Are Analysts Really Too Optimistic?

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Abstract

In this paper, we examine whether the elevated forecasts of analysts relative to their peers are driven by optimism or skill. Empirically, the consensus earnings forecast of firms in the highest quintile of average relative analyst forecasts (ARAF) is 30% more accurate and has significantly better operating performance than that of firms in the lowest quintile, consistent with the idea that relatively high analyst forecasts provide valuable information about future firm performance. In terms of stock market returns, firms with higher ARAF significantly outperform stocks with lower ARAF by 11.2% on an annual basis, and this effect is most pronounced among more uncertain and harder to value firms. Our results are robust to standard risk-adjustments and are persistent even after the implementation of Regulation FD, providing the strongest support for analysts' superior ability to produce valuable information.

JEL classification: G12, G14, G24

Keywords: analyst forecasts, information production, stock returns, forecast accuracy, Regulation FD

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1. Introduction

The recent characterization of analysts in the academic literature and public press has been quite mixed. One strand of the literature portrays these analysts as overly optimistic, while another strand paints them as savvy stock-pickers that are able to select good firms. On the one hand, it is well known that analysts are reluctant to issue negative opinions and recommendations for the stocks they cover (e.g. Barber, Lehavy and Trueman, 2007; O'Brien, McNichols and Lin, 2005; Michaely and Womack, 1999; Lin and McNichols, 1998), since unfavorable recommendations can jeopardize access to company insiders as well as future investment banking business. This leads to consensus opinions and recommendations that are optimistic. However, upwardly biasing forecasts and recommendations could damage the reputation of analysts as well as the reputation of the brokers they work for. Analysts thus face a tradeoff between short-term benefits of higher trading commissions and longer term reputational concerns. Jackson (2005) builds a simple theoretical model and provides empirical evidence of both opportunistic optimism and reputational concerns. More recently, Hribar and McInnis (2011) correlate analyst forecast errors with Baker and Wurgler's (2006, 2007) investor sentiment measure, and find that when sentiment is high, analyst forecasts of one-year-ahead earnings and long-term earnings growth are relatively more optimistic for firms with greater uncertainty.

On the other hand, evidence on the ability of analysts to predict the future performance of firms has received support in recent years. In earlier papers based on published analyst forecasts, Stickel (1995) and Womack (1996) find positive (negative) abnormal returns around the announcement of positive (negative) changes in analysts' stock recommendations. Barber, Lehavy, McNichols and Trueman (2001) also document a profitable trading strategy of purchasing (selling short) stocks with the most favorable (unfavorable) recommendations by analysts. More recently, Das, Guo and Zhang (2006) show that analysts' selective coverage of firms having recently had an initial public offering (IPO) contains positive information about analysts' expectations, and thus leads to superior future performance as measured by returns and operating performance. Thus, growing evidence points to the ability of analysts to select superior stocks, even though some studies have downplayed the benefits of analyst recommendations (e.g. Chan, Karceski, and Lakonishok, 2003; Rajan and Servaes, 1997).

We examine the forecasts of analysts relative to their peers and ask whether relatively high forecasts are driven by optimism or skill. To answer this question, we draw a distinction between optimism and skill. We define skill as a relatively high forecast accompanied by informational content, where informational content is produced by analysts through the obtainment of private information or through the superior analysis of public information. By contrast, we define optimism as a relatively high forecast unaccompanied by informational content. We first examine firm accounting performance in order to determine whether or not there is any informational content in relative analyst forecasts. Our results show that there is considerable informational content in high average relative analyst forecasts. For earnings (prices), the consensus forecast of firms in the highest quintile of average relative analyst forecasts is almost 30% (7%) more accurate than that of firms in the lowest quintile. Moreover, these firms have significantly better operating performance in the subsequent fiscal quarter.

While there is informational content in high relative analyst forecasts, it does not preclude the possibility that skill and optimism coexist. We therefore examine firm stock-market performance in order to determine whether skill or optimism is the dominant feature of relative analyst forecasts. Our results show that stocks with higher average relative analyst forecasts predict significantly higher future stock returns than stocks with lower average relative analyst forecasts.[1] Specifically, a portfolio in the highest quintile of average relative analyst forecasts outperforms a portfolio in the lowest quintile of average relative analyst forecasts by 11.2% on an annual basis. We find this effect to be most pronounced among stocks that are more uncertain and harder to value such as small firms, firms with high volatility or turnover, and young firms. In the quintile of most difficult to value firms, a portfolio in the highest quintile of average relative analyst forecasts outperforms a portfolio in the lowest quintile of average relative analyst forecasts by 16.1% to 22.6% on an annual basis, depending on the measure of uncertainty used. Our results are robust to standard risk-adjustments, and are inconsistent with average relative analyst forecasts as a proxy for analyst optimism or risk. Indeed, our results provide the strongest support for analysts' superior ability to produce valuable information.

In addition, we examine the effect of Regulation Fair Disclosure (Reg FD) on our results. Since Reg FD prohibits firms from disclosing value-relevant information to select analysts without simultaneously disclosing this same information to all market participants, it eliminates the informational advantage enjoyed by the select analysts who received advanced notice of material information. We show that firms with higher average relative analyst forecasts have higher returns both before and after the implementation of Reg FD, but the magnitude of this effect is 6.7 percentage points lower annually post-Reg FD compared to pre-Reg FD. However, analysts still have the ability to generate valuable information in the post-FD period. In particular, in the highest firm volatility quintile, high average relative analyst forecasts have 18.8% higher returns than low average relative analyst forecasts after the implementation of Reg FD, compared to 25.0% before the implementation of Reg FD. We therefore conclude that only a

[1] We use average relative analyst forecasts and firm-level relative analyst forecasts interchangeably in this paper. Unless otherwise specified, we use both to mean the average relative analyst forecasts at the firm-month level.

portion of analysts' ability to produce information was driven by their informational advantage relative to other market participants.

We also consider the possibility that relative analyst forecast is a proxy for other variables that have been found to be important in the literature. In particular, in addition to the usual control variables such as size, book-to-market and momentum, our multivariate tests control for analyst dispersion, earnings momentum, forecast accuracy, consensus recommendations, liquidity and credit rating, among other variables. We find that the relative analyst forecast effect documented in this paper has a distinct impact from the other explanations which have been found in the literature.

We distinguish ourselves from the above literature in three ways. First, our measure of relative analyst forecasts is based on the approach of Cowen, Groysberg, and Healy (2006), who compare a given analyst's forecast for a particular company and time period to the mean forecast for all analysts for the same company and time period within a comparable forecast horizon. Cowen et al. (2006) denote their measure as forecast optimism, and find that analyst optimism is at least partially driven by trading incentives. Hong and Kubik (2008) and Jackson (2005) also use relative analyst forecasts (forecasts greater than the consensus) as a measure of analyst optimism. It is worthwhile to note, however, that although these papers (including Cowen et al., 2006) label relative analyst forecasts as analyst optimism, the authors do not empirically verify this relationship at the firm level. A priori, we do not take a stance on whether relative analyst forecasts represent optimism or not. Indeed, we examine firm accounting and stock-market performance in order to determine how much of the relative forecast is driven by analyst skill versus optimism. Second, our approach is similar to Barber et al. (2001) and Hribar and McInnis (2011) in that we take an investor-oriented, calendar-time perspective. The event-study methodology used in many prior studies, where firms' stock returns are analyzed following the announcement of an analyst forecast, face the challenge that new forecasts are potentially driven by contemporaneous firm conditions. Third, while our work builds on recent empirical work by Das et al. (2006) who show that for newly listed IPOs, selective analyst coverage contains positive information about the firm's future prospects, the average relative analyst forecasts effect found in this paper is more general than the coverage effect in the sense that it is not confined to IPOs or to other newly covered firms.

The main contribution of this paper is to distinguish between analyst optimism and analyst skill, which has hitherto received mixed support in the literature. Our results provide convincing evidence that analysts provide informational value to investors through their forecasts, which continues to hold even after the implementation of Regulation FD. This paper also adds to the literature on market efficiency by documenting positive factor-adjusted returns for firms with high average relative analyst forecasts. The magnitude and significance of our findings, as well as the fact that they hold using both earnings forecasts and price targets, make it unlikely that they are the result of data mining. Furthermore, there is no clear source of increased risk from holding a portfolio of relatively high forecast firms. Our results therefore point to a market which is semi-strong inefficient before transactions costs.

The remainder of the paper is structured as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes the data and summary statistics of our sample. Section 4 examines the informational content of average relative analyst forecasts through analyst forecast accuracy and accounting performance. We report the raw and factor-adjusted returns for univariate sorts, bivariate sorts, and cross-sectional regressions in Section 5. Section 6 examines the impact of Regulation Fair Disclosure. Section 7 reports robustness tests, and Section 8 offers concluding remarks.

2. Literature Review and Hypotheses

Evidence on the ability of analysts to predict the future performance of firms has received support in recent years. In earlier papers based on published analyst forecasts, Stickel (1995) and Womack (1996) find positive (negative) abnormal returns around the announcement of positive (negative) changes in analysts' stock recommendations. Barber et al. (2001) also document a profitable trading strategy of purchasing (selling short) stocks with the most favorable (unfavorable) recommendations by analysts. More recently, Das et al. (2006) show that analysts' selective coverage of newly listed firms (IPOs) contains positive information about analysts' expectations, and thus leads to superior future performance as measured by returns and operating performance. Thus, growing evidence points to the ability of analysts to select superior stocks, even though some studies have downplayed the benefits of analyst recommendations (e.g. Chan et al., 2003; Rajan and Servaes, 1997).

Another strand of literature documents optimism among analysts. Several studies have shown that forecasts made by analysts affiliated with underwriters are optimistically biased and these analysts are reluctant to downgrade stocks with negative news (e.g. Dechow, Hutton and Sloan, 2000; Barber et al., 2007; O'Brien et al., 2005; Michaely and Womack, 1999; Lin and McNichols, 1998). Furthermore, Hong and Kubik (2003) show that analysts are rewarded for making optimistic forecasts, especially for underwriting clients. However, in contrast to this prior research, Cowen et al. (2006) show that affiliated analysts make less optimistic forecasts and recommendations than analysts at non-underwriter firms, suggesting that there are important non-underwriter factors that affect analyst bias, such as trading incentives. Such trading incentives are also supported in Jackson (2005), who shows that optimistic analysts generate more short-term trading volume, but that reputational concerns mitigate analysts' opportunistic behavior. In a recent paper, Hribar and McInnis (2011) correlate analysts' forecast errors with investor sentiment and find that when sentiment is high, analysts' forecasts of one-year-ahead earnings and long-term earnings growth are relatively more optimistic for firms with greater uncertainty. The authors show that adding these forecast errors to a regression of stock returns on sentiment absorbs a significant portion of the explanatory power of sentiment for the cross-section of future returns.

However, if the analyst recommendations used predominantly in the stock selection literature are positively correlated with the analyst forecast errors predominantly used in the analyst optimism literature, then the two strands largely coincide. We use the approach in Cowen et al. (2006) to define a relative analyst forecast measure, and aggregate this measure at the firm-level. Relative analyst forecast is therefore defined as follows:

$$RAF_{i,j,t} = [F_{i,j,t} - \mu(F_{i,[t,t-k]})] \,/\, \sigma(F_{i,[t,t-k]})$$

$F_{i,j,t}$ is analyst j's forecast for firm *i* and for the forecast date *t*; $\mu(F_{i,[t,t-k]})$ is the average forecast of all analysts for the period *t* to *t-k*, for the same fiscal period end date and for the same firm, and $\sigma(F_{i,[t,t-k]})$ is the standard deviation of these forecasts. In words, RAF is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts.[2] The firm-level measure of RAF, which we denote as ARAF, is computed by averaging relative

[2] We repeat our tests using 2 and 4-month horizons instead of a 3-month horizon, and find that our results remain qualitatively similar.

analyst forecasts across all analysts giving a forecast in the month for the same firm.[3] ARAF controls for any company or time-specific factors that affect forecasts, and therefore eliminates the general biases attributed to consensus forecasts or recommendations.

Our goal in this paper is to see whether relatively high forecasts are driven by optimism or skill. We therefore draw a distinction between optimism and skill. We define skill as a relatively high forecast accompanied by informational content, where informational content is produced by analysts through the obtainment of private information or through the superior analysis of public information. By contrast, we define optimism as a relatively high forecast unaccompanied by informational content.

Our first objective is to examine firm forecast accuracy and accounting performance in order to determine whether or not there is any informational content in relative analyst forecasts. If analyst skill is a component of average relative analyst forecasts, then we should observe that firms with higher ARAF have greater informational content than firms with low ARAF. Empirically, this would imply more accurate forecasts and better future accounting performance. Therefore, the null hypothesis is that ARAF is unrelated or negatively related to forecast accuracy and accounting performance. Our alternative hypothesis is:

H1: Higher average relative analyst forecasts have greater informational content (more accurate analyst earnings forecasts and better accounting performance)

Even if we are able to show that firms with higher ARAF have greater informational content than firms with low ARAF in support of H1, this does not exclude the possibility that skill and optimism coexist. Therefore, our second objective is to analyze whether average relative analyst forecasts (ARAF) can predict the cross-section of future stock returns. If ARAF

[3] We repeat our tests using a relative consensus forecast (RCF) measure (specifically, RCF equals current-month consensus earnings forecast minus prior-month consensus earnings forecast, divided by prior-month standard deviation of earnings forecasts), and find that our results remain qualitatively similar.

is predominantly a measure of analyst ability, then it should be positively related to future stock returns. If ARAF is predominantly a measure of analyst optimism, however, then it should be negatively related to future stock returns. A third possibility is that ARAF captures risk. If this is the case, then ARAF should be positively related to future stock returns, but insignificant after risk adjustments, unless it represents a new risk measure. Therefore, the null hypothesis is that ARAF is unrelated to subsequent stock returns. We have two mutually exclusive alternative hypotheses:

H2a: Higher average relative analyst forecasts have higher subsequent stock returns

H2b: Higher average relative analyst forecasts have lower subsequent stock returns

We also examine how the ARAF-return relationship is related to firm uncertainty. Specifically, we expect that if ARAF is a measure of analyst ability or analyst optimism, the ARAF-return relationship should be stronger for firms that are more uncertain or harder to value. If ARAF represents risk, then we have no reason to believe that the ARAF-return relationship would change for more uncertain or harder to value firms, especially after risk adjustments, unless it is inherently more difficult to properly adjust for risk on this subsample of firms.

3. Data and Summary Statistics

3.1. Data

The initial sample is composed of firms covered in Thomson Reuters' I/B/E/S unadjusted detail history file from January 1984 to December 2011. We actually collect I/B/E/S data starting in August 1983, before which data is quite sparse, but require three months of forecasts to calculate our average relative analyst forecasts (ARAF) measure. We retain U.S. analyst EPS forecasts for the one-year fiscal period, and eliminate observations where the analyst code is missing. We eliminate observations for which ARAF is missing and also truncate the sample on ARAF below 1% and above 99% because of errors found in the I/B/E/S detail history file.[4] Finally, we also remove firms that are not covered by the Center for Research in Security Prices (CRSP) or that have a price that is lower than $5 to ensure that the empirical findings are not driven by highly illiquid stocks. Actual EPS is obtained from the I/B/E/S unadjusted detail actuals file, while other accounting data is taken from Compustat. Credit rating is the S&P long-term debt rating obtained from Wharton Research Data Services (WRDS). In a secondary sample, we also collect data on analyst price targets, and repeat all of our tests using this sample. All of our results are qualitatively similar using this alternative sample. However, we do not present price target results (except in Table 3) because the sample begins only in 1999.[5]

3.2. Summary Statistics

Table 1 reports summary statistics for the variables used throughout this paper. Our main variable of interest, average relative analyst forecasts (ARAF), has a mean value of −7.13% and a median value of −1.32%. The negative sign appears consistent with initial analyst optimism since ARAF is defined relative to the average forecast in the same month and the two prior months, and most of the forecasts which make up the mean come before the forecast. Thus, the negative mean and median values of ARAF imply that forecasts tend to be lower than the three month average and that earnings forecasts are revised downward (perhaps due to the release of quarterly earnings reports), suggesting that they were, on average, too high in earlier months. The mean and median market value (MV) of firms in our sample is $4,064.27 million and

[4] A notable example is Microsoft. On five occasions between December 4th 1986 and January 14th 1987, a 1-year EPS forecast of around $20 per share (between $19.40 to $22.14) was given for the fiscal period ending June 30th 1987, even though all of the other 79 forecasts in 1986-87 were around $2 (between $1.62 and $3.06).

[5] These tables are available upon request.

$720.43 million, respectively, and exhibits considerable variation. For example, the smallest firm in our sample is $0.38 million while the largest firm in our sample is $581,098.86 million. Following earlier studies (e.g. Diether, Malloy, and Scherbina, 2002; Avramov, Chordia, Jostova, and Philipov, 2009), we define dispersion in analysts' forecasts (DAF) as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast, as reported in the I/B/E/S Unadjusted Summary History file. DAF has a mean value of 19.08% and a median value of 4.65%, and exhibits some variability (standard deviation of 127.78%). The variability of DAF is also found in Avramov et al. (2009) for a slightly shorter sample period (1985-2003). We compute credit rating (CR) by transforming the S&P long-term debt ratings into conventional numerical scores as found in Avramov et al. (2009). A higher numerical score reflects higher credit risk. Firms in our sample have an average monthly credit rating score of 9.04, which is similar to the average credit rating score in Avramov et al. (2009). We use EPS forecast accuracy (ACC) as a measure of analysts' informational content, and report mean ACC of 0.36 and a median of 0.11. In addition, we control for consensus analyst recommendations since several papers have documented a relation between changes in analyst recommendations and announcement effects as well as post-recommendation stock drift (e.g. Barber et al., 2001; Womack, 1996; Stickel, 1995). We report a mean consensus recommendations (CREC) of 2.19 and a median of 2.18. We use the daily return standard deviation (VOL), share turnover (TURN), and firm age (AGE), measured as the number of months that firms have been listed on CRSP, as further measures of uncertainty. Statistics for these and the remaining firm characteristics are comparable to those found in other studies.

[*Insert Table 1 here*]

In Table 2 we present a correlation matrix to see how ARAF is related to other potentially important control variables from the literature. We find that firms with higher ARAF are generally larger and have smaller book-to-market ratios, as indicated by the positive correlation between ARAF and MV (correlation of 0.03) and the negative correlation between ARAF and BV/MV (correlation of –0.04). The correlation between ARAF and momentum (MOM) is positive and somewhat strong, with a correlation of 0.09. Therefore, controlling for the size (MV), book-to-market (BV/MV) and momentum (MOM) factors will be important in our tests below. We find higher ARAF is associated with lower dispersion in analysts' forecasts (DAF), as indicated by the negative correlation of –0.02. Since Diether et al. (2002) find a negative relationship between dispersion and future returns, we thus control for DAF in our multivariate analysis below to ensure that ARAF is not simply capturing the negative DAF-return relationship. We also find a rather strong and positive relationship between the one-month lagged return (LAGRET) and ARAF (correlation of 0.11). The one-month past return is potentially important because of the short-term reversal in individual stock returns documented by Jagadeesh (1990). However, the positive ARAF-LAGRET relationship would imply a negative relationship between ARAF and future returns. We measure illiquidity (ILLIQ) as in Amihud (2002) and find that ILLIQ is negatively correlated with ARAF, but the relationship is not particularly strong with a correlation of –0.01. Nevertheless, several studies show that higher (lower) illiquidity increases (reduces) a firm's cost of capital (e.g. Acharya and Pedersen, 2005; Pastor and Stambaugh, 2003; Amihud, 2002; Amihud and Mendelson, 1986) and leads to higher (lower) expected returns. Therefore, if ARAF is capturing illiquidity, the negative ARAF-ILLIQ would imply lower future returns. We thus control for illiquidity in our multivariate analysis below, as well as including the Pastor and Stambaugh (2003) liquidity factor for the factor-adjusted returns. The correlation between ARAF and analyst forecast accuracy (ACC) is negative and somewhat strong (correlation of –0.07), which is consistent with the idea that higher average relative analyst forecasts is associated with valuable informational content. Interestingly, we find consensus recommendations (CREC) to be negatively correlated with ARAF, with a correlation of –0.05. According to the previous literature, higher recommendations are associated with higher returns so that that the negative ARAF-CREC relation would imply a negative relationship between ARAF and future returns. We also find earnings momentum (EMOM) to be positively correlated with ARAF (correlation of 0.03). Earnings momentum is calculated as in Doyle, Lundholn, and Soliman (2006) as actual earnings less the most recent consensus earnings forecast, scaled by the end of quarter price. Ball and Brown (1968) first documented earnings momentum, or post-earnings-announcement-drift, that firms reporting unexpectedly higher earnings subsequently outperform firms reporting unexpectedly low earnings, others have also confirmed the robustness of these results (e.g. Foster, Olsen and Shevlin, 1984; Bernard and Thomas, 1989). Therefore, we control for earnings momentum below to ensure that ARAF is not simply picking up a positive EMOM-return relationship. The remaining variables (VOL, TURN, AGE and CR) do not exhibit a remarkably strong relationship with ARAF.

[*Insert Table 2 here*]

4. Forecast Accuracy and Accounting Performance

In Table 3 we provide insight into the informational content of average relative analyst forecasts by examining the relationship between ARAF and analyst forecast accuracy and between ARAF and firm operating performance in the fiscal quarter following the month in which forecasts are observed. If ARAF captures analysts' ability to produce valuable information, then we should find that consensus forecasts of firms with higher ARAF are more accurate than those of firms with lower ARAF. Moreover, the firm operating performance should also be significantly better for high ARAF firms than low ARAF firms.

Table 3 presents the forecast accuracy and operating performance of portfolios of firms sorted monthly into average relative analyst forecasts quintiles. The results are reported for the full sample as well as for bivariate portfolios split into high uncertainty firms (top uncertainty quintile) and low uncertainty firms (bottom uncertainty quintile), where uncertainty is measured by volatility (VOL). Panel A reports median results along with z-tests of median differences between ARAF1 and ARAF5 for relative analyst *earnings* forecasts, and Panel B reports median results along with z-tests of median differences between ARAF1 and ARAF5 for relative analyst *price* targets, our alternative measure. We analyze three operating performance measures: (i) return on assets (ROA) is the ratio of net income to assets; (ii) cash flow return on assets (CROA) is the ratio of operating income before depreciation to assets; and (iii) return on equity (ROE) is the ratio of net income to book value of equity. Each of the measures is industry-adjusted to remove any industry effect which may be driving results. Specifically, we remove the industry median during the same period, where industry is determined by the firm's 2-digit Standard Industrial Classification (SIC).

Focusing on the results for the full sample, we find that forecast accuracy (ACC) is decreasing in ARAF, and the forecasts in the high ARAF portfolio are statistically and economically more accurate – and in particular, less optimistic – than the forecasts in the low ARAF portfolio for both earnings forecasts and price targets. Since ACC is an ex-post measure, this says that consensus forecasts of firms with higher ARAF are more accurate than firms with lower ARAF, which is consistent with average relative analyst forecasts capturing valuable information content.

We further find a strong and positive relationship between ARAF and each of our operating performance measures. In particular, high ARAF portfolios (ARAF5) significantly outperform low ARAF portfolios (ARAF1) operationally by $0.48 to $0.65 per $100 of assets and $0.87 per $100 of equity in median for earnings forecasts. The results for price targets in Panel B are slightly less in magnitude: high ARAF firms significantly outperform low ARAF firms operationally by $0.29 to $0.36 per $100 of assets and $0.44 per $100 of equity in median.[6]

We gain further insight into the informational content of ARAF when we split the sample into firms with high uncertainty and firms with low uncertainty. If analysts are producing valuable information, as captured by average relative analyst forecasts, then we should expect their abilities to be more pronounced for firms that are the hardest to value, since these are firms for which information is not as readily available in the public domain and for which the interpretation and production of information should matter most. The bivariate portfolio results in Table 3 support this hypothesis. In particular, the median difference in ACC between ARAF1 and ARAF5 for earnings forecasts is 9.0 times larger for high uncertainty firms compared to low uncertainty firms (–0.10 versus –0.01), and the median difference for price targets is about 6.0 times larger for high uncertainty firms compared to low uncertainty firms (–0.06 versus 0.01). These large differences also hold for each of our operating performance measures, where we find that the difference in ROA and CROA is about 2.5 times larger for high uncertainty firms compared to low uncertainty firms and about 1.8 times larger for ROE in Panel A for earnings forecasts. We find similar results in Panel B for price targets: ROA is about 3.1 times larger,

[6] It is typical to report median values in studies examining operating performance, as noted by Loughran and Ritter (1997), among others, due to the skewness of accounting ratios. In unreported tests, we confirm that our results also hold in mean.

CROA is about 2.0 times larger, and ROE is about 3.0 times larger for high uncertainty firms compared to low uncertainty firms.

In sum, the Table 3 results provide convincing evidence that higher average relative analyst forecasts captures valuable information content by predicting more accurate forecasts and better operating performance, and these results are most pronounced for firms that are hardest to value and for which information processing by analysts matters the most.

[*Insert Table 3 here*]

5. Stock Market Performance

5.1. Univariate Sorts

In this subsection we present monthly return results for univariate portfolios sorted by average relative analyst forecasts (ARAF). Specifically, each month stocks are sorted into quintiles and the average equal-weighted return is reported for each portfolio.[7] Panel A of Table 4 reports mean portfolio raw and factor-adjusted returns by ARAF quintile, as well as a high minus low ARAF hedge portfolio which is long on firms in the high-ARAF portfolio and short on firms in the low-ARAF portfolio. The results show that average raw returns are positive and monotonically increasing in the ARAF portfolios, indicating that high-ARAF firms significantly outperform low-ARAF firms (at the 1% level of significance) on average by 0.93% on a monthly basis and 11.16% (0.93% × 12 months) on an annual basis. Interestingly, we find that the low-ARAF portfolio is insignificant, suggesting that firms with relatively lower average relative analyst forecasts do not earn reliably positive returns.

[7] In unreported tests, we also compute average value-weighted returns. We find qualitatively similar results, but with lower economic significance. The lower significance is consistent with the bivariate sorts in the next subsection and supports the idea that the ARAF-return relationship is most pronounced for smaller firms.

We also report results for factor-adjusted returns in Panel A of Table 4. These returns are the monthly abnormal returns (intercepts) in percent based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. The results for factor-adjusted returns are also impressive. Specifically, the high minus low ARAF hedge portfolio is 0.98% and highly statistically significant at the 1% level. On an annual basis, the high-ARAF portfolio outperforms the low-ARAF portfolio by 11.76% (0.98% × 12 months). In addition, once we control for known factors, we find that the average returns in the first two quintiles are no longer statistically significant. At first glance, one might expect these portfolios to underperform due to negative information; however, the zero abnormal returns documented in the lowest two quintiles is consistent with the prior literature that analysts are reluctant to issue negative opinions when there is negative information (e.g. Barber et al., 2007; O'Brien et al., 2005; Michaely and Womack, 1999; Lin and McNichols, 1998).

Panel B of Table 4 presents results for conditional returns where we examine average raw and factor-adjusted returns for the subsample of firms that have negative ARAF and for the subsample of firms that have positive ARAF. The results indicate that much of the impact on returns is for firms that have positive ARAF. In particular, for raw returns, negative ARAF firms have average monthly returns of 0.72% and positive ARAF firms have average monthly returns of 1.31%. The difference (0.60%) is statistically significant at the 1% level. The results for factor-adjusted returns are also striking. Firms with negative ARAF have a statistically insignificant average factor-adjusted return of 0.41, while firms with positive ARAF have a statistically significant (at the 1% level) 1.03% average factor-adjusted return. The difference (0.64%) is slightly larger than for raw returns, and also highly statistically different from zero at the 1% level. Similar to the Panel A results, we associate the non-significant average return for negative ARAF to be consistent with the idea that analysts are reluctant to issue negative opinions.

The univariate results, which indicate a positive relation between ARAF and returns, strongly support hypothesis H2a. Further, given the risk-adjustment procedures have no impact on the ARAF-return relationship, we find no support for a risk-based explanation. We turn to bivariate sorts below to see whether the ARAF-return relationship is concentrated among hard to value firms.

[*Insert Table 4 here*]

5.2. Bivariate Sorts

In this section, we analyze returns for bivariate portfolios sorted by ARAF and various firm characteristics. Each month, we form 25 (5 × 5) portfolios by independently sorting the sample firms into five portfolios based on ARAF and five portfolios based on specific firm characteristics and intersecting these portfolios. For brevity, we only report results for the ARAF5 – ARAF1 hedge portfolio with respect to each of the firm characteristic quintiles.

Table 5 presents bivariate portfolio results for MV, BV/MV, MOM, and ILLIQ to see if we are capturing a size, book-to-market, momentum or liquidity effect. Panel A reports bivariate sorts with MV. The results indicate that the average monthly raw return differential between high- and low-ARAF portfolios is significant in four out of the five MV quintiles, suggesting that we are not simply picking up a size effect. However, the results do indicate that the economic impact declines by size quintile, from a 1.75% monthly differential (21.00% annual differential) in the lowest size quintile, to a monthly differential of 0.29% (3.48% annual differential) in the highest size quintile. The larger ARAF5 – ARAF1 differential in the smallest size quintile is consistent with analysts' abilities to produce valuable information being greater among smaller stocks that are generally harder to value. For large stocks, which already receive substantial public coverage, analysts would be expected to have less pronounced abilities to produce valuable information. Interestingly, for factor-adjusted returns, we find high minus low ARAF to be significant in each size quintile, but the economic significance of the ARAF5 – ARAF1 differential is still much stronger in the lowest size quintile (22.32% annual differential) than in the highest size quintile (3.00% annual differential).

Panel B of Table 5 presents the results for two-way cuts on ARAF and BV/MV. We find the ARAF5 – ARAF1 differential to be significant in each BM quintile for both raw returns and factor-adjusted returns. In addition, the economic magnitude of the differential increases in BV/MV, suggesting a positive relationship with a known factor. However, we note that ARAF5 – ARAF1 is still substantial in statistical and economic significance even in the lowest BM quintile. The high minus low ARAF hedge portfolio on average yields a 0.90% return monthly (10.80% annually) for raw returns and a 0.93% return monthly (11.16% annually) for factor-adjusted returns. In the highest BM quintile, this differential is 16.08% annually for raw returns, and 16.08% for factor-adjusted returns.

In Panel C of Table 5 we report bivariate portfolio results for ARAF and MOM. We find a statistically and economically significant high minus low ARAF differential in each MOM quintile, suggesting that our results are not being driven by momentum. Interestingly, the results do not demonstrate a remarkable difference in ARAF5 – ARAF1 by MOM quintile. In particular, we find that among the stocks that experienced the lowest prior year stock returns, the high minus low ARAF return differential is a highly statistically significant 0.74% on a monthly basis (8.88% annually), compared to a monthly differential of 0.69% (8.28% annually) among the stocks that experienced the highest prior-year stock returns. The results for factor-adjusted returns are similar in statistical and economic significance, suggesting that standard risk factors are not driving our results.

Panel D reports bivariate sorts with ILLIQ. The results indicate that the average monthly raw return differential between high- and low-ARAF portfolios is significant in all but the lowest ILLIQ quintiles, suggesting that we are not simply picking up a liquidity effect. However, the results do indicate that the economic impact declines by illiquidity quintile, from a 1.56% monthly differential (18.72% annual differential) in the highest illiquidity quintile, to a monthly differential of 0.23% (2.76% annual differential) in the lowest illiquidity quintile. The larger ARAF5 − ARAF1 differential in the highest illiquidity quintile is consistent with analysts' abilities to produce valuable information being greater among firms with less liquid stock, which are generally smaller and harder to value. For factor-adjusted returns, we also find high minus low ARAF to be significant in all but the lowest illiquidity quintile, with the magnitude of the differences being similar to the raw return.

Overall, the results in Table 5 are consistent with the idea that analysts demonstrate better abilities to produce valuable information for firms that are smaller, riskier (as measured by BV/MV) and whose stock is less liquid, but that they still demonstrate strong abilities among firms that are larger, less risky and with generally more liquid stock even after controlling for known risk factors, which is inconsistent with a risk-based explanation.

[*Insert Table 5 here*]

In Table 6 we present bivariate portfolio results sorted by ARAF and various uncertainty proxies (VOL, TURN, and AGE) to test whether ARAF is related to uncertainty and also to test the differential impact of ARAF5 − ARAF1 by uncertainty quintile. In Panel A of Table 7 we report results for the high minus low ARAF hedge portfolio by VOL quintile. We find a strong monotonic relationship between ARAF5 – ARAF1 and volatility. Among stocks that are the most uncertain and potentially hardest to value, we find that a strategy of going long a high-ARAF portfolio and going short a low-ARAF portfolio leads to an average monthly return of 1.88% and an average annual return of 22.56% (1.88% × 12). In comparison, for stocks in the lowest VOL quintile which exhibit the least uncertainty, the high minus low hedge strategy leads to a statistically significant average monthly return of only 0.43% (5.16% annually). The results for factor-adjusted returns are similar to those of raw returns. In particular, ARAF5 – ARAF1 yields a 2.05% average monthly factor-adjusted return (24.60% annually) for stocks in the highest VOL quintile, and a 0.41% average monthly factor-adjusted return (4.92%) for stocks in the lowest quintile. The ARAF5 – ARAF1 return differentials are thus not explained away by known factors.

In Panel B of Table 6 we form two-way sorts between ARAF and stock turnover (TURN), which is often used as another proxy for uncertainty (e.g. Diether et al., 2002; Lee and Swaminathan, 2000; Harris and Raviv, 1993). Higher stock turnover indicates more trading in a given stock, potentially due to greater investor disagreement on expected stock values. Hence, greater turnover is associated with more uncertainty. Similar to the Panel A results for volatility, we find that a strategy of going long in a high-ARAF portfolio and short in a low-ARAF portfolio yields higher profits for firms that exhibit the most share turnover (i.e. are most uncertain). Specifically, ARAF5 – ARAF1 produces a highly statistically significant monthly average return of 1.34% in TURN5 (16.08% annually), compared to a highly statistically significant monthly average return of 0.95% (11.40% annually) in TURN1. The results are just as strong for factor-adjusted returns, suggesting that the profitability of this strategy is not eliminated by known factors. It is worthwhile to note that although the returns for ARAF5 – ARAF1 are highest for firms in the highest TURN quintile, they are still statistically and economically significant in the lowest TURN quintile.

Lastly, in Panel C of Table 6 we examine bivariate portfolios between ARAF and firm age (AGE). Firm age has also been used as an uncertainty proxy in the previous literature (e.g. Hribar and McInnis, 2011; Baker and Wurgler, 2006) such that younger (older) firms are more (less) uncertain and harder to value. We find ARAF5 – ARAF1 to be statistically significant in each of the AGE quintiles, but the relationship is monotonically decreasing in firm age based on economic significance. Among the youngest firms in our sample (AGE1), we find that high minus low ARAF has a monthly average raw return of 1.53% (18.36% annually). For factor-adjusted returns, the monthly high minus low ARAF differential is a slightly higher 1.60% on average (19.20% annually) for the youngest firms in our sample. For the oldest firms in our sample (AGE5), we find an average monthly differential of 0.28% for ARAF5 – ARAF1 (3.36% annually) for raw returns, and 0.27% monthly (3.24% annually) for factor-adjusted returns.

The bivariate portfolio results between ARAF and uncertainty are consistent with the idea that analysts are able to produce more valuable information for the most uncertain and hardest to value stocks. Therefore, a strategy of going long in high-ARAF stocks and short in low-ARAF stocks yields economically meaningful profits, especially for the most uncertain firms. Furthermore, the Table 6 results are inconsistent with a risk-based explanation since ARAF makes no prediction for why the positive relation between average relative analyst forecasts and returns are substantially different for more uncertain or harder to value firms.

[*Insert Table 6 here*]

5.3. Regression Analysis

Table 7 examines the impact of average relative analyst forecasts (ARAF) on stock market returns while controlling for other determinants that have been found to significantly affect returns. In particular, we include Fama and French (1992) size (Ln(MV)) and book-to-market (BV/MV) characteristics; Carhart's (1997) momentum (MOM) from month 2 to month 12 before our return calculation period; Diether et al.'s (2002) analyst EPS forecast dispersion effect (DAF); quarterly earnings momentum (EMOM); prior-month return (LAGRET) to capture the reversal effect; Avramov et al.'s (2009) S&P long-term debt rating effect (CR); forecast accuracy (ACC); and consensus recommendations (CREC). We also test our prediction that the relationship between ARAF and returns is strongest among firms that have the greatest uncertainty using the three previously defined variables for uncertainty – firm stock market return standard deviation (VOL), share turnover (TURN), and the number of months the firm is listed on CRSP (AGE). We use the Fama-MacBeth approach for the regression analysis. The Fama and MacBeth (1973) procedure is designed to address a time effect where the residuals at a given point in time may be correlated across firms. Therefore, we run cross-sectional regressions by year-month for all firms and report the mean coefficient estimates.

Model 1 reports the regression of one-month stock market returns on a constant, ARAF and the abovementioned controls except for CR. Confirming the univariate results in Table 5, we find that higher ARAF leads to significantly higher stock returns even after controlling for other known determinants of stock returns. While we find the sign and statistical significance on the coefficients of the control variables to be consistent with prior studies, they do not explain away the statistical and economic significance of the coefficient on ARAF. Models 2-4 test our further prediction that the ARAF-return relationship should be strongest among highly uncertain firms. Model 2 includes an interaction term between ARAF and VOL, Model 3 includes an interaction between ARAF and TURN and Model 4 includes an interaction between ARAF and AGE. All three interactions are statistically significant in the anticipated direction, and the conclusion is the same in all three models: average relative analyst forecasts has a significantly greater effect for firms with high uncertainty. In Model 5, we add CR and ACC to the Model 1 specification. Since CR is only available for 197,603 of the 656,736 observations, the number of monthly regressions is reduced to 312 and there are less firm observations in each of these monthly regressions. We add CR to control for the negative CR-return relationship documented in Avramov (2009) and we add ACC to control for the sentiment related positive relationship between forecast error and returns documented in Hribar and McInnis (2011). In our setup, ACC is ex post relative to returns since actual EPS results are made public after the fiscal period end date, whereas all other variables are ex ante. While we find the coefficient on ACC to be negative and statistically significant, the coefficient on ARAF still remains positive and statistically significant, although it is of lower magnitude (0.26 in Model 5 versus 0.48 in Model 1). However, we note that the reduced magnitude is mainly driven by the lower number of observations due to the inclusion of CR, rather than the effect of CR or ACC, since in unreported tests we find that the coefficient on ARAF is of about the same magnitude as in Model 5 when we reduce the sample size but do not include CR and ACC. We also note that both DAF and CR are insignificant in Model 5 unlike the results in Avramov et al. (2009). However, we find DAF to be significantly negative on the 1985-2003 sample periods when taking the natural logarithm of DAF and truncating returns, as is done in Avramov et al. (2009). We also find that the inclusion of CR in the abovementioned conditions takes away the significance of DAF. Finally, in Model 6 we include consensus recommendations (CREC) as an additional explanatory variable to test whether ARAF provides more valuable information than analyst recommendations, which has been shown to be positively related to short-term returns. Since consensus recommendations are only available starting in the year 1999, the number of monthly observations is reduced to 217. Indeed the Model 6 results show that ARAF continues to be a strong and positive determinant of future returns, while CREC is positive, but insignificant.[8] This says that ARAF provides valuable information content, which is above and beyond CREC and our other controls.

To summarize, average relative analyst forecasts has a statistically positive relationship with returns in all specifications in support of H2a, and it's interaction with uncertainty variables is also significant in support of the idea that ARAF is a measure valuable information content.

[*Insert Table 7 here*]

6. Regulation Fair Disclosure

In this section we examine the effect of Regulation Fair Disclosure (Reg FD) on our results. Reg FD, which was implemented on October 23, 2000 by the Securities & Exchanges Commission, prohibits firms from disclosing value-relevant information to select analysts without simultaneously disclosing this same information to all market participants.[9] Reg FD therefore eliminates the informational advantage enjoyed by the select analysts who received advanced notice of material information. To the extent that ARAF is driven by this informational advantage, our results may be affected by this regulatory change.

Table 8 reports raw and factor-adjusted returns for the period before the implementation of Reg FD (1984-2000), as well as the period after the implementation of Reg FD (2001-2011). Hypotheses 2a and 2b are tested in light of Reg FD in the column labeled "All", while the

[8] As an alternative measure, we also used the percentage of a firm's analysts providing a buy recommendation less the percentage providing a sell recommendation (NETBUYPCT). This variable is positive and significant, but does not impact the magnitude or significance of ARAF. Interestingly, when NETBUYPCT is included in the regression alongside CREC, CREC becomes significantly positive.

[9] See Heflin, Subramanyam, and Zhang (2003) for a review.

columns labeled “High VOL” and “Low VOL” test whether the ARAF finding is stronger for harder to value firms. The results for all coverage show that firms with higher average relative analyst forecasts have higher returns both before and after the implementation of Reg FD, consistent with H2a. However, the magnitude of this effect is much lower post-Reg FD. Economically, the ARAF5 – ARAF1 hedge portfolio earns 13.80% on an annual basis (1.15% × 12 months) pre-Reg FD and 7.08% (0.59% × 12 months) post-Reg FD. On a factor-adjusted basis, the equivalent numbers are 14.52% (1.21% × 12 months) pre-Reg FD and 7.44% (0.62% × 12 months) post-Reg FD. This reduced effect post-Reg FD suggests that a large component of informational value pre-Reg FD was driven by the informational advantage enjoyed by select professional analysts. However, we cannot rule out the possibility that a change in economic and market-wide conditions from pre- to post-Reg FD might also have reduced the magnitude of the positive ARAF-return relationship. Nevertheless, it appears that analysts are still able to produce valuable information post-Reg FD.

We now examine the effect of ARAF between high uncertainty firms and low uncertainty firms pre- and post-Reg FD. Interestingly, the results indicate that the difference in the ARAF5 – ARAF1 differential between High VOL and Low VOL is similar in magnitude before the implementation of Reg FD and after the implementation of Reg FD. Economically, the ARAF5 – ARAF1 hedge portfolio is 1.55 percentage points higher for high uncertainty firms compared to low uncertainty firms pre-Reg FD (2.08% – 0.53%) on a monthly basis (18.60 percentage points annually), compared to a 1.29 percentage point difference post-Reg FD (1.57% – 0.28%) on a monthly basis (15.48 percentage points annually). The results for factor-adjusted returns are similar, where we find the ARAF5 – ARAF1 hedge portfolio to be 1.72 percentage points higher for high uncertainty firms compared to low uncertainty firms pre-Reg FD on a monthly basis

(20.64 percentage points annually), compared to a 1.76 percentage point difference post-Reg FD on a monthly basis (21.12 percentage points annually). Therefore, these results suggest that the implementation of Reg FD did not impair the pronounced ability of analysts to produce valuable information for high uncertainty firms relative to low uncertainty firms. Indeed, even among high VOL firms, the ARAF5 – ARAF1 hedge portfolio yields a 2.08% profit monthly pre-Reg FD (24.96% annually) compared to 1.57% post-Reg FD (18.84% annually). We therefore conclude that only a portion of analysts' ability to produce information was driven by their informational advantage relative to other market participants pre-Reg FD. An alternate and more cynical interpretation, which is not mutually exclusive to the aforementioned interpretation, is that private information is still being illicitly extracted by analysts post-Reg FD.

In sum, the Table 8 results show that the informational content provided by ARAF dropped substantially post-Reg FD compared to pre-Reg FD, which might suggest that a large component of information production was driven by the informational advantage enjoyed by select professional analysts prior to Reg FD. However, there does not appear to be strong evidence that analysts were producing more valuable information for high uncertainty firms compared to low uncertainty firms prior to Reg FD, since they still seem to be producing just as valuable information for high uncertainty firms after the implementation of Reg FD.

[*Insert Table 8 here*]

7. Robustness

7.1. Average Relative Analyst Forecasts

First, the main measure used throughout this paper is the average relative analyst forecasts (ARAF). Recall that the relative analyst forecast (RAF) is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. While we use a three month average to establish the relative nature of a specific analyst forecast, this horizon is ad hoc. We therefore repeat our tests using a 2-month and a 4-month horizon to ensure that our results are not dependent on this empirical specification. Our results remain qualitatively similar.

Second, the results presented in this paper use earnings forecasts (except in Table 3, where price targets are also examined). We repeat all of our tests price targets instead of earnings forecasts. Our results are qualitatively similar using prices, suggesting that our findings are not limited to earnings, and can be generalized to other types of forecasts.

Third, ARAF is computed by averaging relative analyst forecasts across all analysts giving a forecast in the month for the firm. While this approach is intuitively appealing, it also suggests that using a firm-month relative consensus measure should lead to similar results. We therefore repeat our tests using a relative consensus forecast (RCF) measure (specifically, RCF equals current-month consensus earnings forecast minus prior-month consensus earnings forecast, divided by prior-month standard deviation of earnings forecasts). Our results remain qualitatively similar.

7.2. New Listings

As discussed in Section 2, Das et al. (2006) find that analysts select stocks through the initiation of unexpected coverage after an IPO, and that this selection is positively correlated with stock market returns and accounting performance in the first three years after the offer. In this section, we examine the difference between the results in Das et al. (2006) and those in this paper by separating our sample into new listings (firms listed on CRSP for three years or less) and old listings (firms listed on CRSP for more than three years). While we have already examined the impact of AGE as an uncertainty variable in Tables 6 and 7, and find that the average relative analyst forecasts effect is strongest among newly listed firms, it is still unclear whether this effect is exclusive to IPOs. Table 9 reports raw and factor-adjusted returns by ARAF quintiles as well as for a hedge portfolio which is long in the ARAF5 portfolio and short in the ARAF1 portfolio. Panel A reports results for the subsample of old listings, while Panel B reports results for the subsample of new listings. We find that even for firms that have been listed for more than three years, high ARAF firms outperform low ARAF firms by 0.80% (0.84%) per month on an unadjusted (factor-adjusted) basis. The results are nevertheless much stronger for firms that have been listed for three years or less. On this subsample, high ARAF firms significantly outperform low ARAF firms by 1.56% (1.65%) per month on an unadjusted (factor-adjusted) basis. These results confirm that the average relative analyst forecasts effect found in this paper is more general than the Das et al. (2006) coverage effect in that it is not confined to IPOs. Furthermore, the average relative analyst forecasts effect on the subsample of new listings is much stronger in magnitude than the Das et al. (2006) coverage effect.

[*Insert Table 9 here*]

7.3. Analyst Optimism

While our finding that ARAF is positively related to stock returns is robust to the inclusion of common factors and other known determinants of stock returns (see Table 7 regressions), it is still possible that this effect is driven by a facet of overvaluation that is not captured by these determinants. If this were the case, then the positive relationship between ARAF and stock returns may actually be a contemporaneous manifestation of overvaluation. For example, Miller (1977) predicts that in the presence of short-sales constraints, the price of a firm tends to reflect the valuations of the most optimistic investors, and thus tend to be upward biased. This is the case because pessimistic investors are forced out of the market when short-sales are not available. If the positive relationship between ARAF and stock returns is a reflection of overvaluation, then we should observe subsequent underperformance as investors discover the true firm value over time. In untabulated results, we examine returns from months 2 to 12 after the forecast month to determine whether such a reversal takes place. We find that the positive ARAF-return relationship significantly persists in the year after the forecast month, confirming that our result is not being driven by overvaluation.

8. Conclusions

In this paper, we examine whether the elevated forecasts of analysts relative to their peers are driven by optimism or skill. We test and confirm that there is a great deal of informational content in analyst relative forecasts by documenting a positive association with subsequent analyst forecast accuracy and operating performance. Specifically, the consensus forecast of firms in the highest quintile of average relative analyst forecasts more accurate than firms in the lowest quintile. In addition, firms with higher average relative analyst forecasts have significantly better operating performance in the subsequent fiscal quarter.

In order to disentangle optimism and skill, we further examine the relationship between average relative analyst forecasts and future stock returns using a calendar-time approach. Our results indicate that stocks with higher average relative analyst forecasts predict significantly higher future stock returns than stocks with lower average relative analyst forecasts. We find this effect to be most pronounced among stocks that are more uncertain and harder to value such as small firms, firms with high volatility or turnover, and young firms. Since these are the types of firms for which analyst ability should be of greatest benefit, these results provide the strongest support for the superior information production ability of analysts.

Finally, we examine the effect of Regulation Fair Disclosure (Reg FD) on our results. Since Reg FD prohibits firms from disclosing value-relevant information to select analysts without simultaneously disclosing this same information to all market participants, it eliminates the informational advantage enjoyed by the select analysts who received advanced notice of material information. We show that firms with higher average relative analyst forecasts have higher returns both before and after the implementation of Reg FD, but the magnitude of this effect is lower post-Reg FD compared to pre-Reg FD. Furthermore, in the highest firm volatility quintile, the average relative analyst forecasts effect remains strong after the implementation of Reg FD. We therefore conclude that only a portion of analysts' ability to produce information was driven by their informational advantage relative to other market participants, barring any potential collusion between managers and analysts.

We consider three alternative interpretations for the relationship between average relative analyst forecasts and stock-market returns: analyst optimism, risk, and data mining. Our findings are inconsistent with average relative analyst forecasts as a measure of analyst optimism since analyst optimism predicts a negative relation between average relative analyst forecasts and future returns, but our results show a persistent positive relation. Our findings also present a challenge for average relative analyst forecasts as a measure of risk. First, we risk-adjust returns using standard risk factors and find results that are as statistically and economically significant as with raw returns. Second, if average relative analyst forecasts is a new risk measure, it is unclear why the positive relation between average relative analyst forecasts and returns are substantially different for more uncertain or harder to value firms. It could also be argued that the results found in this paper are due to random chance (i.e. spurious correlation found through extensive data-snooping). We believe that the magnitude and significance of our findings, as well as the fact that they hold using both earnings forecasts and price targets, make it unlikely that they are the result of data mining. Overall, our results therefore point to a market which is semi-strong inefficient before transactions costs.

We further consider the possibility that relative analyst forecast is a proxy for other variables that have been found to be important in the literature. In particular, in addition to the usual control variables such as size, book-to-market and momentum, our multivariate tests control for analyst dispersion, earnings momentum, forecast accuracy, consensus recommendations, liquidity and credit rating, among other variables. We find that the relative analyst forecast effect documented in this paper has a distinct impact from the other explanations which have been found in the literature.

In addition to being important for investor decision making, this paper has potential policy implications with regards to the current Fair Disclosure regulation in place. Our findings suggest that either the informational advantage enjoyed by select analysts prior to the implementation of Reg FD was not as important as regulators thought it to be, or the informational advantage enjoyed by select analysts prior to the implementation of Reg FD is still being enjoyed after its implementation.

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Table 1: Summary Statistics

ARAF is defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, weighted by the standard deviation of these forecasts. *MV* is the market value of equity defined as the number of shares outstanding times the close price on the last day of trading prior to the month in which returns are calculated (in millions of dollars). *BV* is the book value of equity. *MOM* is the monthly compounded return over the 1 year prior to the month in which returns are calculated. *DAF* is the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast, as reported in the I/B/E/S Unadjusted Summary History file. *LAGRET* is the return in the month prior to the calendar month in which returns are calculated. *VOL* is the daily return standard deviation measured in the month prior to the calendar month in which returns are calculated. *ILLIQ* is computed, as in Amihud (2002), as the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month. *TURN* is the one-month average daily share volume scaled by the outstanding shares multiplied by one hundred. *AGE* is the number of months the firm has been listed on CRSP. *CR* is Standard & Poor's monthly credit rating score. *ACC* is forecast error measured as actual EPS less consensus EPS forecast from I/B/E/S, scaled by the absolute value of consensus EPS forecast. *CREC* is the consensus recommendation from I/B/E/S. *EMOM* is the quarterly earnings momentum, defined as actual EPS less the most recent consensus EPS forecast, scaled by the end of quarter price.

	N	Mean	Std Dev	Median	Min	Max
ARAF (%)	656,736	–7.13	59.70	–1.32	–222.03	207.60
MV ($MM)	656,736	4,064.27	15,743.43	720.43	0.38	581,098.86
BV/MV	488,733	0.52	0.69	0.46	–374.77	124.65
MOM (%)	653,579	17.70	62.01	9.52	–98.56	5,912.50
DAF (%)	614,214	19.08	127.78	4.65	0.00	20,400.00
LAGRET (%)	656,736	1.47	14.39	0.94	–88.02	1,349.51
VOL (%)	656,736	2.69	1.76	2.24	0.00	139.27
ILLIQ	656,723	94.74	2,236.81	7.46	0.00	1,022,727.23
TURN	656,723	0.17	0.25	0.10	0.00	35.09
AGE	656,736	206.71	205.97	143.00	2.00	1,033.00
CR	197,603	9.04	3.47	9.00	1.00	22.00
ACC	603,164	0.36	0.73	0.11	0.00	7.64
CREC	460,046	2.19	0.55	2.18	1.00	5.00
EMOM	583,963	–0.00	0.06	0.00	–32.43	2.19

Table 2: Pearson Correlations

Each month, stocks are sorted into five groups based on average relative analyst forecasts (A*RAF*), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, weighted by the standard deviation of these forecasts. *MV* is the market value of equity defined as the number of shares outstanding times the close price on the last day of trading prior to the month in which returns are calculated (in millions of dollars). *BV* is the book value of equity. *MOM* is the monthly compounded return over the 1 year prior to the month in which returns are calculated. *DAF* is the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast, as reported in the I/B/E/S Unadjusted Summary History file. *LAGRET* is the return in the month prior to the calendar month in which returns are calculated. *VOL* is the daily return standard deviation measured in the month prior to the calendar month in which returns are calculated. *ILLIQ* is computed, as in Amihud (2002), as the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month. *TURN* is the one-month average daily share volume scaled by the outstanding shares multiplied by one hundred. *AGE* is the number of months the firm has been listed on CRSP. *CR* is Standard & Poor's monthly credit rating score. *ACC* is forecast error measured as actual EPS less consensus EPS forecast from I/B/E/S, scaled by the absolute value of consensus EPS forecast. *CREC* is the consensus recommendation from I/B/E/S. *EMOM* is the quarterly earnings momentum, defined as actual EPS less the most recent consensus EPS forecast, scaled by the end of quarter price. T-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 ARAF	1.00													
2 MV	0.03	1.00												
3 BV/MV	–0.04	–0.06	1.00											
4 MOM	0.09	0.01	–0.14	1.00										
5 DAF	–0.02	–0.02	0.04	–0.03	1.00									
6 LAGRET	0.11	0.00	0.01	–0.00	0.00	1.00								
7 VOL	–0.05	–0.09	0.01	0.04	0.05	0.03	1.00							
8 ILLIQ	–0.01	–0.01	0.06	–0.01	0.00	–0.00	0.02	1.00						
9 TURN	0.02	–0.02	–0.05	0.14	0.01	0.03	0.39	–0.02	1.00					
10 AGE	0.00	0.26	0.02	–0.05	–0.02	–0.01	–0.26	–0.02	–0.10	1.00				
11 CR	–0.00	–0.34	0.08	0.09	0.09	0.03	0.34	0.08	0.29	–0.35	1.00			
12 ACC	–0.07	–0.07	0.15	–0.07	0.21	–0.03	0.14	0.01	0.04	–0.06	0.20	1.00		
13 CREC	–0.05	–0.01	0.18	–0.17	0.05	–0.02	–0.14	–0.00	–0.00	0.19	–0.07	0.07	1.00	
14 EMOM	0.03	0.01	–0.07	0.03	–0.02	0.01	–0.02	–0.01	–0.00	0.00	–0.02	–0.05	–0.03	1.00

Table 3: Median Forecast Accuracy and Accounting Performance by Average Relative Analyst Forecasts Portfolio

Each month, stocks are sorted into five groups based on average relative analyst forecasts (A*RAF*), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. Panel A presents results for relative analyst *earnings* forecasts, and Panel B presents results for relative analyst *price targets*. Columns are split by volatility: "All" contains the entire sample; "High VOL" contains the highest volatility quintile; "Low VOL" contains the lowest volatility quintile. *ACC* is forecast error measured as actual EPS less consensus EPS forecast from I/B/E/S, scaled by the absolute value of consensus EPS forecast. *ROA* is the ratio of net income over total assets. Cash flow return on assets (*CROA*) is computed as the ratio of operating income before depreciation over total assets. *ROE* is the ratio of net income over the book value of equity. *ROA*, *CROA* and *ROE* are industry-adjusted by removing the median value from firms in the same 2-digit SIC code in the same month. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	All				High VOL				Low VOL			
	ACC	ROA	CROA	ROE	ACC	ROA	CROA	ROE	ACC	ROA	CROA	ROE
Panel A: Earnings Forecasts												
ARAF1	0.14	0.32	0.51	0.89	0.28	0.05	0.17	0.10	0.07	0.36	0.44	1.21
ARAF2	0.11	0.47	0.71	1.18	0.23	0.17	0.36	0.41	0.06	0.48	0.61	1.45
ARAF3	0.11	0.57	0.81	1.36	0.23	0.31	0.54	0.68	0.06	0.54	0.64	1.59
ARAF4	0.09	0.78	1.11	1.78	0.18	0.62	0.92	1.25	0.05	0.65	0.80	1.88
ARAF5	0.10	0.80	1.16	1.76	0.18	0.81	1.15	1.51	0.06	0.58	0.73	1.71
ARAF5–ARAF1	–0.04***	0.48***	0.65***	0.87***	–0.10***	0.76***	0.97***	1.41***	–0.01***	0.22***	0.28***	0.50***
z-statistic	–38.61	50.34	40.77	53.53	–24.70	30.93	25.58	30.37	–9.37	12.31	9.52	14.76
Panel B: Price Targets												
ARAF1	0.28	0.45	0.72	1.27	0.47	0.09	0.24	0.43	0.17	0.48	0.71	1.58
ARAF2	0.27	0.56	0.85	1.47	0.43	0.21	0.43	0.64	0.17	0.57	0.86	1.81
ARAF3	0.26	0.67	0.98	1.66	0.40	0.44	0.63	1.11	0.18	0.60	0.87	1.83
ARAF4	0.26	0.75	1.12	1.78	0.40	0.53	0.75	1.25	0.18	0.66	0.96	1.93
ARAF5	0.26	0.74	1.08	1.71	0.41	0.55	0.78	1.23	0.18	0.59	0.89	1.78
ARAF5–ARAF1	–0.02***	0.29***	0.36***	0.44***	–0.06***	0.45***	0.54***	0.80***	0.01**	0.11***	0.18***	0.20***
z-statistic	–8.07	19.92	15.82	17.74	–7.51	11.37	9.47	10.58	2.18	4.24	3.67	4.15

Table 4: Univariate Portfolio Returns

Each month, stocks are sorted into five groups based on average relative analyst forecasts (ARAF), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. Panel A reports results for unconditional returns. Panel B reports results for returns conditional on negative or positive ARAF. Factor-adjusted returns are the monthly abnormal returns (intercepts) in percent, based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Raw Returns	Factor-Adjusted Returns
Panel A: Unconditional returns		
ARAF1	0.52	0.19
ARAF2	0.75**	0.41
ARAF3	0.97***	0.68**
ARAF4	1.23***	0.93***
ARAF5	1.45***	1.17***
ARAF5−ARAF1	0.93***	0.98***
t-statistic	9.67	9.53
Panel B: Conditional returns		
ARAF < 0	0.72**	0.39
ARAF>=0	1.31***	1.03***
Pos−Neg ARAF	0.60***	0.64***
t-statistic	9.19	9.12

Table 5: Bivariate Portfolio Returns by Size, Book-to-Market, and Momentum

Each month, stocks are sorted independently into 5×5 groups based on A*RAF* and *MV* (Panel A), *BM* (Panel B) and *MOM* (Panel C). The mean raw return and factor-adjusted return are computed for each group, and the difference between A*RAF* quintile 1 and quintile 5 is reported. Average relative analyst forecasts (A*RAF*) is defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. *MV* is the market value of equity defined as the number of shares outstanding times the close price on the last day of trading prior to the month in which returns are calculated (in millions of dollars). *BV* is the book value of equity in the quarter prior to the month in which returns are calculated. *MOM* is the monthly compounded return over the 1 year prior to the month in which returns are calculated. *ILLIQ* is computed, as in Amihud (2002), as the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month. Factor-adjusted returns are the monthly abnormal return (intercept) in percent based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Raw Returns		Factor-Adjusted Returns	
	ARAF5–ARAF1	t-stat	ARAF5–ARAF1	t-stat
Panel A: Market Value (MV)				
MV1	1.75***	12.98	1.86***	13.03
MV2	1.17***	8.33	1.22***	8.09
MV3	0.65***	5.02	0.66***	4.79
MV4	0.22	1.53	0.31**	2.01
MV5	0.29**	2.13	0.25	1.65
Panel B: BV/MV (BM)				
BM1	0.90***	5.22	0.93***	4.98
BM2	0.97***	6.17	1.03***	6.11
BM3	0.80***	5.33	0.88***	5.53
BM4	0.72***	5.16	0.78***	5.23
BM5	1.34***	9.29	1.34***	8.67
Panel C: Momentum (MOM)				
MOM1	0.74***	4.18	0.84***	4.56
MOM2	0.84***	7.03	0.87***	6.75
MOM3	0.72***	6.94	0.72***	6.57
MOM4	0.80***	7.47	0.82***	7.19
MOM5	0.69***	4.86	0.76***	4.96
Panel D: Illiquidity (ILLIQ)				
ILLIQ1	0.23	1.55	0.21	1.31
ILLIQ2	0.57***	3.76	0.63***	3.84
ILLIQ3	0.67***	5.15	0.71***	5.12
ILLIQ4	1.07***	7.40	1.10***	7.01
ILLIQ5	1.56***	12.35	1.66***	12.26

Table 6: Bivariate Portfolio Returns by Volatility, Turnover, and Firm Age

Each month, stocks are sorted independently into 5×5 groups based on A*RAF* and *MV* (Panel A), *BM* (Panel B) and *MOM* (Panel C). The mean raw return and factor-adjusted return are computed for each group, and the difference between A*RAF* quintile 1 and quintile 5 is reported. Average relative analyst forecasts (A*RAF*) is defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. *VOL* is the daily return standard deviation measured in the month prior to the calendar month in which returns are calculated. *TURN* is the one-month average daily share volume scaled by the outstanding shares multiplied by one hundred. *AGE* is the number of months the firm has been listed on CRSP. Factor-adjusted returns are the monthly abnormal return (intercept) in percent based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Raw Returns		Factor-Adjusted Returns	
	ARAF5–ARAF1	t-stat	ARAF5–ARAF1	t-stat
Panel A: Volatility (VOL)				
VOL1	0.43***	5.34	0.41***	4.80
VOL2	0.75***	6.81	0.73***	6.25
VOL3	0.85***	6.32	0.86***	5.90
VOL4	0.63***	4.06	0.72***	4.34
VOL5	1.88***	10.20	2.05***	10.57
Panel B: Turnover (TURN)				
TURN1	0.95***	10.06	0.99***	9.90
TURN2	0.83***	7.64	0.83***	7.13
TURN3	0.82***	6.42	0.80***	5.90
TURN4	0.85***	5.96	0.97***	6.41
TURN5	1.34***	6.65	1.42***	6.52
Panel C: Firm Age (AGE)				
AGE1	1.53***	10.10	1.60***	9.85
AGE2	1.13***	7.20	1.16***	6.89
AGE3	1.06***	7.66	1.15***	7.78
AGE4	0.59***	4.06	0.67***	4.28
AGE5	0.28**	2.40	0.27**	2.14

Table 7: Regressions of Returns on Average Relative Analyst Forecasts

Results are based on Fama and MacBeth (1973) type cross-section regressions for returns at time *t* on characteristics at time *t*–1. Average relative analyst forecasts (A*RAF*), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. *MV* is the market value of equity defined as the number of shares outstanding times the close price in millions of dollars. *BV* is the book value of equity. *MOM* is the monthly compounded return over the 1 year prior to the month in which returns are calculated. *DAF* is the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast, as reported in the I/B/E/S Unadjusted Summary History file. *LAGRET* is the return in the month prior to the calendar month in which returns are calculated. *VOL* is the daily return standard deviation measured in the month prior to the calendar month in which returns are calculated. *ILLIQ* is computed, as in Amihud (2002), as the absolute daily return divided by the total dollar trading volume for the day, averaged across all trading days of the month. *TURN* is the one-month average daily share volume scaled by the outstanding shares multiplied by one hundred. *AGE* is the number of months the firm has been listed on CRSP. *CR* is Standard & Poor's monthly credit rating score. *ACC* is forecast error measured as actual EPS less consensus EPS forecast from I/B/E/S, scaled by the absolute value of consensus EPS forecast. *CREC* is the consensus recommendation from I/B/E/S. *EMOM* is the quarterly earnings momentum, defined as actual EPS less the most recent consensus EPS forecast, scaled by the end of quarter price. *Ln* is the natural logarithm. T-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$ARAF_{t-1}$	0.48***	0.15	0.36***	0.58***	0.26***	0.39***
	(7.74)	(1.13)	(5.61)	(7.38)	(4.38)	(6.43)
$ARAF_{t-1} \times VOL_{t-1}$		12.53**				
		(2.29)				
$ARAF_{t-1} \times TURN_{t-1}$			1.41***			
			(3.33)			
$ARAF_{t-1} \times AGE_{t-1}$				–0.00*		
				(–1.85)		
$Ln(MV_{t-1})$	0.04	0.04	0.04	0.04	–0.10**	–0.14***
	(0.38)	(0.34)	(0.39)	(0.36)	(–2.22)	(–2.88)
$(BV/MV)_{t-1}$	0.48**	0.49**	0.48**	0.46**	0.43***	0.22
	(2.38)	(2.40)	(2.37)	(2.36)	(3.17)	(1.35)
$MOM_{(t-12:t-1)}$	0.01**	0.01**	0.01**	0.01**	0.00	0.00*
	(2.34)	(2.25)	(2.25)	(2.30)	(1.06)	(1.84)
DAF_{t-1}	–0.11**	–0.13*	–0.11*	–0.09*	0.27	–0.04
	(–1.98)	(–1.88)	(–1.95)	(–1.86)	(1.10)	(–0.60)
$EMOM_{t-1}$	10.69***	11.13***	10.58***	11.67***	9.49	12.93***
	(3.94)	(4.08)	(3.88)	(4.26)	(1.43)	(3.36)
$LAGRET_{t-1}$	–0.02***	–0.02***	–0.02***	–0.03***	–0.02***	–0.01**
	(–4.64)	(–5.04)	(–4.76)	(–4.96)	(–3.93)	(–2.39)
VOL_{t-1}	–0.15**	–0.14**	–0.14**	–0.17***	–0.11	–0.14**
	(–2.46)	(–2.56)	(–2.32)	(–3.10)	(–1.50)	(–2.07)
$ILLIQ_{t-1}$	–0.00**	–0.00**	–0.00**	–0.00**	0.02	–0.00**
	(–2.47)	(–2.39)	(–2.57)	(–2.08)	(0.88)	(–2.15)
$TURN_{t-1}$	0.75*	0.69	0.86*	0.33	0.51	0.36
	(1.71)	(1.57)	(1.91)	(0.51)	(0.82)	(0.90)
AGE	0.03	0.05	0.04	0.05	0.03	0.08
	(0.68)	(1.01)	(0.70)	(0.98)	(0.67)	(1.36)
CR_{t-1}					0.01	

					(0.24)	
ACC_{t-1}					–0.94***	
					(–4.69)	
$CREC_{t-1}$						0.04
						(0.44)
N	331	331	331	331	312	217

Table 8: Trivariate Portfolio Returns by Regulation FD and Volatility

Each month, stocks are sorted into five groups based on average relative analyst forecasts (A*RAF*), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. Columns are split by regulation FD and volatility: "All" contains the entire sample; "High VOL" contains the highest volatility quintile; "Low VOL" contains the lowest volatility quintile. Panel A reports results for raw returns, while Panel B reports results for factor-adjusted returns. Factor-adjusted returns are the monthly abnormal return (intercept) in percent based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Pre-Regulation FD (1984-2000)			Post-Regulation FD (2001-2010)		
	All	High VOL	Low VOL	All	High VOL	Low VOL
Panel A: Raw Returns						
ARAF1	0.66^{*}	–0.27	1.03^{***}	0.31	–0.76	0.69^{*}
ARAF2	0.89^{**}	–0.06	1.16^{***}	0.52	0.07	0.82^{**}
ARAF3	1.13^{***}	0.54	1.24^{***}	0.73	0.32	0.90^{***}
ARAF4	1.54^{***}	1.06^{*}	1.47^{***}	0.75	0.47	0.93^{***}
ARAF5	1.81^{***}	1.81^{***}	1.57^{***}	0.90^{*}	0.81	0.97^{***}
ARAF5–ARAF1	1.15^{***}	2.08^{***}	0.53^{***}	0.59^{***}	1.57^{***}	0.28^{**}
t-statistic	11.02	9.41	4.99	3.24	4.88	2.26
Panel B: Factor-Adjusted Returns						
ARAF1	0.28	–0.60	0.61^{**}	0.73	–0.00	0.70^{*}
ARAF2	0.40	–0.62	0.66^{**}	1.01^{*}	0.98	0.88^{**}
ARAF3	0.77^{*}	0.36	0.77^{***}	1.22^{**}	1.28	0.92^{**}
ARAF4	1.13^{***}	0.74	0.99^{***}	1.26^{**}	1.56^{*}	0.98^{***}
ARAF5	1.49^{***}	1.60^{**}	1.08^{***}	1.35^{**}	2.00^{**}	0.94^{***}
ARAF5–ARAF1	1.21^{***}	2.19^{***}	0.47^{***}	0.62^{***}	2.00^{***}	0.24^{*}
t-statistic	10.75	9.11	4.17	2.96	5.59	1.67

Table 9: Univariate Portfolio Returns for New and Old Listings

Each month, stocks are sorted into five groups based on average relative analyst forecasts (A*RAF*), defined as the relative analyst forecasts averaged across all analysts giving a forecast in that month for this firm. Relative analyst forecast is the analyst's forecast less the average forecast of all analysts in the same month and the two prior months, for the same fiscal period end date and for the same firm, scaled by the standard deviation of these forecasts. Panel A reports results for firms that have been in CRSP for more than 3 years (i.e. not newly listed firms). Panel B reports results for firms that have been in CRSP for 3 years or less (i.e., newly listed firms). Factor-adjusted returns are the monthly abnormal return (intercept) in percent based on the Fama and French (1993) three-factor model augmented by Carhart's (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% level, respectively.

	Raw Returns	Factor-Adjusted Returns
Panel A: Firms listed for more than 3 years		
ARAF1	0.66**	0.32
ARAF2	0.84***	0.51
ARAF3	1.04***	0.74**
ARAF4	1.26***	0.96***
ARAF5	1.47***	1.17***
ARAF5–ARAF1	0.80***	0.84***
t-statistic	8.30	8.15
Panel B: Firms listed for 3 years or less		
ARAF1	–0.13	–0.41
ARAF2	0.33	0.03
ARAF3	0.69	0.50
ARAF4	1.18***	0.92**
ARAF5	1.43***	1.24***
ARAF5–ARAF1	1.56***	1.65***
t-statistic	9.50	9.32