyst bias's ability to capture the return impact of 60 additional anomalies from Hou, Xue, and Zhang (2020). Each belongs to one of their six categories: Momentum, Value-versus-Growth, Investments, Profitability, Intangibles, and Trading Frictions. We select the 10 from each category yielding the greatest intra-category sample size. Table V's 60 anomalies appear in rows with labels from Hou, Xue, and Zhang (2020). Each row reports time series averages of coefficients on only the primary return predictor variables along with their Fama MacBeth test statistics.

Table V's 180 cross-sectional regressions employ three prototypical specifications in each of its 60 anomaly rows. Each prototype regresses month $t+1$ returns on some subset of the

[17] Table IV's Hotelling T-squared statistics use the $T \times K$ (T=months, K=anomaly coefficients) panel of 6 or 5 ζ_t^k coefficients of eq. 5, as estimated in Table IV Specification 15:

$$T\text{-}squared = \frac{T-K}{(T-1)K}\ \overline{\zeta}\ \left(\widehat{\Sigma}_{\overline{\zeta}}\right)^{-1}\ \overline{\zeta}' \ \sim\ F_{K,T-K}, \qquad where\ \ \widehat{\Sigma}_{\overline{\zeta}} = \frac{1}{T-1}\sum_{i=1}^{T}(\zeta_t-\overline{\zeta})(\zeta_t-\overline{\zeta})'$$

complete specification's regressors, given by

$$
\begin{aligned}
r_{t+1} \quad = \quad & c_t + \underbrace{\Sigma_{k=1}^{6}\zeta_t^k Z_{it}^k}_{6\ key\ anomalies} + \underbrace{\gamma_t^q X_{it}^q}_{anomaly\ q\ of\ 60} \\
& + \underbrace{\omega_{0t}\left(\widehat{AB}_{it}\right) + \omega_{1t}\left(\widehat{AB}_{it} \times HTV_{it}\right)}_{anomaly-correlated\ analyst\ bias} \\
& + \underbrace{\theta_{0t}\left(\widehat{AB}_{it}^{\perp Z_t}\right) + \theta_{1t}\left(\widehat{AB}_{it}^{\perp Z_t} \times HTV_{it}\right)}_{anomaly-free\ analyst\ bias} + e_{it}.
\end{aligned} \tag{6}
$$

X_{it}^q is anomaly q of 60 anomaly characteristics listed in Table V's rows. This regressor appears in all three specification prototypes. Prototype 1 only contains anomaly q as a regressor. Prototype 2 adds to prototype 1 the two pairs of analyst bias components. Note that the full specification prototype, 3, like specification 15 of Table IV, omits anomaly-correlated analyst bias $\widehat{AB}$ because of multicollinearity, but retains the latter's interaction with HTV.

Table V's last rows summarize results across the 60 anomalies as follows: *# Significant at 5%* is each column's number of coefficients significant at the 5% level; *# of 37 with coeff. shrink* (or *# of 37 with t-stat shrink*) is how many of 37 significant anomalies in prototype 1's specification, which excludes analyst bias, witness shrinkage in their coefficient (or t-statistic) magnitude in prototypes 2 or 3, which include bias regressors—i.e., column (1) vs. (2) or (1) vs. (3); *% decrease in t-stat* is the average percentage decrease in t-statistic magnitude of 37 significant anomalies accounted for by analyst bias—from columns (1) to (2) or (1) to (3).

Table V's first three columns list the anomaly's coefficient γ and t-statistic across the three specification prototypes. The next column reports on anomaly correlated bias ω_0 in specification prototype 2. The remaining three column pairs consist of one pair for the coefficient on the anomaly-correlated interaction with HTV, ω_1, and two pairs for the anomaly-free component and its interaction with the same two specification prototypes, θ_0 and θ_1.

Table V's most salient observation is the estimated coefficients on the interaction terms, ω_1 and θ_1. For HTV firms, and irrespective of anomalies used in the regression, both the anomaly-free and anomaly-correlated biases inversely predict returns at the 5% level.[18] Of the 9 cases out of 240 that miss the 5% significance threshold, all but one pair miss the threshold by negligible amounts. The exception, anomaly-correlated bias's interaction ω_1 in the R&D expense to sales ratio regression (first row of the "Intangible" group's 10 anomalies), is due to the sample-limiting requirement that firms have an R&D expense to sales ratio. In fact, the ratio of R&D expense to sales itself cannot explain returns within this limited sample, even without other regressors. The only variable that predicts returns for this sample of firms is anomaly-free analyst bias's interaction with HTV, θ_1. Indeed, this regressor's prototype 2 coefficient and t-statistic are at their largest values for this anomaly out of 60. The same finding applies to its coefficient and t-statistic for the prototype 3 specification.

In the vast majority of cases, the anomaly is the horse that loses in the head-to-head race against analyst bias. Controlling for the 6 major anomalies has little impact on this finding. Another key observation is that neither analyst bias component predicts returns for ETV firms, as indicated by the universally insignificant estimates for ω_0 and θ_0. This finding is consistent with earlier tables, whether based on regressions involving the 6 major anomalies or return spreads derived from double sorts.

The prototype 2 column in Table V's bottom rows indicate that even without the 6 major anomaly controls, only 13 of 60 anomalies (about 20%) are 5% significant when we control for analyst bias. Adding major anomaly controls barely alters this conclusion. Of these 13, 6 are from the Investment anomaly group; Table IV's results suggest this might be linked to bias's inability to explain the asset growth anomaly. Of the remaining 7 significant anomalies, 1 is tied to Intangibles, which we noted above has a restricted data sample, and 3, all in the Trading Friction category, are tied to different measures of idiosyncratic volatility. All 37 significant anomalies, however, saw their t-statistics shrink with the inclusion of the analyst bias regressors, by an average of 40%. Whether the 13 significant anomalies can remain significant with better estimates of analyst bias is an open question for future research.

[18] Two factors account for the minor differences in coefficients and test statistics for anomaly-free bias across rows: first, the bias component is not perfectly orthogonal to the 60 anomalies; second, samples differ across rows due to data availability.

Overall, however, the anomalies in the 60-anomaly zoo are "paper tigers," not real animals.

Robustness Table VI explores the robustness of our findings. Panels A, B, and C focus on the robustness of Table II, Table IV, and Table V, respectively.

Panel A, using equal weights within cells, reports that the standout rows for each of the six major anomalies are similar to those based on Table II's value weighting. For example, with credit risk's standout row, value weighting produced raw return and alphas spreads between the extreme quintiles of 157 and 151 bp per month, respectively. Panel A shows that the comparable spreads for equal weighting are 141 and 134 bp per month, respectively.

Panel B column 2a is identical to Table IV's specification 2 (repeated in Panel B's left column), but with the inclusion of an additional control for HTV. Column 2a shows that both interaction regressors, the products of a component of analyst bias and the HTV dummy, remain highly significant when a separate control for HTV alone is included in the regression. Moreover, the non-interacted HTV regressor is insignificant. Thus, one cannot attribute Table IV's finding of return predictability from analyst bias in HTV firms to HTV's correlation with return-predicting anomalies. By itself, HTV is inversely related to future returns (Panel B column 2b). However, Table IV's bias regressors do not forecast future returns because of an omitted variable bias tied to HTV or anomalies that correlate with HTV.

Likewise, one cannot attribute Table IV's erosion of significance in major anomaly regressors to the mere presence of HTV in the interaction term. While not reported in a table, all six major anomalies remain significant predictors of returns in regressions with only an HTV control. It is analyst bias combined with HTV, and not HTV *per se* or analyst bias *per se* that renders five of the six major anomalies insignificant.

Panel C lists anomaly data, paralleling Table V's bottom rows, which summarize the predictive efficacy of 60 anomalies. Its "Benchmark" column is from Table V's prototype 2 (which omits major anomaly controls). Columns 1-5 subtract various percentile breaks for analyst bias in prototypes 2's bias regressors, including the interactions. Column 6 is like columns 2-5, except it demeans analyst bias rather than subtracting a percentile cutoff.

Column 7 adds an *HTV* regressor to prototype 2.

Each Panel C column portrays a similar result. Compared to the benchmark, column 7's inclusion of an additional regressor for *HTV* reduces neither the number of significant anomalies explained, nor the number of significant anomaly coefficients or *t*-statistics that shrink. Like Panel B, Panel C indicates that it is analyst bias within *HTV* firms, and neither analyst bias nor *HTV per se* that eliminates the ability of many anomalies to forecast returns.

Panel C's columns 1-4, which subtract a number up to the 40th percentile are virtually identical to the benchmark column. Column 5 and 6 exhibit declines in analyst bias's ability to subsume anomalies. Overall, however, the declines are too small to assign them any meaning. In short, Table VI's key takeaway is that the paper's results are highly robust.

III. A Model of Market Beliefs

The paper's empirical results are consistent with a model in which share prices, distorted by extreme analyst bias, revert (partially or fully) to their fair values based on two forces. The first is a more rational assessment of fundamentals. For some firms with consensus forecasts in the extreme tails of the analyst bias distribution, the forecasters are "getting caught." The market initially believes the analyst forecast, but eventually, other unbiased information comes out to dispel the notion that the forecast should be believed. For firms in the left tail of the analyst bias distribution, the alternative information likely generates upward revision in market participants' earnings estimates; for right-tail firms, alternative information lead to downward revisions by the market. If the information does not come out, the market continues to follow the consensus forecast in valuing the firm. In this case, a second force, the tendency of the consensus forecast to mean revert, could also move distorted stock prices towards their fair values.

The simplest model that captures this plausible intuition has market participants value a firm at the beginning of each month based on the prevailing consensus analyst forecast. At month end, with probability p, the market receives an unbiased earnings signal from another source. If the signal is received, market participants revalue the firm. The signal could be earnings guidance by the firm, quarterly earnings releases, press commentary, or any other earnings-specific information from a source other than the analysts.

Without loss of generality, we assume that, if the signal is received, the market completely discards the consensus analyst forecast and, instead, employs the alternative information to form its earnings expectations. This extreme assumption simplifies algebra, enhancing pedagogy. Specifically, if the firm's analyst forecast bias remains constant over the month, the assumption implies that the expected difference in the market's earnings forecast over a month is the product of (i) the probability that the alternative information is received and (ii) the degree to which the new information alters the market's earnings forecast. We shortly discuss how to generalize the model to allow the market's reliance on the analyst diminish rather than disappear when alternative information is disclosed.[19]

The model's transparency is also facilitated by avoiding the Jensen's inequality effects of convexity and concavity on the market's inferences. To abstract from this complexity, we assume that the market's valuation is a linear function of its earnings forecast, and in turn, the market's earnings forecast is a linear function of the information the market believes. Specifically, (and dropping the firm subscript i to simplify notation), at the end of month $t-1$, the market's earnings per share forecast is a positive linear function of a consensus analyst EPS forecast that contains a bias, B:

$$MktForecastEPS_{t-1}^{T} = b_0 + b_1 ConForecastEPS_{t-1}^{T} \tag{7}$$

$$= b_0 + b_1(EPS^{T} + \tilde{u}_{t-1}^{T} + B_{t-1}), \tag{8}$$

where $\tilde{u}_{t-1}^{T}$ is the end of month $t-1$ analyst *ex-post* forecast error in the absence of a bias,

[19] Anomaly profits double on corporate event days and are 7 times larger on earnings announcement days (Engelberg, McLean, and Pontiff, 2018), lending support to the model's conclusion that analyst-driven mispricing corrects when investors receive alternative signals that diminish reliance on analysts' biased forecasts.

and the market's valuation based on this forecast is:

$$P_{t-1} = k_0 + k_1 MktForecastEPS^T_{t-1}. \tag{9}$$

At the end of month t, no signal is revealed with probability $1 - p$. In this case,

$$MktForecastEPS^T_t = b_0 + b_1 ConForecastEPS^T_t \tag{10}$$

$$= b_0 + b_1(EPS^T + \tilde{u}^T_t + B_t), \tag{11}$$

the date t share price is

$$P_t = k_0 + k_1 MktForecastEPS^T_t, \tag{12}$$

and the change in the share price is

$$\Delta P_t = k_1 b_1 (B_t + \tilde{u}^T_t - B_{t-1} - \tilde{u}^T_{t-1}). \tag{13}$$

In the case where a signal is received,

$$MktForecastEPS^T_t = b_0 + b_1 SignalEPS^T_t \tag{14}$$

$$= b_0 + b_1(EPS^T + \tilde{v}^T_t), \tag{15}$$

where v^T_t is the end of month t *ex-post* forecast error of the signal, and the price change is:

$$\Delta P_t = k_1 b_1 (\tilde{v}^T_t - B_{t-1} - \tilde{u}^T_{t-1}). \tag{16}$$

Hence, the expected change in the price is

$$E[\Delta P_t] = k_1 b_1 [-pB_{t-1} + (1 - p)(B_t - B_{t-1})]. \tag{17}$$

Because $k_1 b_1$ is positive and because the bias tends to mean revert, the expected price change of firms with low analyst bias at $t - 1$ exceeds that of firms with higher bias. The parameters that, when multiplied, determine the price change are the P/E ratio (k_1), the market's "gullibility parameter" (b_1), and the probability of an unbiased signal being received (p).

Mean reversion in analyst forecast bias is supported by Figure II. Figure II plots the event-time paths of both average anomaly-correlated analyst bias ($\widehat{AB}$, Plot A) and average anomaly-free analyst bias ($\widehat{AB}^{\perp Z}$, Plot B) for the two extreme quintile portfolios ranked at event date 0. The (solid with × marker) red-(dashed) green pair of lines of the top bias quintile (at the top of the graph, each representing a credit category) decline over the subsequent 18 months; the red-green pair of lines of the bottom bias quintile (at the bottom of the graph) increase over the subsequent 18 months. For firms in the two extreme predicted bias quintiles, mean reversion is greatest in the first month after bias ranking. The optimism bias ranking decreases over subsequent months for firms with large amounts of analyst optimism bias and increases for firms at the opposite end of the spectrum. The price change contributed by the alternative information—an effect that relies on changes in investor gullibility—is the difference between the total price change and price change from the mean reversion shown in the figure.

The model allows market beliefs to offset analysts optimistic tendency, or to offset analysts' biases within certain groups of stocks. For example, differing values of b_1 for stocks with different levels of fundamental uncertainty allow cross-sectional heterogeneous price inflation and deflation from analyst bias. The market's sensitivity to analyst forecasts, and ultimately the bias inherent in such forecasts, might differ across groups with different levels of fundamental uncertainty for a variety of reasons. Differences in p, k_1, and b_1 across uncertainty categories could therefore explain why risk-adjusted return spreads, arising from cross-sectional differences in analyst bias, are only evident for hard-to-value firms.

One can generalize the algebra above to represent a dynamic model where the market partially relies at all times on both the consensus analyst forecast and on the most recent realization of an alternative signal that is refreshed with a Poisson process. Only two additional assumptions are required. First, the reliance on the month-end alternative signal must exceed the beginning-of-month reliance if the alternative signal is refreshed. In other words, the market's gullibility must decline when the Poisson realization is achieved. For the model to be dynamically consistent and stationary, the market's gullibility parameter, b_1, must also increase in months where the Poisson realization does not take place. The rate of increase in gullibility in those months is determined by the rate of gullibility decrease in the Poisson realization months, the Poisson intensity of the event, and the degree of mean reversion in analyst forecast bias for states with no alternative information revelation.

The model's alternative signal and the de-biased analyst forecast errors, v_t^T and u_t^T, are assumed to be martingales. At the root of this assumption is a tautology: A stock's price must be the sum of a rational component—a fair value—and a (positive, zero, or negative) behavioral component that mean reverts. To allow data to distinguish the behavioral component from the fair value component, we have to assume that changes in a stock's fair value, adjusted for risk and the time value of money, are purely random. The model's linearity and the Bayesian conclusion that rational current-year earnings estimates—wherever they appear in the model—follow a martingale, achieves this goal.

IV. Conclusion

Hard-to-value stocks tend to have extreme amounts of some firm characteristic that place them in the short leg of many popular anomaly-based trading strategies. At the same time, the earnings uncertainty and valuation complexity of these firms engender investor gullibility. The greater prevalence of extreme analyst optimism among such hard-to-value stocks could lead to demand that generates irrationally high prices. Subsequent convergence of inflated prices to fair values would explain the characteristic-return relation. The profitability of most anomalies that short these stocks disappears once analyst bias is controlled for. In the rare cases when analysts tend to be conservative about hard-to-value stocks, the stocks appear to be undervalued, despite being in the short leg of anomaly strategies.

If some investors march to analysts' biased forecast tunes, distorting prices and generating profitable trades for others, why aren't arbitrageurs stepping in to eliminate the mispricing?

First, arbitrage may be limited (Shleifer and Vishny 1997) by the concentration of analyst-driven mispricing in stocks with the greatest fundamental uncertainty. Indeed, investors who overweight biased analyst forecasts can be viewed as Shleifer and Vishny's noise traders. Second, other market frictions, like short sale constraints, may be a deterrent. For example, Miller (1977) rationalizes how heterogeneous beliefs coupled with short sale constraints lead to overpricing in the short leg of anomaly strategies. However, Miller (1977) cannot justify why some stocks in anomalies' shorts are *underpriced*. Analyst optimism and pessimism can explain both, and thus represents a parsimonious and, per Occam's razor, plausible conjecture that might explain the profitability of anomaly strategies.

The fact that analyst bias influences returns only for hard-to-value stocks makes it intuitively plausible that analysts "directly cause" the beliefs of investors. Indeed, we cited earlier work that documents the degree to which investors follow analysts. However, like most empirical work in finance, this is a correlational study. Only controlled randomized experiments can definitively prove causation. Thus, we cannot rule out that analysts and investors share the same biases about earnings expectations because of a common third source that we do not observe. If this third source drives the paper's results, our study still advances the field of asset pricing. In this case, analysts bias becomes a fundamental tool that we can estimate *ex ante*, which proxies for shared misperceptions about earnings. Replacing a cornucopia of return predicting characteristics with a measurable proxy for stock-specific optimism and pessimism makes abnormal returns easier to understand and model.

The advantages of a behavioral focus on analyst bias are reinforced by the discovery of three heretofore undiscovered facts. First, when analyst forecasts are relatively conservative, the ensuring positive abnormal returns are consistent with undervalued stocks converging to fair value, even when the stock's anomaly characteristic indicates that a short sale is appropriate. Second, most characteristic-based anomalies disappear when we control for analyst bias, including 5 of 6 major anomalies. Finally, an entirely new analyst bias construct—predicted analyst bias that is orthogonal to anomaly characteristics—predicts returns in almost the same way and degree as the component of analyst bias that is correlated with anomalies.

Our paper also presents a model of analyst bias's return predictability that is consistent with our empirical findings. The model, cast in a static two-period setting, is generalizable to more periods. The model's parameters allow demand for the shares of certain types of firms to be more susceptible to analyst biases—for example, when fundamental uncertainty is high. Investors in these firm types are naturally more receptive to the analysts' biased forecasts or other sources of irrational sentiment. For these firms, price deviation from fair value is larger for a given amount of bias. The model also shows how two forces—reductions in investors' forecast biases due to news releases from alternative sources, as well as mean reversion in analyst forecast bias—interact to generate abnormal returns.

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.

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 remain a mystery, despite promising forays into this area by Easterwood and Nutt (1999) and Lim (2001). It would also be interesting to study whether ownership clientele alters the effect of analyst bias. While Mikhail, Walther, and Willis (2007) examine the trading responses of different investors to analysts reports, the variation in ownership composition may influence the degree to which analyst bias distorts prices. Finally, there are a vast number of firms that have analyst forecasts that are not collected by I/B/E/S. The non-existence of an I/B/E/S forecast does not imply that these firms are not subject to analyst bias from "semi-private" earnings forecast. Collecting forecast data on these firms and re-running our study on them could provide valuable out-of-sample verification or refutation of our findings.

Appendix Estimating unobservable bias

Realized analyst forecast error, $AB_{i,t}$, consists of two terms. The first is true analyst bias, defined as the adjustment that converts the analyst's earnings forecast into a rationally computed expectation of future earnings.[20] The second term is mean zero noise from random variables, like future events, that lie outside the analyst's information set at the time of the forecast. Formally,

$$AB = \overbrace{\mathbb{E}[AB|\psi,\phi]}^{\text{true analyst bias}} + \nu, \qquad \mathbb{E}[\nu|\psi,\phi] = 0, \tag{18}$$

where ψ is the information set jointly available to an econometrician and analysts, and ϕ is the additional information available to analysts but not the econometrician.[21] Formally, ψ and ϕ are sub-σ-algebras that we order into the filtrations (i.e., information hierarchies) $\mathcal{F}_1 = \{\psi\} \subset \mathcal{F}_2 = \{\psi, \phi\}$.

Rationally computed expectations of future earnings imply that the realized analyst bias, AB, is centered on true bias and the error has a mean of zero conditional on the analyst's information set, $\mathbb{E}[\nu|\psi,\phi] = 0$. This error is zero conditional on the econometrician's information set, as implied by the tower property of conditional expectations:

$$\mathbb{E}\left[\mathbb{E}\left[AB_{i,t} \mid \mathcal{F}_2\right] \middle| \mathcal{F}_1\right] = \mathbb{E}[AB_{i,t}|\mathcal{F}_1] \quad \Longrightarrow \quad \mathbb{E}[\nu|\psi] = 0. \tag{19}$$

In less technical terms, if a random variable has a conditional expectation of zero with respect to a finer partition of the state space, it does so with respect to the coarser partition as well.

The tower property implies that the rationally computed estimate of the true bias by an econometrician, $\mathbb{E}[AB|\psi]$, can replace the true bias, $\mathbb{E}[AB|\psi,\phi]$, as a regressor and generate a consistent estimate of the future return's regression coefficient on the unobservable true bias.

[20] Such rationally computed expectations are not rational expectations in the Grossman Stiglitz equilibrium sense, where rational expectations connote conditioning on the equilibrium price. Our application of the term "rational expectations," has been widely used in contexts like ours, e.g., Fama's seminal interest rate research testing whether the forward rate is a rational expectation of future realized interest rates.

[21] ψ and ϕ could be construed as public and private signals, but can be interpreted more generally here.

Consistency follows from the fact that true bias can be represented as an unbiased estimate (by an econometrician) of true bias plus conditionally mean zero noise. Formally,

$$\mathbb{E}[AB|\psi,\phi] = \mathbb{E}[AB|\psi] + u, \qquad \mathbb{E}[u|\psi] = 0 \tag{20}$$

To prove this, take expectations of both sides of equation (20) using the $\mathcal{F}_1$ filtration (the econometrician's information set ψ) to form the expectation.

$$\mathbb{E}\left[\mathbb{E}[AB|\psi,\phi]\;\middle|\;\psi\right] = \mathbb{E}\left[\mathbb{E}[AB|\psi]\;\middle|\;\psi\right] + \mathbb{E}[u|\psi]. \tag{21}$$

By the tower property of expectations again, the first term on the right hand side of equation (21) is identical to the left hand side, implying that the remaining term, $\mathbb{E}[u|\psi] = 0$, making u uncorrelated with $\mathbb{E}[AB|\psi]$.

Using estimated bias in regressions that explain future returns

Because $\mathbb{E}[AB|\psi]$ and u are orthogonal, regressing any dependent variable on the econometrician's estimate of analyst bias, $\mathbb{E}[AB|\psi]$, asymptotically generates the same coefficients as regressing on true analyst bias, $\mathbb{E}[AB|\psi,\phi]$. Regressing future returns on true analyst bias, a regressor that cannot be observed, has the theoretical model structure:

$$R_{t+1} = \gamma_0 + \gamma_1\mathbb{E}[AB|\psi_t,\phi_t] + \delta_{t+1}, \qquad \mathbb{E}[\delta_{t+1}|\psi_t,\phi_t] = 0, \tag{22}$$

From equations (18)-(19), this regression is identical to

$$R_{t+1} = \gamma_0 + \gamma_1\mathbb{E}[AB|\psi_t] + \epsilon_{t+1}, \qquad \epsilon_{t+1} = \gamma_1 u_t + \delta_{t+1}, \tag{23}$$

which can be estimated because its regressor is observable. Moreover, $E[AB|\psi_t]$ is uncorrelated with u_t, as shown above, and with δ_{t+1} (for the same reasons),[22] implying ϵ_{t+1} and $\mathbb{E}[AB|\psi_t]$ are uncorrelated. Thus, γ_1's estimate (from the regression we can estimate) consis-

[22]The orthogonality condition for δ follows from it being measurable with respect to a different filtration (the one that contains the future realized returns) than $u \in \mathcal{F}_2$, or $\mathbb{E}[AB_{i,t}|\psi_t] \in \mathcal{F}_1$.

tently estimates γ_1, the theoretical coefficient on the true but unknowable analyst bias.

We obtain the same consistent estimate if we separately project earnings and the analyst forecast on the econometrician's information set, then use the difference instead of $\mathbb{E}[AB|\psi_t]$.

$$R_{t+1} = \gamma_0 + \gamma_1\Big(\mathbb{E}[AF|\psi_t] - \mathbb{E}[EPS|\psi_t]\Big) + \epsilon_{t+1}.$$

where EPS is earnings expressed in the same units as the analyst forecast. This is because the regressors in the last two equations are identical due to the linearity of expectations.

The key to OLS estimator consistency is that u_t in equation (23) is perfectly correlated with true analyst bias, $\mathbb{E}[AB|\psi, \phi]$, but orthogonal to the econometrician's information, $\{\psi\}$. By contrast, we obtain inconsistent estimates of the effect of true analyst bias on returns, γ_1, if instead we estimate analyst bias as:

$$AB_{Alt} = AF_t - \mathbb{E}[EPS|\psi_t] = \mathbb{E}[AB|\psi_t] + \underbrace{\big(AF_t - \mathbb{E}[AF|\psi_t]\big)}_{\substack{deviation\ of\ Alt \\ bias\ from\ ours}}. \tag{24}$$

which projects earnings on the econometrician's information set but does not do the same to the analyst's earnings forecast.[23] To illustrate what happens if we estimate the same return regression on AB_{Alt} rather than on $\mathbb{E}[AB|\psi_t]$, add and subtract $\gamma_1(AF_t - \mathbb{E}[AF|\psi_t])$ to the regression of returns on true bias (equation 22), and, after substituting for the true bias using equation (20), regroup terms:

$$\begin{aligned} R_{t+1} &= \gamma_0 + \gamma_1 \underbrace{\mathbb{E}[AB|\psi_t, \phi_t]}_{=\mathbb{E}[AB|\psi_t]+u_t} + \delta_{t+1} + \Big[\gamma_1\big(AF_t - \mathbb{E}[AF|\psi_t]\big) - \gamma_1\big(AF_t - \mathbb{E}[AF|\psi_t]\big)\Big] \\ &= \gamma_0 + \gamma_1\Big(\underbrace{\mathbb{E}[AB|\psi_t] + AF_t - \mathbb{E}[AF|\psi_t]}_{AB_{Alt}}\Big) + \xi_{t+1} \end{aligned} \tag{25}$$

$$\text{where} \quad \xi_{t+1} = \underbrace{\gamma_1 u_t + \delta_{t+1}}_{\substack{\epsilon_{t+1}\ in\ eq.(23) \\ orthogonal\ to\ \psi_t}} - \gamma_1\underbrace{\big(AF_t - \mathbb{E}[AF|\psi_t]\big)}_{orthogonal\ to\ \psi_t}, \quad \Longrightarrow \quad cov(\xi_{t+1}, \psi_t) = 0. \tag{26}$$

[23] This explains why alternative approaches, like So (2013), generate inconsistent estimates of the effect of true analyst bias on future returns.

While the error, ξ_{t+1}, is uncorrelated with ψ_t, it is correlated with AB_{Alt}, since, from our equation (24),

$$cov(AB_{Alt}, \xi_{t+1}) = \underbrace{cov(\mathbb{E}[AB|\psi_t], \xi_{t+1})}_{=0\ as\ \xi \perp \psi} + cov\Big(AF_t - \mathbb{E}[AF|\psi_t], \xi_{t+1}\Big). \tag{27}$$

Substituting equation (26) into the last term of equation (27),

$$\begin{aligned} cov(AB_{Alt}, \xi_{t+1}) &= cov\Big(AF_t - \mathbb{E}[AF|\psi_t], \gamma_1 u_t + \delta_{t+1}\Big) - \gamma_1 var\Big(AF_t - \mathbb{E}[AF|\psi_t]\Big) \\ &= \gamma_1 \Big[cov\Big(AF_t - \mathbb{E}[AF|\psi_t], u_t\Big) - var\Big(AF_t - \mathbb{E}[AF|\psi_t]\Big)\Big]. \end{aligned} \tag{28}$$

Since, by the associative law of arithmetic and the linearity of expectations,

$$u_t = \big(AF_t - \mathbb{E}[AF|\psi_t]\big) - \big(\mathbb{E}[EPS|\psi_t, \phi_t] - \mathbb{E}[EPS|\psi_t]\big), \tag{29}$$

equation (28) simplifies to

$$cov(AB_{Alt}, \xi_{t+1}) = -\gamma_1 cov\Big(\underbrace{AF_t - \mathbb{E}[AF|\psi_t]}_{\substack{deviation\ of\ Alt \\ bias\ from\ our \\ bias\ estimate}}, \underbrace{\mathbb{E}[EPS|\psi_t, \phi_t] - \mathbb{E}[EPS|\psi_t]}_{\substack{deviation\ of\ de\text{-}biased\ analyst\ EPS \\ forecast\ from\ econometrician's \\ EPS\ forecast}}\Big) \tag{30}$$

which is non-zero, leading to an inconsistent estimate of γ_1, whenever ϕ_t, the analyst's incremental information, helps forecast EPS.

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Table I. Descriptive Statistics

Each month t, we sort stocks into quintiles based on anomaly-correlated analyst bias ($\widehat{AB}_t$, left) and anomaly-free analyst bias ($\widehat{AB}_{i,t}^{\perp Z}$, right, which is orthogonal to credit risk, past-six-month returns, SUE, dispersion, asset growth, and gross profitability). 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 bias quintiles, and then regressing the time-series of quintile portfolio returns on the MKT (CAPM) or Fama and French (2015) factors. Panel B reports the average number of observations in 5×5 independent sorts on credit rating and anomaly-correlated analyst bias ($\widehat{AB}_{it}$, left) or anomaly-free analyst bias ($\widehat{AB}_{it}^{\perp Z}$, right). Also reported are observations across independent sorts on hard-to-value score, HTV_{it}, and $\widehat{AB}_{it}$ or $\widehat{AB}_{it}^{\perp Z}$. The HTV dummy indicates whether the stock is in the short tercile of at least four of the six anomalies: credit risk, past-returns, SUE, dispersion, asset growth, and gross profitability. Otherwise, the firm is easy-to-value, ETV_{it}.

Panel A: Characteristics across quintiles

	Anomaly-correlated Analyst Bias					Anomaly-free Analyst Bias				
Characteristic	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}_1^{\perp Z}$	$\widehat{AB}_2^{\perp Z}$	$\widehat{AB}_3^{\perp Z}$	$\widehat{AB}_4^{\perp Z}$	$\widehat{AB}_5^{\perp Z}$
AB (%)	0.59	3.22	7.24	17.30	48.85	12.95	14.48	15.44	16.05	18.24
$\widehat{AB}$ (%)	−5.19	4.62	12.80	24.40	57.38	17.59	17.25	17.55	18.53	20.95
$\widehat{AB}^{\perp Z}$ (%)	16.37	16.83	16.98	17.00	17.07	8.75	16.19	19.22	22.08	28.26
Market capitalization ($bln)	19.75	14.13	10.51	7.07	3.54	15.17	8.44	6.86	7.00	9.14
Book-to-market ratio	0.55	0.65	0.71	0.77	0.85	0.63	0.71	0.75	0.77	0.73
S&P numeric rating	7.85	8.29	9.00	10.10	11.85	9.55	9.30	9.28	9.33	9.80
Past six-month return (%)	19.32	10.80	6.97	2.19	−8.23	7.00	6.42	6.08	6.03	6.48
SUE	1.89	1.00	0.54	0.13	−0.55	0.61	0.54	0.51	0.52	0.58
Dispersion in analyst forecasts	0.03	0.04	0.05	0.08	0.23	0.11	0.09	0.08	0.09	0.11
Asset growth	0.14	0.13	0.13	0.16	0.17	0.16	0.12	0.12	0.13	0.18
Gross profitability	0.34	0.31	0.29	0.29	0.27	0.34	0.32	0.30	0.30	0.33
Fraction NIG firms	0.17	0.22	0.30	0.45	0.70	0.43	0.37	0.36	0.37	0.44
Fraction Hard-to-Value firms	0.02	0.03	0.08	0.17	0.43	0.17	0.13	0.13	0.13	0.16
Coverage (# of analysts))	16.49	14.23	12.78	11.38	9.78	15.40	13.96	13.11	12.60	12.24
Month $t+1$ return (%)	0.97	1.02	1.12	1.02	0.85	1.05	0.93	0.97	1.00	0.88
Month $t+1$ CAPM alpha (%)	0.21	0.26	0.31	0.08	−0.30	0.06	0.04	0.09	0.10	−0.07
CAPM beta	0.87	0.89	0.97	1.17	1.50	1.20	1.01	1.02	1.03	1.12
Month $t+1$ 5-factor alpha (%)	−0.12	−0.16	−0.07	−0.27	−0.56	0.01	−0.26	−0.20	−0.22	−0.32
MKT beta	1.01	1.04	1.06	1.20	1.41	1.16	1.07	1.08	1.10	1.15
SMB beta	0.17	0.23	0.32	0.47	0.72	0.34	0.41	0.37	0.45	0.49
HML beta	0.04	0.23	0.39	0.58	0.81	0.17	0.31	0.33	0.35	0.24
RMW beta	0.37	0.39	0.28	0.21	−0.03	−0.08	0.31	0.33	0.37	0.29
CMA beta	0.26	0.21	0.06	−0.16	−0.36	0.02	0.07	0.00	0.02	0.03

Panel B: Observations across 5×5 independent sorts

CR1	67.65	55.36	42.14	25.16	9.96	47.17	43.42	40.56	39.66	36.76
CR2	46.56	45.13	40.14	31.37	15.68	23.10	30.95	34.81	34.32	27.28
CR3	23.37	30.25	33.99	33.90	24.08	27.41	33.30	34.31	34.03	32.37
CR4	16.69	23.22	31.91	44.60	51.06	27.49	28.99	29.46	30.25	32.78
CR5	8.84	9.15	14.95	28.08	62.32	34.61	23.21	20.74	21.60	30.61
ETV: Easy-to-value	156.56	154.35	148.04	132.13	91.74	132.18	138.52	139.50	139.30	133.36
HTV: Hard-to-value	2.81	5.00	11.38	27.21	67.63	27.61	21.36	20.39	20.56	26.44

Table II. Portfolio Returns Sorted on Analyst Bias and Anomaly Variables

Stocks are sorted into portfolios based on a 5×5 independent sort on month t anomaly-correlated analyst bias, $\widehat{AB}_{i,t}$, and an anomaly variable (noted in the heading of each panel) known as of month t. The table reports, for each portfolio, the time-series average of value-weighted month $t+1$ portfolio returns (in percent per month) as well as the return differential between the extreme portfolios (with sample t-statistics in parentheses, bold if significant at the 5% level). The last column presents the corresponding return differential based on Fama and French (2015) 5-factor risk-adjusted portfolio returns.

	Anomaly-correlated Analyst Bias						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: Credit risk							
CR1	0.80	0.86	1.07	1.20	1.12	−0.32	−0.14
	(**3.93**)	(**4.10**)	(**4.42**)	(**4.54**)	(**3.24**)	(−1.20)	(−0.55)
CR2	0.89	0.95	0.98	0.94	1.01	−0.11	0.08
	(**3.67**)	(**3.94**)	(**3.74**)	(**2.94**)	(**2.24**)	(−0.19)	(0.26)
CR3	0.92	1.08	1.04	1.06	0.68	0.24	0.38
	(**3.01**)	(**3.91**)	(**3.68**)	(**3.18**)	(1.72)	(0.74)	(1.20)
CR4	0.89	0.84	0.87	0.89	0.67	0.22	0.25
	(**2.15**)	(**2.29**)	(**2.42**)	(**2.22**)	(1.41)	(0.66)	(0.61)
CR5	1.80	1.18	0.90	0.31	0.23	1.57	1.51
	(**2.82**)	(**2.02**)	(1.57)	(0.60)	(0.43)	(**2.78**)	(**2.86**)
CR1−CR5	−1.01	−0.32	0.18	0.89	0.89		
	(−1.68)	(−0.65)	(0.36)	(**2.22**)	(**2.12**)		
Panel B: Momentum (Jegadeesh and Titman, 1993, past 6-month returns)							
R6(loser)	2.01	1.25	0.92	0.91	0.56	1.44	1.32
	(**3.97**)	(**2.72**)	(**2.31**)	(**2.23**)	(1.16)	(**2.92**)	(**2.81**)
R6(2)	0.98	1.01	1.26	0.97	0.80	0.17	0.42
	(**3.20**)	(**3.52**)	(**4.72**)	(**3.03**)	(**1.96**)	(0.62)	(1.66)
R6(3)	0.84	1.07	0.95	1.07	1.08	−0.24	−0.14
	(**3.33**)	(**4.52**)	(**3.61**)	(**3.68**)	(**2.89**)	(−0.87)	(−0.58)
R6(4)	0.72	0.72	0.90	0.87	1.04	−0.32	−0.20
	(**3.18**)	(**3.13**)	(**3.56**)	(**3.05**)	(**2.80**)	(−1.16)	(−0.77)
R6(winner)	0.88	0.82	0.88	1.02	0.87	0.01	−0.04
	(**3.25**)	(**3.12**)	(**3.04**)	(**2.97**)	(**2.17**)	(0.04)	(−0.14)
Winner−Loser	−1.13	−0.43	−0.04	0.11	0.30		
	(**−2.19**)	(−1.00)	(−0.11)	(0.30)	(0.76)		
Panel C: SUE							
SUE1	1.20	1.06	0.86	0.91	0.62	0.58	1.07
	(**3.93**)	(**4.01**)	(**3.18**)	(**2.99**)	(1.50)	(1.72)	(**3.44**)
SUE2	0.84	0.94	0.89	1.23	0.85	−0.01	0.14
	(**3.26**)	(**3.76**)	(**3.23**)	(**3.77**)	(**2.03**)	(−0.02)	(0.48)
SUE3	0.75	0.91	0.91	1.02	0.93	−0.18	0.16
	(**3.13**)	(**3.71**)	(**3.42**)	(**3.29**)	(**2.29**)	(−0.59)	(0.58)
SUE4	0.70	0.91	1.13	0.99	0.54	0.17	0.23
	(**2.97**)	(**3.89**)	(**4.29**)	(**2.90**)	(1.34)	(0.53)	(0.83)
SUE5	0.87	0.83	1.06	0.82	0.75	0.12	0.30
	(**3.81**)	(**3.44**)	(**3.74**)	(**2.21**)	(1.57)	(0.30)	(0.84)
SUE5−SUE1	−0.33	−0.22	0.20	−0.09	0.13		
	(−1.45)	(−1.10)	(1.13)	(−0.38)	(0.38)		

Table II. (continued)

	Anomaly-correlated Analyst Bias						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 D: Dispersion (Diether, Malloy, and Scherbina, 2002)							
DISP1	1.01	1.09	1.15	0.97	1.31	−0.30	−0.05
	(**4.93**)	(**5.06**)	(**4.55**)	(**3.29**)	(**2.77**)	(−0.67)	(−0.18)
DISP2	1.03	0.89	0.99	1.09	0.60	0.43	0.63
	(**4.57**)	(**4.02**)	(**4.09**)	(**3.46**)	(1.31)	(1.22)	(1.84)
DISP3	0.91	0.85	1.05	0.97	0.49	0.42	0.43
	(**3.67**)	(**3.53**)	(**4.04**)	(**3.17**)	(1.11)	(1.23)	(1.42)
DISP4	1.22	0.88	1.06	0.89	0.59	0.63	0.71
	(**4.07**)	(**3.14**)	(**3.59**)	(**2.83**)	(1.48)	(1.90)	(**2.31**)
DISP5	1.36	0.93	1.04	1.02	0.57	0.80	0.68
	(**2.74**)	(**2.27**)	(**2.79**)	(**3.00**)	(1.40)	(**2.03**)	(1.87)
DISP1−DISP5	−0.35	0.16	0.11	−0.05	0.74		
	(−1.00)	(0.49)	(0.42)	(−0.23)	(1.69)		
Panel E: Asset growth (Cooper, Gulen, and Schill, 2008)							
AG1	0.95	1.09	1.17	1.08	0.99	−0.04	0.27
	(**3.54**)	(**4.03**)	(**3.96**)	(**3.10**)	(**2.33**)	(−0.13)	(1.09)
AG2	1.11	0.95	1.25	1.15	0.65	0.47	0.65
	(**4.98**)	(**4.08**)	(**4.75**)	(**3.57**)	(1.53)	(1.62)	(**3.06**)
AG3	0.84	0.93	1.10	1.00	0.78	0.06	0.39
	(**3.64**)	(**4.12**)	(**4.31**)	(**3.26**)	(1.95)	(0.19)	(1.64)
AG4	0.77	0.91	0.94	0.99	0.70	0.06	0.29
	(**3.05**)	(**3.55**)	(**3.51**)	(**3.03**)	(1.67)	(0.21)	(1.10)
AG5	0.80	0.70	0.72	0.47	0.17	0.63	0.76
	(**2.64**)	(**2.39**)	(**2.24**)	(1.21)	(0.38)	(**2.25**)	(**2.83**)
AG1−AG5	0.16	0.39	0.45	0.61	0.82		
	(0.83)	(**1.96**)	(**2.37**)	(**2.78**)	(**3.58**)		
Panel F: Gross Profitability (Novy-Marx, 2013)							
GP1	0.86	0.81	1.01	0.93	0.25	0.61	0.89
	(**3.38**)	(**3.54**)	(**4.03**)	(**2.79**)	(0.58)	(**2.06**)	(**2.99**)
GP2	0.75	0.91	0.88	0.80	0.93	−0.18	0.21
	(**2.62**)	(**3.26**)	(**2.93**)	(**2.26**)	(**2.12**)	(−0.59)	(0.77)
GP3	0.84	0.91	1.05	1.11	0.96	−0.12	−0.01
	(**2.97**)	(**3.19**)	(**3.47**)	(**3.27**)	(**2.16**)	(−0.36)	(−0.04)
GP4	0.92	1.06	1.24	0.92	1.06	−0.15	0.19
	(**3.52**)	(**3.98**)	(**4.14**)	(**2.63**)	(**2.47**)	(−0.50)	(0.76)
GP5	0.93	1.07	0.97	1.01	0.86	0.06	0.47
	(**4.11**)	(**4.52**)	(**3.48**)	(**3.12**)	(**2.02**)	(0.20)	(1.82)
GP5−GP1	0.06	0.26	−0.04	0.09	0.61		
	(0.30)	(1.27)	(−0.17)	(0.39)	(**2.15**)		

Table III. Portfolio Returns Sorted on Analyst Bias and Hard-to-Value Score

Panel A (B) presents value-weighted month $t+1$ portfolio returns (in percent per month) based on independent sorts on the hard-to-value score, HTV_{it}, and anomaly-correlated analyst bias, $\widehat{AB}_{it}$ (anomaly-free analyst bias, $\widehat{AB}_{it}^{\perp Z}$). The HTV dummy indicates whether the stock is in the short tercile of at least four of the six anomalies: credit risk, past-returns, SUE, dispersion, asset growth, and gross profitability. Otherwise, the firm is easy-to-value, ETV_{it}.

Panel A: Raw returns based on sorts on HTV_{it} and $\widehat{AB}_{it}$

	Anomaly-correlated Analyst Bias						FF 5-factor
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
ETV: Easy-to-value	0.87	0.86	1.00	1.02	0.95	−0.08	0.24
	(**3.96**)	(**3.75**)	(**3.90**)	(**3.43**)	(**2.54**)	(−0.30)	(1.21)
HTV: Hard-to-value	1.64	1.15	0.71	0.66	0.30	1.33	1.15
	(1.77)	(**2.16**)	(1.67)	(1.60)	(0.64)	(**2.37**)	(**1.96**)
ETV−HTV	−0.77	−0.30	0.28	0.36	0.64		
	(−1.02)	(−0.62)	(0.98)	(1.59)	(**3.15**)		

Panel B: Raw returns based on sorts on HTV_{it} and $\widehat{AB}_{it}^{\perp Z}$

	Anomaly-free Analyst Bias						FF 5-factor
Returns	$\widehat{AB}1^{\perp Z}$	$\widehat{AB}2^{\perp Z}$	$\widehat{AB}3^{\perp Z}$	$\widehat{AB}4^{\perp Z}$	$\widehat{AB}5^{\perp Z}$	$\widehat{AB}1^{\perp Z}-\widehat{AB}5^{\perp Z}$	$\widehat{AB}1^{\perp Z}-\widehat{AB}5^{\perp Z}$
ETV: Easy-to-value	0.94	0.83	1.01	0.94	0.92	0.02	0.16
	(**3.66**)	(**3.60**)	(**4.23**)	(**3.87**)	(**3.67**)	(0.13)	(1.38)
HTV: Hard-to-value	0.94	1.05	0.76	0.35	0.17	0.78	1.13
	(1.90)	(**2.19**)	(1.63)	(0.73)	(0.38)	(**2.23**)	(**3.54**)
ETV−HTV	−0.01	−0.22	0.25	0.59	0.75		
	(−0.02)	(−0.64)	(0.73)	(1.80)	(**2.46**)		

Table IV. Analysts and Anomalies in Cross-Sectional Regressions

The table presents coefficients and sample t-statistics from Fama-MacBeth cross-sectional regressions (eq. 5) of month $t+1$ returns on month t anomaly-correlated analyst bias, $\widehat{AB}_{i,t}$, anomaly-free analyst bias, $\widehat{AB}_{i,t}^{\perp Z}$, their interaction with the hard-to-value dummy, HTV_{it}, indicating that the stock belongs to the short tercile of at least four of the six anomalies: credit risk [$Rating_t$], past six-month returns [MOM_t], earnings momentum [SUE_t], dispersion [$DISP_t$], asset growth [AG_t], and gross profitability [GP_t], all measured as of month t. The Hotelling T-squared statistics (see Footnote 17) for the significance of the six and five anomalies (excluding asset growth) are reported at the bottom.

	Analysts		Anomalies						Analyst and anomalies						
Specification	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Constant	1.03	0.98	1.48	0.71	0.82	0.97	0.96	0.72	1.22	0.89	0.94	0.98	1.05	0.87	1.03
	(**3.62**)	(**3.31**)	(**7.27**)	(**2.85**)	(**3.11**)	(**3.95**)	(**3.78**)	(**2.65**)	(**4.96**)	(**3.07**)	(**3.22**)	(**3.36**)	(**3.60**)	(**2.81**)	(**3.73**)
$\widehat{AB}_{i,t}^{\perp Z}$	−0.95	−0.41							−0.53	−0.47	−0.44	−0.41	−0.45	−0.47	−0.69
	(−1.53)	(−0.46)							(−0.60)	(−0.53)	(−0.48)	(−0.46)	(−0.50)	(−0.52)	(−0.81)
$\widehat{AB}_{i,t}^{\perp Z} \times HTV$		−3.80							−2.99	−3.52	−3.81	−3.75	−3.50	−3.40	−2.45
		(−**2.83**)							(−**2.60**)	(−**2.72**)	(−**2.83**)	(−**2.80**)	(−**2.67**)	(−**2.53**)	(−**2.31**)
$\widehat{AB}_{i,t}$	−0.83	−0.04							0.14	−0.01	0.02	−0.08	−0.11	−0.08	
	(−**2.05**)	(−0.11)							(0.45)	(−0.02)	(0.04)	(−0.21)	(−0.27)	(−0.20)	
$\widehat{AB}_{i,t} \times HTV$		−1.13							−1.24	−1.01	−1.12	−1.03	−1.03	−1.13	−0.78
		(−**2.96**)							(−**3.37**)	(−**2.69**)	(−**2.94**)	(−**2.71**)	(−**2.74**)	(−**2.98**)	(−**2.39**)
$Rating_t$			−0.06						−0.02						−0.02
			(−**2.36**)						(−0.93)						(−0.75)
MOM_t				0.72						0.33					0.51
				(**1.99**)						(0.84)					(1.32)
SUE_t					0.10						0.02				0.02
					(**3.91**)						(1.04)				(0.80)
$DISP_t$						−0.98						−0.04			−0.09
						(−**3.04**)						(−0.14)			(−0.34)
AG_t							−0.49						−0.41		−0.34
							(−**3.86**)						(−**3.26**)		(−**3.08**)
GP_t								0.53						0.30	0.26
								(**2.31**)						(1.11)	(0.99)
Adjusted R^2 (%)	2.66	3.40	2.52	2.26	0.69	1.18	0.55	0.80	4.93	5.11	3.69	3.80	3.89	4.19	7.82
														Hotelling's T-squared (6 anomalies=0)	2.47
														p-value	0.02
														Hotelling's T-squared (5 anomalies=0)	0.94
														p-value	0.45

Table V. Extending the Results to 60 Additional Anomalies

The table reports coefficients (with their sample t-statistics in parentheses) from 240 sets of Fama and MacBeth (1973) cross-sectional regressions, employing four prototypical specifications for each of 60 anomalies. The 60 anomalies are from Hou, Xue, and Zhang (2020), 10 from each of their six categories: Momentum, Value-versus-Growth, Investments, Profitability, Intangibles, and Trading Trictions. The names in the first column follow Hou, Xue, and Zhang's (2020) naming convention, numbering, and anomaly calculations. Each prototype regresses month $t+1$ returns on each of 60 anomaly variables as well some subset of the complete specification's regressors, given by

$$\begin{aligned} r_{t+1} \;=\; & c_t + \underbrace{\gamma_t^q X_{it}^q}_{anomaly\ q\ of\ 60} + \underbrace{\Sigma_{k=1}^{6}\zeta_t^k Z_{it}^k}_{6\ key\ anomalies} \\ & + \underbrace{\omega_{0t}\left(\widehat{AB}_{it}\right) + \omega_{1t}\left(\widehat{AB}_{it} \times HTV_{it}\right)}_{anomaly-correlated\ analyst\ bias} + \underbrace{\theta_{0t}\left(\widehat{AB}_{it}^{\perp Z_t}\right) + \theta_{1t}\left(\widehat{AB}_{it}^{\perp Z_t} \times HTV_{it}\right)}_{anomaly-free\ analyst\ bias} + e_{it}. \end{aligned} \quad (31)$$

where X_{it}^q is anomaly q of 60 anomalies listed in each row. This regressor appears in all four specification prototypes. Specification prototype 1 omits both the six major anomaly controls ($Z_{it} = [Rating_t, MOM_t, SUE_t, DISP_t, AG_t, GP_t)$, as well as the four regressors that estimate the two analyst bias components and their interactions with HTV. Prototype 2 only omits the former Z. The full regressor specification prototype, 3, like Specification 15 of Table IV, omits anomaly-correlated analyst bias $\widehat{AB}$ (due to multicollinearity with the Z) but retains its interaction with HTV as a regressor. The last four rows summarize the results across the 60 anomalies. *# Significant at 5% (of 60)* is the number of the 60 coefficients in the corresponding column that are significant at the 5% level. *# of 37 significant w/coeff. shrink* (*# of 37 significant w/t-stat shrink*) is the number of the 37 significant anomalies which become less profitable (less statistically significant) after accounting for analyst bias—the decrease from column (1) to column (2) without controls or the decrease from column (1) to column (3) when controls are included. *% t-stat shrinks (signif. only avg.)* summarizes the average percentage decrease in the anomaly's statistical significance after accounting for analyst bias.

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
6 Anomaly Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Analyst Bias Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prototype	1	2	3	2	2	3	2	3	2	3
Variable	X_q			$\widehat{AB}$	$\widehat{AB} \times HTV$		$\widehat{AB}^{\perp Z}$		$\widehat{AB}^{\perp Z} \times HTV$	
Coefficient	$\widehat{\gamma_q}$			$\widehat{\omega_0}$	$\widehat{\omega_1}$		$\widehat{\theta}_0$		$\widehat{\theta}_1$	
Momentum										
A.1.2 Abr	1.82	0.60	0.02	−0.04	−1.10	−0.78	−0.41	−0.66	−3.91	−2.50
	(**3.30**)	(1.10)	(0.03)	(−0.11)	(**−2.88**)	(**−2.38**)	(−0.46)	(−0.77)	(**−2.93**)	(**−2.36**)
A.1.3 Re	0.88	0.83	0.76	−0.03	−1.07	−0.73	−0.41	−0.64	−3.76	−2.42
	(**3.42**)	(**2.52**)	(**2.37**)	(−0.09)	(**−2.83**)	(**−2.25**)	(−0.46)	(−0.75)	(**−2.84**)	(**−2.32**)
A.1.5 R^{11}	0.51	0.23	0.40	0.04	−0.94	−0.74	−0.62	−0.69	−3.79	−2.44
	(**2.00**)	(0.85)	(1.56)	(0.11)	(**−2.53**)	(**−2.29**)	(−0.74)	(−0.85)	(**−3.00**)	(**−2.34**)
A.1.7 Rs	0.06	0.04	0.03	−0.03	−1.14	−0.80	−0.51	−0.78	−3.58	−2.29
	(**2.67**)	(1.66)	(1.27)	(−0.09)	(**−2.96**)	(**−2.42**)	(−0.57)	(−0.91)	(**−2.64**)	(**−2.12**)
A.1.8 Tes	0.01	0.00	−0.00	−0.07	−1.12	−0.84	−0.57	−0.76	−3.51	−2.13
	(0.90)	(0.13)	(−0.19)	(−0.19)	(**−2.93**)	(**−2.56**)	(−0.63)	(−0.86)	(**−2.58**)	(−1.95)
A.1.9 dEf	1.04	0.61	0.48	−0.04	−1.05	−0.73	−0.43	−0.70	−3.78	−2.47
	(**4.45**)	(**2.30**)	(1.82)	(−0.10)	(**−2.73**)	(**−2.22**)	(−0.48)	(−0.82)	(**−2.83**)	(**−2.34**)
A.1.10 Nei	0.03	−0.00	0.00	−0.03	−1.16	−0.79	−0.54	−0.81	−3.66	−2.40
	(1.69)	(−0.06)	(0.05)	(−0.07)	(**−3.06**)	(**−2.44**)	(−0.59)	(−0.95)	(**−2.75**)	(**−2.28**)
A.1.11 52w	1.31	0.66	0.25	0.10	−0.96	−0.66	−0.80	−0.84	−3.37	−2.42
	(**2.41**)	(1.21)	(0.50)	(0.32)	(**−2.55**)	(**−2.04**)	(−0.97)	(−1.04)	(**−2.75**)	(**−2.30**)
A.1.12 ϵ^6	0.02	0.01	0.01	0.00	−1.13	−0.78	−0.54	−0.74	−3.75	−2.45
	(**2.73**)	(1.58)	(1.23)	(0.01)	(**−2.99**)	(**−2.40**)	(−0.61)	(−0.88)	(**−2.82**)	(**−2.31**)
A.1.13 ϵ^{11}	0.00	0.00	0.00	−0.02	−1.11	−0.77	−0.40	−0.70	−3.81	−2.51
	(1.72)	(1.43)	(0.79)	(−0.04)	(**−2.93**)	(**−2.35**)	(−0.45)	(−0.82)	(**−2.87**)	(**−2.34**)

Table V. (continued)

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
6 Anomaly Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Analyst Bias Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prototype	1	2	3	2	2	3	2	3	2	3
Variable	X_q			$\widehat{AB}$	$\widehat{AB} \times HTV$		$\widehat{AB}^{\perp Z}$		$\widehat{AB}^{\perp Z} \times HTV$	
Coefficient	$\widehat{\gamma}_q$			$\widehat{\omega_0}$	$\widehat{\omega_1}$		$\widehat{\theta}_0$		$\widehat{\theta}_1$	
Value vs Growth										
A.2.1 Bm	0.06	0.09	0.13	−0.08	−1.09	−0.75	−0.48	−0.75	−3.93	−2.47
	(0.73)	(1.11)	(1.69)	(−0.21)	(**−2.88**)	(**−2.32**)	(−0.54)	(−0.89)	(**−2.98**)	(**−2.31**)
A.2.2 Bmj	−0.06	−0.02	−0.02	−0.04	−1.04	−0.70	−0.49	−0.75	−3.67	−2.43
	(**−2.97**)	(−0.82)	(−1.21)	(−0.11)	(**−2.79**)	(**−2.18**)	(−0.54)	(−0.88)	(**−2.81**)	(**−2.31**)
A.2.3 Bm^q	−0.09	−0.05	−0.05	−0.01	−1.13	−0.79	−0.35	−0.65	−3.21	−2.04
	(**−3.80**)	(−1.84)	(**−2.13**)	(−0.02)	(**−3.01**)	(**−2.44**)	(−0.40)	(−0.76)	(**−2.46**)	(−1.91)
A.2.4 Dm	−0.03	−0.01	−0.02	−0.04	−1.03	−0.69	−0.48	−0.75	−3.61	−2.42
	(**−2.56**)	(−1.00)	(−1.40)	(−0.11)	(**−2.77**)	(**−2.16**)	(−0.53)	(−0.87)	(**−2.78**)	(**−2.30**)
A.2.5 Dm^q	−0.05	−0.02	−0.03	−0.01	−0.91	−0.57	−0.56	−0.87	−3.57	−2.36
	(**−3.94**)	(−1.63)	(**−2.20**)	(−0.02)	(**−2.41**)	(−1.73)	(−0.63)	(−1.01)	(**−2.77**)	(**−2.25**)
A.2.6 Am	−0.01	−0.01	−0.01	−0.04	−1.07	−0.72	−0.46	−0.73	−3.64	−2.44
	(**−2.17**)	(−0.95)	(−1.39)	(−0.09)	(**−2.86**)	(**−2.23**)	(−0.51)	(−0.85)	(**−2.79**)	(**−2.31**)
A.2.7 Am^q	−0.02	−0.01	−0.01	−0.03	−1.02	−0.68	−0.48	−0.75	−3.62	−2.42
	(**−3.58**)	(−1.31)	(−1.77)	(−0.08)	(**−2.73**)	(**−2.10**)	(−0.53)	(−0.87)	(**−2.78**)	(**−2.29**)
A.2.9 Ep	0.09	0.08	0.03	−0.02	−1.12	−0.75	−0.42	−0.69	−3.77	−2.46
	(1.02)	(0.72)	(0.32)	(−0.06)	(**−2.96**)	(**−2.31**)	(−0.47)	(−0.81)	(**−2.85**)	(**−2.37**)
A.2.10 Ep^q	0.34	0.17	0.20	−0.02	−1.05	−0.70	−0.53	−0.77	−3.75	−2.52
	(1.05)	(0.40)	(0.49)	(−0.06)	(**−2.78**)	(**−2.13**)	(−0.59)	(−0.90)	(**−2.80**)	(**−2.37**)
A.2.12 Cp	−0.18	−0.08	−0.09	−0.03	−1.04	−0.70	−0.54	−0.81	−3.79	−2.49
	(**−2.37**)	(−0.85)	(−1.07)	(−0.07)	(**−2.79**)	(**−2.18**)	(−0.60)	(−0.95)	(**−2.89**)	(**−2.41**)
Investment										
A3.1 Aci	−0.12	−0.09	−0.08	−0.00	−1.09	−0.77	−0.49	−0.75	−3.35	−2.39
	(**−2.14**)	(−1.35)	(−1.28)	(−0.00)	(**−2.89**)	(**−2.33**)	(−0.54)	(−0.86)	(**−2.46**)	(**−2.14**)
A.3.4 dPia	−0.70	−0.50	−0.24	−0.03	−0.99	−0.68	−0.48	−0.74	−3.60	−2.55
	(**−2.74**)	(−1.83)	(−0.87)	(−0.09)	(**−2.65**)	(**−2.09**)	(−0.53)	(−0.87)	(**−2.78**)	(**−2.44**)
A.3.5 Noa	−0.49	−0.50	−0.39	−0.04	−1.11	−0.77	−0.35	−0.67	−3.20	−2.40
	(**−4.01**)	(**−3.81**)	(**−2.33**)	(−0.09)	(**−2.95**)	(**−2.37**)	(−0.38)	(−0.77)	(**−2.46**)	(**−2.27**)
A.3.5 dNoa	−0.62	−0.59	−0.29	−0.06	−1.07	−0.78	−0.43	−0.79	−3.49	−2.35
	(**−3.87**)	(**−3.71**)	(−1.42)	(−0.16)	(**−2.84**)	(**−2.40**)	(−0.47)	(−0.92)	(**−2.66**)	(**−2.23**)
A.3.6 dLno	−1.00	−0.81	−0.28	−0.05	−1.08	−0.78	−0.49	−0.72	−3.45	−2.46
	(**−3.92**)	(**−3.21**)	(−1.02)	(−0.13)	(**−2.87**)	(**−2.37**)	(−0.53)	(−0.85)	(**−2.65**)	(**−2.31**)
A.3.7 Ig	−0.12	−0.08	−0.04	−0.03	−1.03	−0.69	−0.35	−0.65	−4.06	−2.78
	(**−2.35**)	(−1.43)	(−0.83)	(−0.08)	(**−2.74**)	(**−2.09**)	(−0.39)	(−0.76)	(**−3.06**)	(**−2.62**)
A.3.8 2Ig	−0.08	−0.07	−0.06	−0.03	−1.07	−0.72	−0.41	−0.68	−3.67	−2.56
	(**−3.05**)	(**−2.38**)	(**−2.10**)	(−0.07)	(**−2.84**)	(**−2.19**)	(−0.46)	(−0.80)	(**−2.77**)	(**−2.43**)
A.3.10 Nsi	−1.80	−1.55	−1.18	−0.02	−1.11	−0.79	−0.47	−0.72	−3.41	−2.36
	(**−6.13**)	(**−5.10**)	(**−4.00**)	(−0.04)	(**−2.93**)	(**−2.41**)	(−0.52)	(−0.84)	(**−2.58**)	(**−2.19**)
A.3.14 Ivg	−0.14	−0.19	−0.08	−0.03	−1.14	−0.85	−0.30	−0.45	−3.66	−2.65
	(−1.84)	(**−2.15**)	(−1.04)	(−0.08)	(**−2.88**)	(**−2.31**)	(−0.33)	(−0.50)	(**−2.56**)	(**−2.17**)
A.3.17 Ta	−1.57	−1.05	−0.58	−0.04	−1.12	−0.78	−0.52	−0.82	−3.74	−2.42
	(**−2.18**)	(−1.22)	(−0.75)	(−0.11)	(**−2.97**)	(**−2.41**)	(−0.56)	(−0.94)	(**−2.79**)	(**−2.30**)

Table V. (continued)

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
6 Anomaly Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Analyst Bias Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prototype	1	2	3	2	2	3	2	3	2	3
Variable	X_q			$\widehat{AB}$	$\widehat{AB} \times HTV$		$\widehat{AB}^{\perp Z}$		$\widehat{AB}^{\perp Z} \times HTV$	
Coefficient	$\widehat{\gamma}_q$			$\widehat{\omega_0}$	$\widehat{\omega_1}$		$\widehat{\theta}_0$		$\widehat{\theta}_1$	
Profitability										
A.4.1 Roe	0.63	0.45	0.33	−0.02	−1.18	−0.84	−0.32	−0.56	−3.79	−2.50
	(**2.84**)	(**2.34**)	(1.94)	(−0.04)	(**−3.14**)	(**−2.55**)	(−0.36)	(−0.68)	(**−2.86**)	(**−2.22**)
A.4.2 dRoe	0.42	0.24	0.24	−0.11	−1.12	−0.78	0.02	−0.32	−4.16	−2.61
	(**2.24**)	(1.52)	(1.62)	(−0.27)	(**−2.97**)	(**−2.35**)	(0.03)	(−0.38)	(**−3.00**)	(**−2.27**)
A.4.3 Roa	2.10	1.30	1.07	−0.05	−1.16	−0.82	−0.40	−0.53	−3.65	−2.48
	(**3.49**)	(**2.18**)	(1.44)	(−0.12)	(**−3.10**)	(**−2.53**)	(−0.46)	(−0.65)	(**−2.74**)	(**−2.24**)
A.4.4 dRoa	2.46	1.63	1.36	−0.13	−1.07	−0.79	−0.15	−0.52	−4.01	−2.54
	(**2.84**)	(1.65)	(1.44)	(−0.32)	(**−2.89**)	(**−2.40**)	(−0.17)	(−0.62)	(**−2.97**)	(**−2.25**)
A.4.6 Cto	−0.10	−0.07	−0.03	−0.12	−1.17	−0.89	−0.67	−0.82	−3.12	−2.20
	(**−2.74**)	(−1.73)	(−0.94)	(−0.30)	(**−3.03**)	(**−2.70**)	(−0.74)	(−0.94)	(**−2.22**)	(**−1.99**)
A.4.10 Gla	0.24	0.10	0.18	−0.15	−1.15	−0.81	−0.10	−0.51	−3.95	−2.43
	(1.38)	(0.48)	(0.58)	(−0.38)	(**−3.06**)	(**−2.45**)	(−0.11)	(−0.61)	(**−2.94**)	(**−2.16**)
A.4.11 Gla^q	0.51	0.28	0.22	−0.05	−1.20	−0.85	−0.51	−0.77	−2.97	−1.99
	(**2.39**)	(1.13)	(0.45)	(−0.13)	(**−3.09**)	(**−2.55**)	(−0.55)	(−0.87)	(**−2.14**)	(−1.80)
A.4.24 O	−0.05	0.05	0.05	−0.12	−1.12	−0.78	−0.82	−0.97	−3.69	−2.40
	(−1.44)	(1.14)	(1.24)	(−0.30)	(**−2.98**)	(**−2.41**)	(−0.92)	(−1.19)	(**−2.77**)	(**−2.29**)
A.4.26 Z	0.02	−0.02	−0.03	−0.07	−1.18	−0.80	−0.40	−0.58	−3.54	−2.33
	(1.01)	(−1.10)	(−1.40)	(−0.18)	(**−3.09**)	(**−2.43**)	(−0.46)	(−0.71)	(**−2.65**)	(**−2.15**)
A.4.32 Bl	−0.02	0.00	0.00	−0.05	−1.13	−0.79	−0.51	−0.77	−3.75	−2.43
	(−1.40)	(0.06)	(0.32)	(−0.13)	(**−2.99**)	(**−2.44**)	(−0.56)	(−0.88)	(**−2.80**)	(**−2.27**)
Intangibles										
A.5.6 Rds	−0.16	−0.26	0.28	0.03	0.08	0.33	0.68	0.60	−6.04	−4.73
	(−0.19)	(−0.38)	(0.42)	(0.07)	(0.14)	(0.56)	(0.71)	(0.66)	(**−3.45**)	(**−2.88**)
A.5.8 Ol	0.14	0.12	0.08	−0.09	−1.12	−0.80	−0.84	−1.16	−3.47	−2.30
	(**2.01**)	(1.54)	(1.25)	(−0.23)	(**−2.90**)	(**−2.42**)	(−0.86)	(−1.29)	(**−2.52**)	(**−2.17**)
A.5.9 Ol^q	−0.29	−0.28	−0.28	0.02	−1.18	−0.84	−0.42	−0.71	−3.63	−2.31
	(**−5.17**)	(**−4.30**)	(**−4.80**)	(0.05)	(**−3.11**)	(**−2.56**)	(−0.46)	(−0.83)	(**−2.69**)	(**−2.14**)
A.5.18 Age	0.00	0.00	0.00	−0.02	−1.13	−0.78	−0.46	−0.70	−3.46	−2.39
	(**2.05**)	(1.17)	(0.89)	(−0.06)	(**−3.01**)	(**−2.41**)	(−0.51)	(−0.81)	(**−2.70**)	(**−2.25**)
A.5.20 dSi	0.05	0.07	0.04	−0.01	−1.15	−0.87	−0.33	−0.47	−3.67	−2.65
	(0.99)	(1.17)	(0.58)	(−0.02)	(**−2.91**)	(**−2.37**)	(−0.35)	(−0.52)	(**−2.60**)	(**−2.19**)
A.5.21 dSa	0.12	0.04	−0.08	0.01	−1.17	−0.79	−0.45	−0.78	−3.57	−2.43
	(1.73)	(0.48)	(−0.91)	(0.02)	(**−3.06**)	(**−2.40**)	(−0.51)	(−0.89)	(**−2.55**)	(**−2.19**)
A.5.22 dGs	0.12	0.12	0.15	−0.03	−1.20	−0.90	−0.43	−0.63	−3.21	−2.03
	(1.25)	(1.11)	(1.49)	(−0.08)	(**−3.15**)	(**−2.72**)	(−0.48)	(−0.74)	(**−2.42**)	(−1.93)
A.5.23 dSs	−0.28	−0.27	−0.22	−0.09	−1.12	−0.82	−0.25	−0.63	−3.67	−2.26
	(−1.95)	(−1.71)	(−1.49)	(−0.26)	(**−2.85**)	(**−2.36**)	(−0.28)	(−0.72)	(**−2.65**)	(**−1.96**)
A.5.26 Ana	0.01	−0.00	−0.01	−0.14	−1.10	−0.79	−0.47	−0.63	−3.79	−2.49
	(0.87)	(−0.37)	(−1.07)	(−0.36)	(**−2.94**)	(**−2.43**)	(−0.51)	(−0.77)	(**−2.85**)	(**−2.37**)
A.5.46 Ala	−0.38	−0.27	−0.01	−0.03	−1.02	−0.71	−0.41	−0.56	−3.69	−2.53
	(−1.80)	(−1.21)	(−0.06)	(−0.07)	(**−2.72**)	(**−2.19**)	(−0.47)	(−0.66)	(**−2.79**)	(**−2.42**)

Table V. (continued)

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
6 Anomaly Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
Analyst Bias Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prototype	1	2	3	2	2	3	2	3	2	3
Variable		X_q		$\widehat{AB}$	$\widehat{AB} \times HTV$		$\widehat{AB}^{\perp Z}$		$\widehat{AB}^{\perp Z} \times HTV$	
Coefficient		$\widehat{\gamma}_q$		$\widehat{\omega_0}$	$\widehat{\omega_1}$		$\widehat{\theta}_0$		$\widehat{\theta}_1$	
Trading Frictions										
A.6.2 Ivff	−34.40	−19.70	−19.10	0.22	−1.04	−0.63	−0.69	−0.87	−3.16	−2.38
	(−**3.97**)	(−**2.42**)	(−**3.09**)	(0.66)	(−**2.80**)	(−1.94)	(−0.83)	(−1.06)	(−**2.59**)	(−**2.27**)
A.6.4 Ivc	−31.46	−17.69	−17.47	0.22	−1.02	−0.62	−0.72	−0.92	−3.12	−2.35
	(−**3.80**)	(−**2.26**)	(−**2.91**)	(0.66)	(−**2.73**)	(−1.91)	(−0.87)	(−1.12)	(−**2.57**)	(−**2.24**)
A.6.5 Ivq	−35.02	−19.19	−18.92	0.21	−1.08	−0.65	−0.67	−0.86	−3.31	−2.45
	(−**3.89**)	(−**2.31**)	(−**3.04**)	(0.61)	(−**2.88**)	(−**2.02**)	(−0.80)	(−1.03)	(−**2.66**)	(−**2.32**)
A.6.6 Tv	−28.88	−14.46	−15.26	0.17	−1.01	−0.62	−0.78	−1.01	−3.14	−2.38
	(−**3.42**)	(−1.75)	(−**2.29**)	(0.54)	(−**2.72**)	(−1.91)	(−0.97)	(−1.25)	(−**2.64**)	(−**2.28**)
A.6.15 Pps	0.00	−0.00	−0.00	−0.07	−1.12	−0.75	−0.42	−0.68	−3.88	−2.56
	(0.85)	(−0.73)	(−1.71)	(−0.21)	(−**2.99**)	(−**2.30**)	(−0.47)	(−0.81)	(−**3.06**)	(−**2.42**)
A.6.18 Mdr	−7.19	−3.43	−3.86	0.04	−1.01	−0.64	−0.62	−0.87	−3.40	−2.33
	(−**3.17**)	(−1.64)	(−**2.43**)	(0.12)	(−**2.74**)	(−**2.01**)	(−0.73)	(−1.05)	(−**2.72**)	(−**2.23**)
A.6.19 Ts	−0.00	−0.01	−0.03	−0.06	−1.07	−0.74	−0.41	−0.71	−3.86	−2.51
	(−0.06)	(−0.16)	(−0.79)	(−0.15)	(−**2.83**)	(−**2.28**)	(−0.46)	(−0.83)	(−**2.89**)	(−**2.36**)
A.6.20 Isc	−0.04	−0.03	−0.06	−0.06	−1.09	−0.76	−0.39	−0.69	−3.86	−2.49
	(−1.22)	(−1.05)	(−1.78)	(−0.14)	(−**2.87**)	(−**2.32**)	(−0.44)	(−0.81)	(−**2.88**)	(−**2.35**)
A.6.21 Isff	−0.04	−0.04	−0.06	−0.06	−1.11	−0.77	−0.40	−0.70	−3.83	−2.46
	(−1.35)	(−1.25)	(−1.90)	(−0.15)	(−**2.90**)	(−**2.35**)	(−0.44)	(−0.81)	(−**2.86**)	(−**2.32**)
A.6.22 Isq	−0.06	−0.04	−0.06	−0.05	−1.11	−0.76	−0.39	−0.70	−3.86	−2.50
	(−1.71)	(−1.16)	(−1.59)	(−0.12)	(−**2.90**)	(−**2.34**)	(−0.44)	(−0.82)	(−**2.87**)	(−**2.36**)
# Significant at 5% (of 60)	37	13	12	0	59	55	0	0	60	56
# of 37 significant w/coeff. shrink		36	37							
# of 37 significant w/t-stat shrink		37	37							
% t-stat shrinks (signif. only avg.)		40%	47%							

Table VI. Robustness

Panel A repeats Table II but reports equally weighted portfolio returns (in percent per month) for the 'standout rows'. The last column presents the corresponding return differential based on Fama and French (2015) 5-factor risk-adjusted portfolio returns. Panel B repeats Table IV's specification 2, but with the inclusion of an additional control for HTV. Panel C lists the summary data about the return predictive efficacy of the 60 anomalies as in Prototype 2 Table V specification 2 (the 'Benchmark' case). In Columns (1) to (5) we subtract the n^{th} percentile each month from each $\widehat{AB}$ ($\widehat{AB}^{\perp Z}$) that month (both as standalone variables, and in their interactions with HTV). Column (6) demeans the analyst bias components in Prototype 2. Column (7) adds an HTV regressor Prototype 2.

Panel A: Equally weighted returns in Table II's 5 × 5 sorts

	Anomaly-correlated Analyst Bias						FF 5-factor
	$\widehat{AB}1$	$\widehat{AB}2$	$\widehat{AB}3$	$\widehat{AB}4$	$\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$	$\widehat{AB}1-\widehat{AB}5$
CR5	1.92	1.27	1.21	0.54	0.52	1.41	1.34
	(**3.36**)	(**2.45**)	(**2.61**)	(1.16)	(1.02)	(**2.77**)	(**2.84**)
R6(loser)	1.93	1.51	1.18	0.93	0.56	1.38	1.40
	(**3.77**)	(**3.35**)	(**2.92**)	(**2.14**)	(1.10)	(**2.75**)	(**2.98**)
SUE1	1.05	1.05	0.94	0.96	0.44	0.60	1.22
	(**3.27**)	(**3.99**)	(**3.42**)	(**3.00**)	(0.99)	(1.79)	(**4.08**)
DISP5	1.35	0.99	1.02	1.07	0.47	0.87	0.74
	(**2.66**)	(**2.40**)	(**2.64**)	(**3.12**)	(1.15)	(**2.17**)	(**1.97**)
AG5	0.80	0.71	0.75	0.46	0.08	0.73	0.89
	(**2.66**)	(**2.41**)	(**2.33**)	(1.19)	(0.17)	(**2.60**)	(**3.29**)
GP1	0.90	0.84	1.04	0.93	0.24	0.66	1.02
	(**3.46**)	(**3.65**)	(**4.14**)	(**2.74**)	(0.53)	(**2.09**)	(**3.30**)

Panel B: Including an HTV control in Table IV's specification 2

Specification	2	2a	2b
Constant	0.98	0.99	0.96
	(**3.31**)	(**3.52**)	(**3.72**)
$\widehat{AB}_{i,t}^{\perp Z}$	−0.41	−0.51	
	(−0.46)	(−0.58)	
$\widehat{AB}_{i,t}^{\perp Z} \times HTV$	−3.80	−3.98	
	(−**2.83**)	(−**2.37**)	
$\widehat{AB}_{i,t}$	−0.04	−0.04	
	(−0.11)	(−0.11)	
$\widehat{AB}_{i,t} \times HTV$	−1.13	−1.15	
	(−**2.96**)	(−**2.62**)	
HTV		0.15	−0.81
		(0.42)	(−**3.61**)

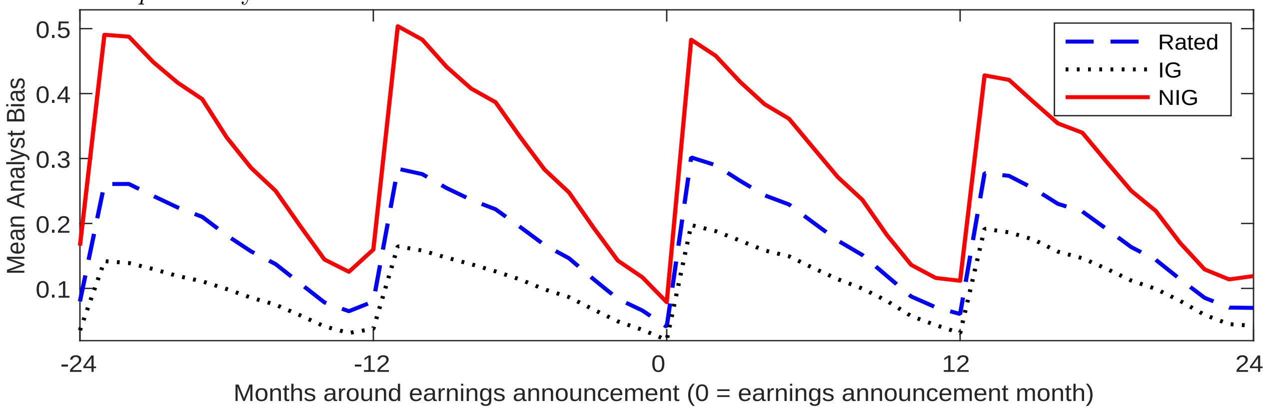
Panel C: Alternative specification prototypes of Table V

Column		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Subtract n^{th} percentile					Subtract	Add
	Benchmark	10^{th}	20^{th}	30^{th}	40^{th}	50^{th}	Mean	HTV
# Significant at 5% (of 60)	13	13	13	13	15	15	15	13
# of 37 significant w/coeff. shrink	36	36	36	36	34	34	34	36
# of 37 significant w/t-stat shrink	37	37	37	37	37	36	35	37
% t-stat shrinks (signif. only avg.)	40	41	40	39	38	37	36	42

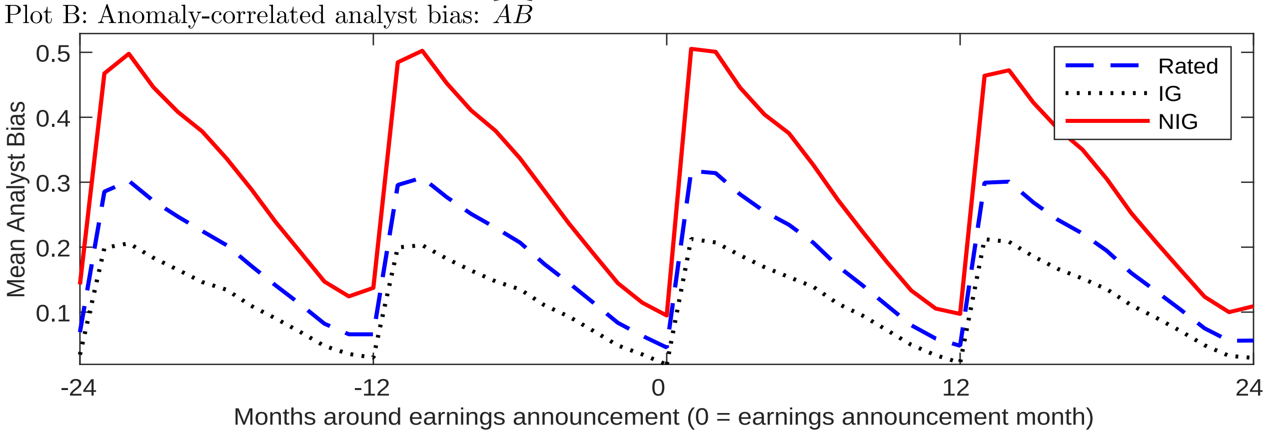
Figure I. Analyst bias around 10K earnings announcements

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 rated firms, as well as for investment-grade (IG) and non-investment-grade (NIG) firms. Panel A (B) [C] reports *ex post* analyst bias AB (anomaly-correlated analyst bias $\widehat{AB}$) [anomaly-free analyst bias $\widehat{AB}^{\perp Z}_{i,t}$].

Plot A: *Ex post* analyst bias: AB



Plot B: Anomaly-correlated analyst bias: $\widehat{AB}$



Plot C: Anomaly-free analyst bias: $\widehat{AB}^{\perp Z}$

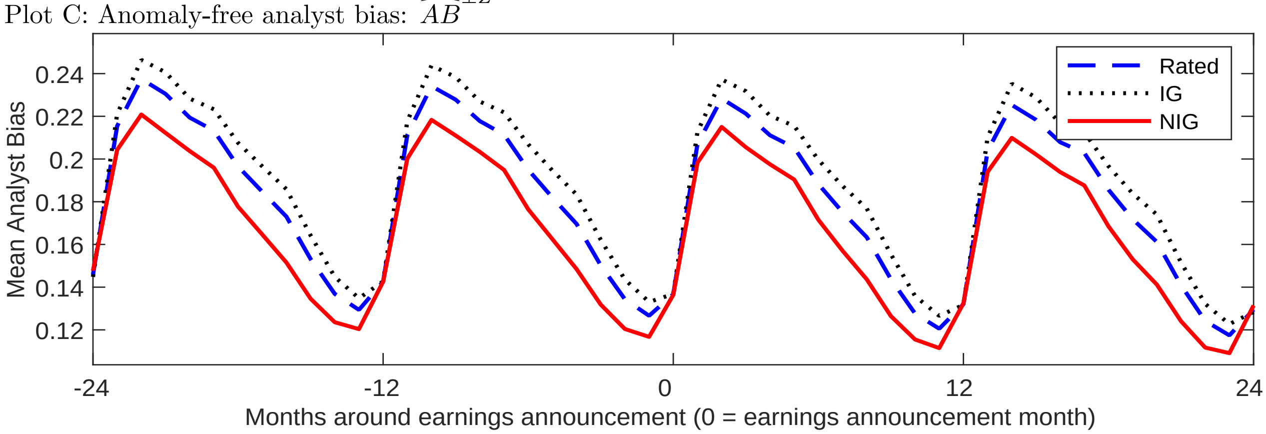
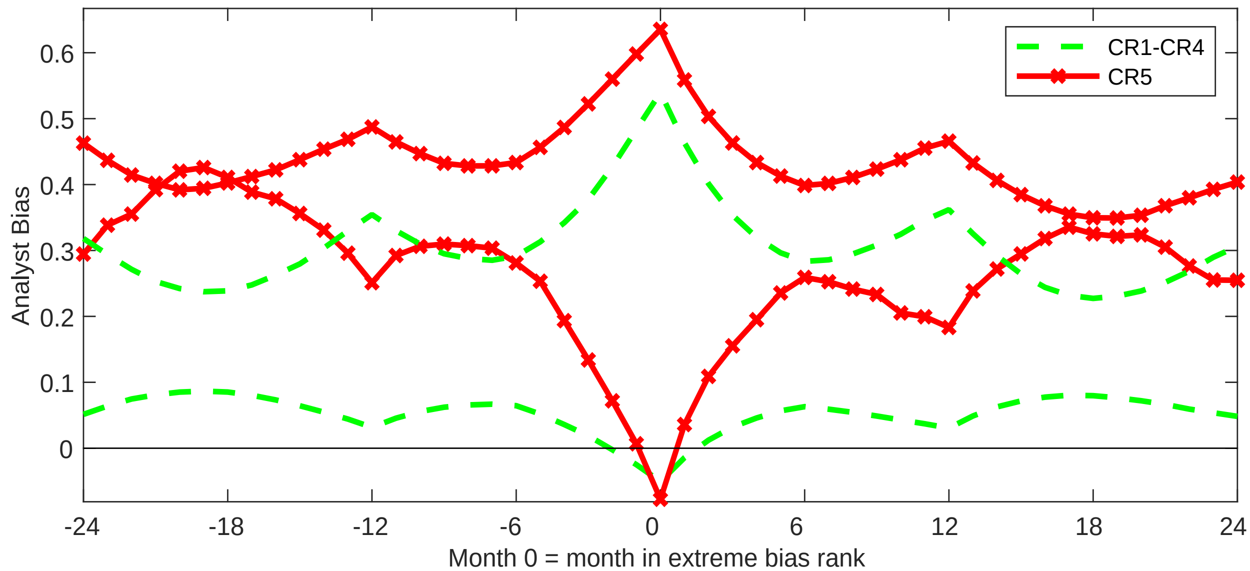


Figure II. Analyst bias around extreme bias ranks
The figure presents, in event time, mean anomaly-correlated analyst bias ($\widehat{AB}$, Plot A) and anomaly-free analyst bias ($\widehat{AB}_{i,t}^{\perp Z}$, Plot B) around month 0 in which a firm is in the lowest (two bottom lines) or highest (two top lines) anomaly-correlated analyst bias quintile.

Plot A: Anomaly-correlated analyst bias ($\widehat{AB}$)



Plot B: Anomaly-free analyst bias ($\widehat{AB}_{i,t}^{\perp Z}$)