Alpha in Analysts*

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Abstract

This paper examines the investment value in sell-side analyst price targets. We treat each analyst as a portfolio manager and use their price targets to construct 12-month implied return forecasts. We invest in self-financing long-short portfolios for individual analysts, where we go long on stocks with positive forecasts and go short on those with negative forecasts, and the weights in the portfolio are proportional to the magnitude of the implied returns. Our empirical analysis shows that while the average analyst does not generate statistically significant alpha relative to the returns of a long-only portfolio benchmark, a subset of analysts exhibits persistent alpha. Motivated by this heterogeneity, we introduce a "fund-of-analysts" framework that first predicts analyst performance and then dynamically allocates weights across analysts based on predicted analyst performances. Our results show that this meta-portfolio strategy can yield significant alpha over long-only benchmarks, providing new insights into the role of analyst heterogeneity in equity market pricing.

Keywords: Analysts, Price targets, Trading strategy

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1 Introduction

Sell-side analyst research is a cornerstone of equity markets, serving as a key source of information for institutional and retail investors alike. For long, the academic literature has scrutinized sell-side analyst predictions and recommendations, where many studies examine how forecast errors, bias, and revisions contain valuable information for equity pricing (see, e.g., Womack (1996), Clement (1999)). Yet, despite a voluminous literature on earnings forecasts and recommendation revisions, relatively few papers study *price targets*—the explicit estimates of future stock prices (see, e.g., Brav and Lehavy (2003), Asquith et al. (2005)). Price targets offer a direct translation of an analyst's prediction into an implied 12-month stock return forecast (see Bradshaw et al. (2012)). We use the implied returns to form portfolios for each analyst, where the stock weights depend on the magnitude and sign of the analyst's return forecast.

Despite the growing attention on price targets, most prior work analyzes them at the stock level—investigating how different analysts covering the same firm arrive at disparate target prices (Asquith et al. (2005); Bonini et al. (2007); Bradshaw et al. (2012); Brav and Lehavy (2003); Palley et al. (2024)). In contrast, we view *each analyst as a portfolio manager* whose price targets are tradable signals, which we use to evaluate the performance of individual analysts. In this way, we evaluate the performance of these *analyst-implied portfolios*, and we gauge if analysts as *individuals* produce alpha beyond a naive buy-and-hold benchmark of the same stocks they cover.

In the first part of this paper, we construct a long-short strategy for each analyst: we go long stocks with positive implied returns (target price above current price) and short those with negative implied returns, where the portfolio weights are proportional to the magnitude of the forecasted returns. Next, we measure each analyst's alpha against an equally-weighted long-only portfolio of the same stocks. Our empirical tests use a large, comprehensive dataset of analyst price targets from IBES and stock specific information from CRSP, spanning more than two decades. Consistent with some prior findings on analyst stock-picking efficacy (Mikhail et al. (1999); Bradshaw et al. (2012)), our results show that, on average, the typical analyst does not generate statistically significant alpha when regressed on a naive baseline. However, a *nontrivial subset* of analysts does exhibit substantial forecasting skill, with statistically significantly positive alpha over time.[1]

Building on this heterogeneity in performance, we develop a **fund-of-analysts** framework, wherein an investor allocates capital across analysts based on the forecasts of each analyst's performance. Conceptually, this parallels a "fund-of-funds" model: the investor forms a meta-portfolio of analyst-implied portfolios, where the weights are dynamically updated according to each analyst's track record. First, we use characteristics of analysts—such as historical performance, volatility of implied returns, and coverage breadth—to forecast the profitability of each analyst's implied portfolios. Then, based on our predictions of analyst's future returns, we build a meta-portfolio where we allocate more wealth to analysts with higher predicted returns and less wealth to analysts with lower predicted returns. Our results demonstrate that dynamically allocating wealth to each analysts' implied portfolios (i.e., tilting away from predicted underperformers and toward those who we believe will perform well) can yield statistically significant alpha when regressed on standard passive (i.e., buy and hold) benchmarks.

Overall, our contribution is twofold. First, we introduce a novel approach to measuring

[1]A relevant piece of work that studies analyst performance is Stickel (1992) who finds that the earnings forecasts from all-American analysts (i.e. star analysts) tend to be more accurate than those who are not all-American analysts.

analyst-level skill, considering the analyst as a portfolio manager. Second, we develop a "fund-of-analysts" approach to show that one can extract alpha from a large and diverse panel of analysts—a perspective that has received little attention in the empirical literature on the sell-side research. Our findings complement existing evidence on the informative value of analyst recommendations (Tamura (2002); Gleason and Lee (2003); Da and Schaumburg (2011); Bradshaw et al. (2012)) and extend it to price targets, and we emphasize that understanding analyst heterogeneity is critical for investors. Our results are also related to a strand of the literature that corrects the analysts' forecasts to produce better investment signals (see Dechow and You (2020); Loudis (2024)), where our contributions provide a new perspective which predicts analyst portfolio returns instead of correcting forecasts for each stock.

The remainder of the paper is structured as follows. Section 2 introduces the methodology to construct implied portfolios and outlines the regression framework to estimate alpha for each analyst. Section 3 describes our data sources from CRSP and IBES. Section 4 presents empirical results on individual analysts' alpha and implements the fund-of-analysts approach, highlighting how investors dynamically allocate capital across analysts to exploit temporal differences in forecasting skill. Section 5 concludes.

2 Setup

For each calendar month m, suppose analyst i covers stocks $s_1, \ldots, s_N$ with current prices $P_1^m, \ldots, P_N^m$ and provides 12-month price targets $\hat{P}_1^{m+12}, \ldots, \hat{P}_N^{m+12}$ for each stock. Then, for each stock, the price target of analyst i implies the return forecast

$$\hat{R}_k^{m+12} = \frac{\hat{P}_k^{m+12} - P_k^m}{P_k^m},$$

where $\hat{R}_k^{m+12}$ denotes the implied return for asset k at 12 months after month m.

Now, suppose an investor trusts analyst i and invests in a long-short portfolio based on the price forecasts of the analyst. The investor takes long positions in stocks with positive return forecasts and takes short positions in stocks with negative return forecasts. Additionally, the weight of the investor's long-short strategy is proportional to the magnitude of the return forecasts implied by the analyst. To compute the weights, let

$$K_+ \ = \ \left\{k : \hat{R}_k^{m+12} > 0\right\} \quad \text{and} \quad K_- \ = \ \left\{k : \hat{R}_k^{m+12} < 0\right\}$$

denote the set of stocks with positive and negative forecasted returns, respectively. Then, each stock $k \in K_+$ (i.e., each stock with positive implied return) is assigned a long position with weight

$$w_k^+ \ = \ \frac{\hat{R}_k^{m+12}}{\sum\limits_{j \in K_+} \hat{R}_j^{m+12}},$$

and each stock $k \in K_-$ (i.e., each stock with negative implied return) is assigned a short position with weight

$$w_k^- \ = \ \frac{-\hat{R}_k^{m+12}}{-\sum\limits_{j \in K_-} \hat{R}_j^{m+12}}.$$

The absolute value of these weights sum to one in each of the long and short buckets, respectively, whenever K_+ and K_- are nonempty. Therefore, the investor constructs a self-financing long-short portfolio based on the recommendations made by analyst i.[2]

Next, let R_k^{m+12} denote the *realized* return of stock k between month m and month $m+12$, that is,

$$R_k^{m+12} \;=\; \frac{P_k^{m+12} - P_k^{m}}{P_k^{m}}\,,$$

where P_k^{m+12} is the price of stock k observed 12 months after m.

Therefore, the profit and loss (PnL) of the long-short portfolio, following the recommendations of analyst i, for the investor's strategy at month m marked to month $m+12$ is

$$\mathrm{PnL}_i^{m+12} \;=\; \sum_{k\in K_+} w_k^+\, R_k^{m+12} \;-\; \sum_{k\in K_-} w_k^-\, R_k^{m+12}\,.$$

Here, PnL_i^{m+12} is also a measurement of the overall quality of analyst i's price targets. Overall, if the analyst's price targets forecasts are accurate, the PnL incurred from the long-short portfolio should be large and positive. In particular, if an analyst's recommendation is valuable, a regression of the alpha of the analyst's PnL against an equally-weighted portfolio taking long positions on all the stocks the analyst covers should be positive and statistically significant. Consider

$$\mathrm{M}_i^{m+12} = \frac{1}{n}\sum_{x=1}^{n} R_x^{m+12}\,,$$

[2]When either K_+ or K_- is empty, the portfolio is no-longer self-financing and the investor takes a net long or short position of stocks.

where M_i^{m+12} denotes the PnL from trading an equally weighted long-only portfolio on all the stocks that analyst i covers in month m, and run the regression

$$\mathrm{PnL}_i^{m+12} = \alpha_i + \beta\, \mathrm{M}_i^{m+12} + \epsilon_{m+12} \tag{1}$$

for each analyst i over their career span. If the α of an analyst is positive and statistically significant over their career, there is evidence to believe that they are skilled and that they provide valuable insights into predicting stock returns.[3]

Now, assume that an investor has full access to all the analysts price forecasts, and the investor uses a "fund-of-fund" strategy that invests her wealth into portfolios formed from each analyst's implied portfolio. That is, the investor considers each analyst as a portfolio manager, and she invests a portion of her wealth on each of the analyst's implied portfolios.

Let c_i^m denote the proportion of the investor's wealth allocated as advised by analyst i in month m, assuming a total of I analysts, then twelve months later the investor collects

$$\mathrm{PnL}^{m+12} = \sum_{i=1}^{I} c_i\, \mathrm{PnL}_i^{m+12}\,.$$

A special case, analogous to the concept of "consensus" in the literature, arises when the investor is agnostic to the ability of each analyst, so she chooses to believe in each of

[3]An analogy of why we run the regression in Equation (1) is when an investor holds a collection of stocks, and an analyst provides some recommendation to hold or sell the stock. Regression (1) informs us how much additional value the recommendations of this particular analyst brings to the investor.

them equally. In that case, the investor collects a "consensus PnL"

$$\mathrm{PnL}^{\mathrm{Consensus}}_{m+12} = \frac{1}{I}\sum_{i=1}^{I} \mathrm{PnL}^{m+12}_{i}\,.$$

Similar to investing according to the forecasts of individual analysts, the investor also wants to understand if, collectively, the analysts provide useful information in addition to a strategy that buys and holds all stocks. Consider the universe of stocks $s_1, \ldots, s_N$ that are covered by at least one analyst; an uninformed investor can choose to invest equally in these stocks and collect

$$\mathrm{PnL}^{\mathrm{Uninformed}}_{m+12} = \frac{1}{N}\sum_{b=1}^{N} \mathrm{R}^{m+12}_{b}$$

in month $m+12$. If the collection of analysts provides additional value to the investor, then the intercept α in the regression

$$\mathrm{PnL}^{m+12} = \alpha + \beta\,\mathrm{PnL}^{\mathrm{Uninformed}}_{m+12} + \epsilon_m$$

should be positive and statistically significant.

Consider an investor who estimates analyst skills and ranks the analysts from best to worst, and she uses this ranking to build a portfolio. One way to rank analysts is to model the PnL incurred by the analyst as a function of the individual characteristics of the analyst. In this way, each month, the investor makes a prediction $\widehat{\mathrm{PnL}}^{m+12}_{i}$ of each analyst's future PnL. Consider

$$\mathrm{PnL}^{m+12}_{i} = g(\mathrm{A}_i \mid \mathrm{F}_m)\,,$$

where the PnL of analyst i from month m to month $m+12$ is a function g of the analyst-specific characteristics A_i conditional on the information set F_m available at time up until month m. Here, analyst-specific characteristics A_i may contain predictors such as the previous performance of the analyst, how well the analyst ranks among their peers throughout their career, etc.

The prediction $\widehat{\mathrm{PnL}}_i^{m+12}$ is a proxy for how much the investor trusts each analyst. Therefore, the proportion of wealth c_i^m that the investor assigns to the analyst is proportional to $\widehat{\mathrm{PnL}}_i^{m+12}$. In particular, to make the long-short portfolio self-financing, the investor *longs* the implied portfolio of analysts whose predicted $\widehat{\mathrm{PnL}}_i^{m+12}$ is positive, and *shorts* the implied portfolio of those whose predicted $\widehat{\mathrm{PnL}}_i^{m+12}$ is negative, while ensuring that the total long allocation equals the total short allocation, i.e., the investor's strategy is self-financing.[4] Concretely, define

$$I_+ = \left\{ i : \widehat{\mathrm{PnL}}_i^{m+12} > 0 \right\} \quad \text{and} \quad I_- = \left\{ i : \widehat{\mathrm{PnL}}_i^{m+12} < 0 \right\}.$$

Then, for each analyst $i \in I_+$, the investor's "long weight" is

$$c_i^+ = \frac{\widehat{\mathrm{PnL}}_i^{m+12}}{\sum\limits_{j \in I_+} \widehat{\mathrm{PnL}}_j^{m+12}},$$

and for each analyst $i \in I_-$, the investor's "short weight" is

$$c_i^- = \frac{-\widehat{\mathrm{PnL}}_i^{m+12}}{-\sum\limits_{j \in I_-} \widehat{\mathrm{PnL}}_j^{m+12}},$$

[4]The analysts' PnLs are PnL of long-short portfolios themselves, so we can short an analyst's implied portfolio.

so, by construction, $\sum_{i \in I_+} c_i^+ = 1$ and $\sum_{i \in I_-} c_i^- = 1$.

Because going "long" a positive forecast and "short" a negative forecast in each analyst's implied portfolio does not require net initial capital, the fund-of-analysts portfolio is self-financing. Then, the total realized *informed* PnL at month $m + 12$ becomes

$$\mathrm{PnL}_{m+12}^{\mathrm{Informed}} = \sum_{i \in I_+} c_i^+ \, \mathrm{PnL}_i^{m+12} - \sum_{i \in I_-} c_i^- \, \mathrm{PnL}_i^{m+12},$$

where PnL_i^{m+12} is the *realized* PnL each analyst i generates from their implied portfolio over the same 12-month horizon. Thus, the investor, informed by forecasts of analyst performances, constructs a "fund-of-analysts", allocating larger absolute weights to the analysts with higher predicted performance (for longs) or with lower predicted performance (for shorts).

Similarly, we test if this "fund-of-analysts" approach results in statistically significant alpha when regressed on a long-only, equally-weighted strategy that buys all stocks covered by at least one analyst. In this way, we test if the price forecasts for sell-side investment analysts contain useful information in predicting stock returns over the one-year horizon.

3 Data

Stock returns, firm characteristics, and other data are from the WRDS online database. We select all common stocks publicly traded on the NYSE (New York Stock Exchange), AMEX (American Stock Exchange), and NASDAQ (National Association of Securities Dealers Automated Quotations). Daily market data, such as prices, trading volumes, and returns, are from the Center for Research in Security Prices (CRSP). Analyst price forecasts are from IBES (Institutional Brokers' Estimate System).

The starting date for each analyst's price forecasts is the $ACTDATS$ column in the IBES database, and we use data from CRSP to compute the 12-month implied return. Our sample contains all analyst recommendations available from January 1999 to November 2024.

4 Results

First, we examine if individual stock analysts, when viewed as portfolios, carry statistically significant alpha against an equally-weighted portfolio of the stocks they cover.

Table 1 shows that investment analysts, on average, exhibit statistically insignificant α regressed on an equally-weighted portfolio of stocks that they cover. The α from price targets of analysts are small in magnitude and not significantly different from zero across all experience buckets of analysts. For analysts at different experience levels and for all analysts on average, their price targets imply a portfolio with statistically significant returns that generally increase with their experience level. In particular, analysts with more than five years of experience exhibit the highest raw return of approximately 8% for each of the 12-months portfolio the analysts hold each month. However, for each bucket of analyst experiences, the portfolio implied by the price targets of analysts cannot outperform the equally-weighted long-only portfolio with the stocks each analyst covers. On average, the baseline outperforms the analyst implied portfolios by around 2% per month.

Table 1: Performance metrics by analyst experience

Performance metrics for analysts categorized by years of experience. The metrics include α, the abnormal return estimated from a factor model against equally weighted portfolio of stocks the analyst covers, with corresponding cross-sectional t-statistics in parentheses. The parameter β represents the market beta, capturing systematic risk exposure. Return denotes the average annualized return of the analysts' stock recommendations, with t-statistics shown in parentheses. Baseline is the average return of the benchmark portfolio, which is an equally-weighted long-only portfolio holding the stocks that the analyst covers. Stocks represents the average number of stocks covered per analyst in each experience group in each month.* Count refers to the total number of analysts in each category. Sig. 5% and Sig. 1% indicate the number of analysts whose α estimates are statistically significant at the 5% and 1% levels, respectively.

Experience	α	β	Return	Baseline	Stocks	Count	Sig. 5%	Sig. 1%
<1 year	0.002 (0.30)	0.766	0.020 (2.02)	0.025	1.64	3491	182	61
1-2 years	0.001 (0.30)	0.792	0.026 (2.68)	0.046	2.11	1920	143	40
2-5 years	−0.001 (−0.19)	0.754	0.054 (7.72)	0.084	2.67	2169	256	89
5+ years	0.001 (0.61)	0.726	0.079 (18.25)	0.114	3.68	2242	281	107
Overall	0.001 (0.41)	0.758	0.042 (9.60)	0.062	2.43	9822	862	297

* Not all analysts release forecasts for every stock they cover each month. E.g., on average an analyst covers 5.6 stocks each year, but they report forecasts for 2.4 stocks each month. Over the lifetime of an analyst, they cover, on average, 13.3 stocks.

In general, analysts with a longer career span tend to follow more stocks, and the stocks that the analysts follow tend to be more successful (the average return of the baseline is higher for analysts who survive longer). Thus, we ask if analysts survive longer because they cover more successful stocks by chance or because they pick stocks with more growth potential. To explore this question, we count the number of analysts with different career lengths who exhibit statistically significant α at 5% and 1% significance levels.

Recall that, although we find that the portfolios implied from analysts' price targets exhibit statistically insignificant α on average, individual analysts can still demonstrate significant outperformance over simple buy and hold portfolios. Specifically, if the number of analysts with significant α exceeds what would be expected under a random binomial distribution, this would suggest that at least some analysts may possess genuine stock price forecast skill rather than benefiting purely from chance.

Table 2: Fraction of analysts with significant α and binomial tests by experience

For each experience group: total number of analysts (Count), number of analysts with statistically significant α at the 5% level (Sig. 5%) and 1% level (Sig. 1%), fraction of the group these analysts represent (% Sig.), and one-sided binomial test p-value. The binomial test null hypothesizes that the true fraction of analysts with significant α is exactly 5% (or 1%), i.e., arising purely by chance. A low p-value indicates that more analysts are significant than would be expected if there were no skill component in their forecasts.

Experience	**Count**	**Significant at 5%**			**Significant at 1%**		
		Number	**% Sig.**	***p*-value**	**Number**	**% Sig.**	***p*-value**
$<$ 1 year	3,491	182	5.21%	0.2919	61	1.74%	0.0000
1–2 years	1,920	143	7.45%	0.0000	40	2.08%	0.0000
2–5 years	2,169	256	11.81%	0.0000	89	4.10%	0.0000
$>$ 5 years	2,242	281	12.53%	0.0000	107	4.77%	0.0000
Overall	9,822	862	8.78%	0.0000	297	3.02%	0.0000

The results in Table 2 indicate that the percentage of analysts with statistically significant α generally increases with experience. Among analysts with less than one year of experience, 5.21% achieve significance at the 5% level, a proportion that is not significantly different from what would be expected under the null ($p = 0.284$). However, at the 1% level, 1.74% of analysts exceed the threshold, which is significantly higher than the expected 1% rate. For analysts with 1–2 years of experience, 7.45% of them achieve significance at the 5% level, suggesting that a higher-than-random fraction of these analysts exhibits genuine forecasting ability. Similarly, at the 1% level, 2.08% of analysts exceed the threshold, reinforcing the notion that skill is emerging within this group. Among more experienced analysts, the fraction with statistically significant α rises sharply. For those with 2–5 years of experience, 11.81% are significant at the 5% level , and 4.10% at the 1% level. The trend continues for the most experienced analysts (more than 5 years), where 12.53% of them are significant at the 5% level and 4.77% at the 1% level, both highly significant results.

Across all analysts, 8.78% demonstrate significant α at the 5% level, with a corresponding binomial test $p = 0.000$, strongly rejecting the null hypothesis that skill is entirely absent. Similarly, 3.02% are significant at the 1% level, further reinforcing the idea that some analysts do exhibit genuine forecasting ability.

The results in Table 2 suggest that while analysts, on average, do not generate statistically significant α, the proportion of those who do increases with experience. This provides preliminary evidence that while it is possible that some analysts survive longer because they cover inherently better-performing stocks, at least some analysts do develop skill in forecasting stock returns.

Recall that Table 1 shows that the baseline return—the average return of an equally-weighted portfolio of covered stocks—rises with experience, indicating that more seasoned analysts tend to follow stronger-performing stocks. This suggests that luck in stock assignment is a factor in survival of analysts. Next, we examine if the proportion of analysts with significant α also increases with tenure. Table 2 shows that the proportion of analysts with significant α at both the 5% and 1% levels far exceeds what we expect from random assignments, particularly among more experienced analysts. This suggests that, beyond merely covering better stocks, at least some analysts improve their ability to identify potential trading opportunities over time.

Now, consider investors who have access to all analyst price targets. Recall we assume investors follow a "fund-of-analysts" strategy where proportions of their wealth invested in portfolios depends on how well they believe in each analyst's price targets.

First, we consider a naive strategy where the investors allocate equal proportions of their wealth into portfolios implied by each analyst's price targets. We compare the performance of this strategy to that of a naive baseline where the investor invests in an equally-weighted long-only portfolio of all stocks that are covered by at least one analyst in the month of the forecast (i.e., the union of all stocks covered by analysts). We also consider an infeasible, perfect foresight strategy where the investor knows beforehand which analysts are in the top or bottom 2.5% among their cohort in that month. We include these infeasible strategies to motivate that an investor might want to choose to believe in some analysts more or less than in others and trade a "fund-of-analysts" strategy.

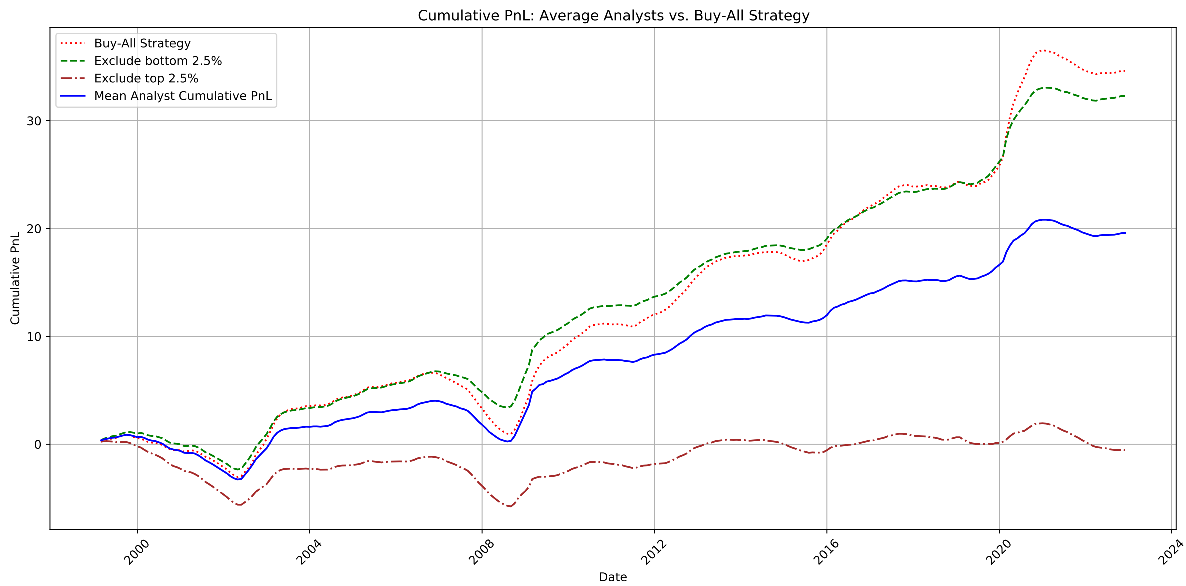

Figure 1: Cumulative returns of fund-of-analysts strategies.

Figure 1 plots the cumulative returns of the four portfolio strategies evaluated in Table 1. The Baseline strategy (red dash-dots) is the passive benchmark, while the Mean Analyst strategy (blue solid line) represents an equally-weighted allocation across analysts. The Exclude Bottom 2.5% strategy (green dashes) removes the worst-performing analysts, while the Exclude Top 2.5% strategy (brown dots) excludes the best-performing analysts, where both assume perfect foresight.

In Figure 1, the naive strategy of buying all the analysts underperforms a buy-and-hold strategy with all stocks, showing that an average analyst does not have any stock price forecasting skill. However, the performance of the perfect foresight infeasible strategies, where the investor knows beforehand who the best and worst analysts are, show that there is considerable heterogeneity in forecasting performance of analysts in any given month. Also, if the investor excludes the worst analysts and invests equally in all other analysts, the performance of her portfolio would be similar to that of being long the market. On the other hand, note that the returns of the portfolio that excludes the bottom 2.5% analysts is nearly zero. This shows that on any given month, only a small number of analysts provides useful price targets while others can be roughly perceived as providing only noise to investors.

In Table 3, we present the values of the performances of strategies in Figure 1. The Mean Analyst strategy, which weights the portfolios derived from every analyst's price targets equally, realizes a monthly return of 0.0685 with 0.2004 volatility. Although the strategy's Sharpe ratio (0.3416) is positive, the α of the portfolio is statistically insignificant and marginally negative with a t-stat of -0.674 , underscoring the absence of the outperformance relative to the Baseline. Consistent with Figure 1, the average analyst does not seem to provide any additional information to the market.

On the other hand, the Exclude Bottom 2.5% portfolio demonstrates that removing

Table 3: Performance metrics of fund-of-analysts strategies

Performance metrics for different fund-of-analysts strategies. Mean Analyst refers to the strategy that takes equally weighted positions in all analyst portfolios; Exclude Bottom 2.5% and Exclude top 2.5% refer to the perfect foresight infeasible strategy where the investor knows which analysts will perform poorly/well at the 2.5% percentile; Baseline refers to a strategy where the investor takes long-only equally weighted portfolios in all stocks that analysts cover. Here, Mean Return is the average monthly return of the strategy; Volatility is the standard deviation of monthly returns; Sharpe is the mean return divided by volatility, assuming a risk-free rate of zero; α represents the abnormal return estimated from a regression against the Baseline, with the corresponding t-Stat testing its significance; and β represents the market beta, capturing systematic risk exposure relative to the Baseline.

Strategy	Mean Return	Volatility	Sharpe	Alpha	t-Stat	Beta
Mean Analyst	0.0685	0.2004	0.3416	−0.0034	−0.674	0.5932
Exclude Bottom 2.5%	0.1130	0.2407	0.4693	0.0226	5.528	0.7466
Exclude Top 2.5%	−0.0019	0.1538	−0.0124	−0.0523	−9.919	0.4166
Baseline	0.1211	0.3107	0.3896	–	–	–

a small cohort of poor forecasters enhances risk-adjusted performance. After discarding these worst-performing analysts, with perfect foresight, the portfolio's mean return (0.1130) is close to that of the Baseline (0.1211), while its Sharpe ratio (0.4693) exceeds that of the Baseline (0.3896). Notably, the strategy achieves a statistically significant α of 0.0226 ($t = 5.528$), indicating that cutting out low-skill forecasters generates significant excess returns, even after accounting for systematic exposure ($\beta = 0.7466$).

Meanwhile, excluding the Top 2.5% performing analysts results in a substantial performance drag: the mean return becomes slightly negative (−0.0019) and the α is both large in magnitude (−0.0523) and highly significant ($t = -9.919$). This underscores that a small contingent of analysts (which changes over time) contributes disproportionately to overall stock price forecasting abilities.

Taken together, these findings highlight two key points. First, the average analyst does not reliably add value beyond a equally-weighted portfolio of the stocks they cover. Second, there exists a nontrivial subset of analysts whose forecasts do exhibit meaningful skill. The central challenge for investors is to identify these outperformers—or at least to filter out the worst performers—on a dynamic and systematic basis.

Motivated by this evidence, we next assume that an investor *models* how much credence to place in each analyst's forecasts, rather than naively pooling them all or discarding some of them indiscriminately. Specifically, the investor predicts each analyst's expected return at the beginning of each month. She updates her projections based on performance signals, and she scales her investment weight in each analyst's implied portfolio according to these evolving beliefs. Specifically, when an analyst is predicted to have larger PnL, she invests in a larger proportion of her wealth into the analyst. By continually learning and re-weighting analysts' price targets, investors can pursue a more refined "fund-of-analysts" strategy that captures real forecasting skill. We use the refined "fund-of-analysts" strategy to re-evaluate if investors can extract meaningful information from analyst price targets.

The investor uses the past performance metrics of each analyst to model the future expected returns of portfolios based on each analyst's predictions.

We use an expanding regression approach to estimate each analyst's expected performance every month with data available up to 12 months before the given month. Specifically, for month t, we regress the realized PnL of each analyst's price targets up through $t-12$ months on a set of predictor variables that captures the analyst's recent accuracy, risk profile, and coverage breadth. With this restriction on the training window, we study a realistic investment scenario where month t's portfolio decisions use information available at the time of investment decisions, thus preventing any lookahead bias in our out-of-sample evaluation. We use all available previous data to retrain the regression model every month.

Note that we do not aim to produce the best possible analyst PnL prediction model. We include a class of intuitive predictors to mimic an environment where investors use analysts' previous performances to decide how much to believe in each analyst.

Table 4: Predictor variables and definitions

Predictor	**Definition**
performance percentile	Analyst's percentile rank by historical performance (accuracy, returns) relative to peers. Higher values indicate stronger track records.
stock percentile	Percentile rank of the breadth of an analyst's stock coverage, capturing how many tickers the analyst covers compared to peers.
recent percentile	Percentile rank of the analyst's most recent six-month rolling performance, highlighting recency effects in forecasting skill.
std percentile	Percentile rank of the analyst's return volatility, assessing relative riskiness of the analyst's calls.
rolling std 6m	The analyst's realized return volatility measured over a rolling six-month window up until 12 months before.
rolling mean 6m	The analyst's realized average return over a rolling six-month window up until 12 months before

Table 4 provides an overview of the predictor variables we use in our rolling regression. These predictors capture key aspects of an analyst's historical forecasting performance. With a mix of ranking-based cross-sectional features and rolling historical measures, an investor captures both static analyst characteristics and dynamic changes in the analysts' forecasting effectiveness.

Once the regression estimates are obtained, we use the fitted model to predict each analyst's expected return from month t to month $t + 12$. Recall that we allocate positive (long) weights, proportional to the magnitude of their predicted PnL, to analysts forecasted to deliver positive PnL, whereas those projected to lose money receive negative (short) weights. This approach aligns with investors who adjust their decisions at every rebalance period, and the portfolio composition changes every month as new data arrive and as the relative performances of each analyst changes over time.

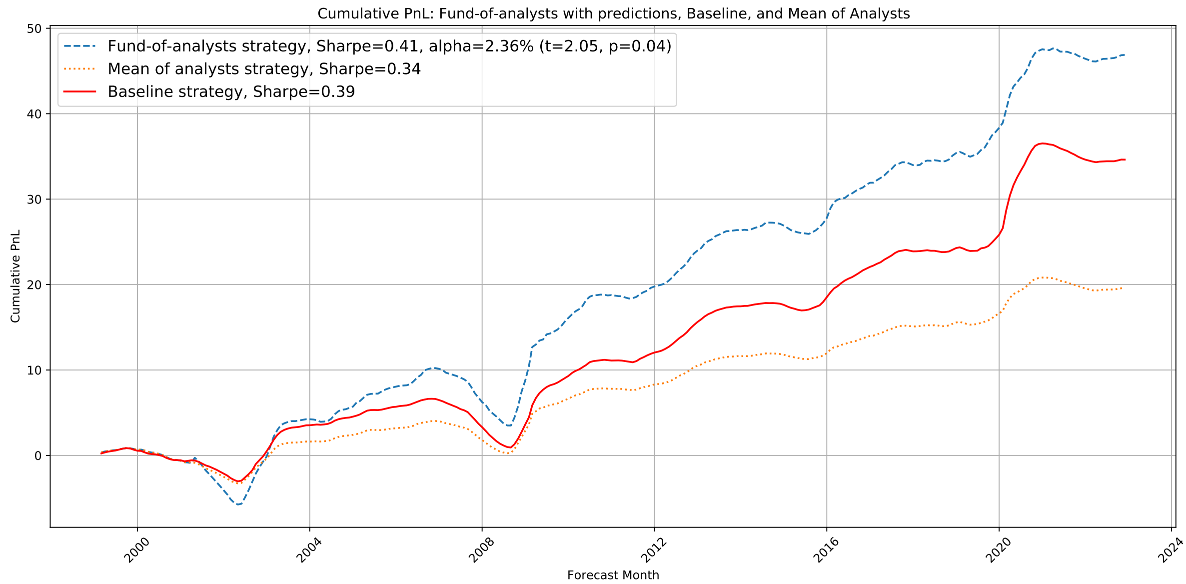

Figure 2: Cumulative returns of refined fund-of-analysts strategies.

Figure 2 presents the cumulative PnL of the fund-of-analysts strategy after we predict analysts' future PnL and use the expanding-window regression to update the weight of each analyst in the portfolio. After fitting an expanding regression with six predictors, we achieve a portfolio that outperforms the baseline (and the average analyst) in terms of having higher Sharpe ratio and statistically significant alpha compared to the baseline. In particular, the alpha of the strategy that uses our forecast of analysts price target performance is 2.36% per month and statistically significant when regressed on the baseline strategy of an equally weighted portfolio of all stocks that are covered by at least one analyst. This preliminary evidence shows that when appropriately adjusting for and selection of analysts' abilities among their cohort, investors can extract useful information from their price target forecasts beyond a simple buy-and-hold strategy.

Recall that we run the predictive expanding-window regression with the predictors in Table 4 every month. Next, we report the coefficient from the last regression window in Table 5.

Table 5: Predictive Regression Results

Coefficients from the final expanding window regression in December 2023. The dependent variable is the one-year-ahead PnL of each analyst. The independent variables include several predictors related to performance, recent trends, and statistical properties listed in Table 4. The regression is estimated using ordinary least squares, with standard errors reported. The table includes significance tests for each coefficient.

Predictor	Coefficient	Std. Err	T-Stat	P-Value	2.5%	97.5%
performance_percentile	0.0469	0.013	3.706	0.000	0.022	0.072
recent_percentile	−0.0309	0.011	−2.889	0.004	−0.052	−0.010
rolling_std_6m	0.0193	0.002	8.489	0.000	0.015	0.024
rolling_mean_6m	−0.0216	0.004	−5.017	0.000	−0.030	−0.013
std_percentile	0.0580	0.011	5.356	0.000	0.037	0.079
stock_percentile	−0.0422	0.010	−4.268	0.000	−0.062	−0.023

From the perspective of a predictive regression model, we observe in Table 5 that analyst price target performance is positively correlated to their long-term cross-sectional ranking in performance and standard deviation, and the performance is negatively correlated to the number of stocks they cover, their short-term cross-sectional ranking in performance, and their short-term absolute performance. All these effects are strongly statistically significant at 1% level.

In other words, Table 5 shows that analyst price target forecasting ability exhibits long-term persistence and short term mean-reversion. Additionally, analysts who cover more stocks tend to perform worse.

Next, we explore how are our results related to exposures to common risk factors. We run a linear regression that explains the returns of our trading strategies using the Fama–French three factors. In particular, in each month, we take the 12-month forward-looking return of each factor and use these returns to explain the returns of our strategies.

Table 6: Fama–French Three-Factor Regression Results

Results of regressing each strategy's excess returns on the Fama-French three-factor model. Alpha represents the intercept and measures the unexplained return of the strategy after controlling for systematic risk factors. The betas capture the exposure to the market (Mkt), size (SMB), and value (HML) factors. The t-statistics are reported in brackets. Statistical significance is denoted as follows: † $p < 0.05$, * $p < 0.1$, ‡ $p < 0.01$.

Strategy	Alpha	Mkt Beta	SMB Beta	HML Beta	R-squared
Regression Strategy	$0.0282^{\dagger}$	$1.5774^{\ddagger}$	$1.1420^{\ddagger}$	−0.0113	0.631
	(2.087)	(13.406)	(6.470)	(−0.110)	
Mean Strategy	−0.0022	$0.8205^{\ddagger}$	$0.5564^{\ddagger}$	−0.0468	0.689
	(−0.380)	(14.305)	(7.032)	(−1.004)	
Baseline Strategy	0.0024	$1.2910^{\ddagger}$	$1.2135^{\ddagger}$	0.0730	0.789
	(0.347)	(21.321)	(7.005)	(1.090)	

Table 6 reports the alpha and exposures for the portfolios in Figure 2. We notice that after considering for the Fama–French 3 factors, the strategy where one first predicts analyst performances and then trades accordingly yields statistically significant monthly alpha whereas both the consensus analyst strategy and the long-only strategy yield statistically insignificant alpha. Additionally, after predicting analyst performances and trading accordingly, the portfolio gains a much larger exposure to the market and to the SMB factor, potentially suggesting that the trading strategy is more exposed to systematic risk factors commonly associated with small-cap and market-wide movements. The significant market beta suggests that a substantial portion of the strategy's returns can be attributed to general market movements, while the high SMB beta indicates a tilt towards smaller firms.

The exposure to the HML factor is near zero and statistically insignificant for the Regression Strategy, implying that the portfolio does not inherently favor value or growth stocks. This is in contrast to the Baseline Strategy, which exhibits a slightly positive

HML beta, albeit also statistically insignificant.

From a risk-adjusted return perspective, the significant positive alpha of the Regression Strategy suggests that after controlling for systematic risks, the strategy continues to generate excess returns. In contrast, both the Mean Strategy and the Baseline Strategy show alphas close to zero, indicating that their returns are likely explainable by systematic risk exposures rather than skill-based alpha generation.

5 Conclusion

In this paper, we revisited the role of sell-side analyst price targets, where we adopt a novel perspective that treats each analyst as a portfolio manager and use their price targets to construct 12-month return predictions. Our analysis shows that although the average analyst does not generate statistically significant alpha relative to a naive long-only benchmark, a nontrivial subset of analysts consistently exhibits genuine forecasting skill. This heterogeneity in performance suggests that both luck and skill play roles in analysts' long-term success.

Motivated by these findings, we introduced a fund-of-analysts framework that dynamically allocates capital across individual analyst-implied portfolios based on predictive signals derived from historical performance, volatility measures, and coverage breadth of each analyst. Our results demonstrate that underweighting poor forecasters and overweighting analysts with stronger track records can generate significant excess returns relative to passive strategies. In particular, our expanding-window regression approach, which updates investor beliefs each month, confirms that appropriately adjusting weights based on predicted performance enhances the risk-adjusted performance of the overall portfolio.

These insights extend the existing literature on the informational content of analyst price targets and offer practical guidance for investors seeking to extract value from sell-side research. Overall, our work provides a new perspective on analyst forecasting, emphasizing that, when harnessed correctly, the diversity in analyst views can be transformed into a meaningful investment signal.

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