Journal of Asset Management (2023) 24:108–120
https://doi.org/10.1057/s41260-022-00283-z

ORIGINAL ARTICLE

Analyst target price and dividend forecasts and expected stock returns

Jinji Hao[1] · **Jonathon Skinner**[2]

Revised: 13 June 2022 / Accepted: 8 August 2022 / Published online: 21 August 2022

Abstract
This paper examines whether adding expected dividend yields implied by analyst dividend forecasts to expected capital gains implied by analyst target prices improves the portfolio strategy of buying stocks with the highest expected returns and selling stocks with the lowest expected returns. We find that the strategy based on the expected total returns performs only slightly better at the 1-month horizon because the short-term return predictability of the expected dividend yield is weak. We find that the strategy generates significant abnormal returns regardless of sorting the stocks universally or within industries, although sorting stocks within industries improves the performance.

Keywords Target price · Dividend forecast · Return predictability

JEL Classification G11 · G12 · G14

Introduction

A prominent question in the accounting and finance literature surrounds the value added to the market by the financial analyst forecasts. More broadly, researchers and practitioners have been interested in whether analyst forecasts provide the market with information that is not already reflected in stock prices. In particular, the literature has been investigating whether analyst forecasts can reveal expected returns on stocks that can be used to inform our investment decisions.

The question is indeed more natural from a direct perspective because the total return on a stock depends on its future price and dividend payment. If we can get accurate forecasts of both the future price and dividend, we have a chance to obtain an informative forecast of the stock return. That is

$$E_t(r_{t+1}) = \frac{E_t(P_{t+1}) + E_t(D_{t+1})}{P_t} - 1, \tag{1}$$

where $E_t(r_{t+1})$, $E_t(P_{t+1})$, and $E_t(D_{t+1})$ are the expected return, price, and dividend of a stock next period. It turns out that the analysts provide forecasts for both the future price and dividend of stocks. They issue target price forecasts, which correspond to $E_t(P_{t+1})$. They also announce dividend per share (DPS) forecasts, which correspond to $E_t(D_{t+1})$. Then we can easily compute an expected return on a stock from analyst forecasts.

However, it is surprising that when examining the cross-sectional return predictability of analyst forecasts, the literature along this line (see, e.g., Brav and Lehavy 2003; Da and Schaumburg 2011; Da et al. 2016) has considered only the target price and computed its implied return, as is called TPER, by

$$\text{TPER}_t = \frac{\text{TP}_{t+1}}{P_t} - 1, \tag{2}$$

where TP_{t+1} is the target price forecast. Hence, this TPER is only about the expected capital gains and ignores the expected dividend yield. Nevertheless, the literature documents that TPER has cross-sectional return predictability with a long-short strategy based on the 1-year target prices generating significant abnormal returns. But the evidence comes with two caveats. First, the return predictability is

✉ Jinji Hao
jinji.hao@vuw.ac.nz

Jonathon Skinner
jonathonskinner00@gmail.com

[1] School of Economics and Finance, Victoria University of Wellington, Wellington, New Zealand

[2] New Zealand's Exchange, Wellington, New Zealand

concentrated at the short-term horizons within a month. Second, the return predictability in Da and Schaumburg (2011) and Da et al. (2016) comes from the relative valuation within sectors, that is, the stocks must be sorted within industries rather than being sorted universally.

The main goal of this paper is to evaluate the potential gains in the cross-sectional return predictability when the expected dividend yields implied by analyst DPS forecasts are also considered. We compute an expected return on a stock, as is called TDER, according to the definition of the total return above,

$$\mathrm{TDER}_t = \frac{\mathrm{TP}_{t+1} + \mathrm{DPS}_{t+1}}{P_t} - 1, \tag{3}$$

where DPS_{t+1} is the DPS forecast.[1]

Moreover, there is another reason for why incorporating dividend forecasts may improve the return predictability beyond that delivered by the target prices. The expected dividend yield captures the value/growth characteristic of stocks. Stocks with low expected dividend yields are growth stocks and, therefore, should have lower expected returns.

We use the monthly analyst consensus target price and DPS forecasts 1 year ahead for the US stocks in the IBES database from May 2002 to December 2020. Our empirical findings are twofold. First, we find that the return predictability of TDER, which includes dividend forecast, at the 1-month horizon is only slightly stronger than that of TPER, which uses only target price. A long-short strategy based on TDER generates an abnormal return which is only four basis points (0.48% annualized) higher than that of TPER on a monthly basis. This is irrespective of sorting the stocks universally or within industries. We show that this is because the return predictability of the expected dividend yield is weak at the short-term 1-month horizon.

Second, we find that in our sample and using our way of constructing TPER or TDER, there is return predictability at the 1-month horizon even when stocks are sorted universally rather than within industries.[2] Sorting stocks within industries does strengthen the results. This is consistent with the evidence in Kadan et al. (2012) that analysts not only have expertise in the stocks within the industries they cover but also have expertise in the industries themselves. Sorting stocks universally reflects analyst expertise both across and within industries.

The paper is organised as follows. In Sect. 2, we review the relevant literature. Section 3 describes the data used, and Sect. 4 explains the methodology. We present the empirical findings in Sect. 5. Section 6 interprets the empirical findings and suggests areas of interest for future research, and Sect. 7 concludes.

Literature review

In this section, we review the literature on trading strategies based on analyst forecasts, especially the target price forecasts. We also review the studies on how analysts form target price forecasts. Finally, we review a few international studies on the accuracy of analyst target price and dividend forecasts.

Analyst-based trading strategies

Research as to whether investors can profit from financial analysts' publicly available recommendations dates back to Cowles (1933). Cowles selected sixteen financial services firms and recorded their stock recommendations over the course of four and a half years from 1928 to 1932. Cowles found that out of the sixteen firms, only six provided recommendations that beat the market index and the groups average return performed worse than the market index by − 1.43%. Furthermore, statistical tests of the best individual records indicated that the positive results were likely the result of chance.

Grossman and Stiglitz (1980) argue that analysts must offer some value to the market from their research and insights. Grossman and Stiglitz advocate that market prices could not possibly contain all available information, otherwise there would be no demand for analysts' services. The study asserts that information is costly to process, and this must be compensated in the form of abnormal trading profits.

Stickel (1995) investigates the effect that changes in an analyst's buy or sell recommendations have on stock prices in addition to the significance of the analyst's reputation. The paper finds that the marginal effect on stock prices of

[1] One may argue that the analyst target prices may already incorporate future dividends. However, most analyst reports clearly state that one-year price targets are derived using blended valuation approaches less the next 12-months dividends. This can also be seen from a textbook approach for estimating a target price, the dividend discount model, which probably is the benchmark model for estimating a target price. Suppose at the beginning of 2022 analysts are interested in the target price of Apple at the end of 2022. They would discount the forecasted dividends of Apple after 2022 back to the end of 2022, which is the target price. Then this target price does not include the dividends to be paid within 2022.

[2] Brav and Lehavy (2003) also find abnormal profits when they sort stocks universally. But their abnormal profits are obtained using individual analysts' target prices and over the period beginning two days prior and ending two days subsequent to the target price announcement. Instead, we examine the abnormal returns at the one-month horizon after the release of the consensus target price and dividend forecasts.

an analyst's recommendation moving from a buy to a strong buy is greater than the marginal effect of moving from a hold to a buy. Additionally, Stickel finds that analysts with a greater reputation have more influence on stock price changes.

Womack (1996) builds on the previous research studying the market reactions to changes in analyst buy and sell recommendations. Womack concludes that analysts do appear to have market timing and stock picking abilities. The paper finds that immediate reactions to a change in recommendations are not mean reverting, this supports previous suggestions that analysts do in fact provide additional information with their recommendations. Additionally, Womack finds that brokers are seven times more likely to issue a buy recommendation than a sell recommendation due to personal costs incurred by analysts for issuing unfavourable information.

Although the previous research suggests that permanent price changes occur following analyst recommendations, Barber et al. (2001) investigate the practical feasibility of the strategy. They find that purchasing recommended stocks and short selling less favourable stocks with daily rebalancing result in an abnormal return beyond 4%. This finding, however, is caveated by the fact that the transaction costs associated with the strategy reduce investors' abnormal returns to zero.

Brav and Lehavy (2003) study the long-term co-movement of analyst target prices and the market stock prices. The study finds that on average, the 1-year-ahead target price is 28% higher than the current stock price. They find that analyst recommendations are the primary driver that merge a stock's price and underlying value together in the long run. This suggests that analyst recommendations do have a long-term effect on stock prices.

Finally, Boni and Womack (2006) investigate the role of analysts as industry specialists. The paper argues that analysts tend to specialise within specific industries and therefore primarily create value by ranking stocks within their specialist industry. The study finds that an industry-based recommendation strategy, that is, purchasing highly recommended stocks and short selling unfavourable stocks within a single industry, yields a much greater return-to-risk ratio to investors than if stocks had been sorted universally.

Target price-based trading strategies

In addition to their work studying the co-movement of target price and stock price, Brav and Lehavy (2003) investigate post-event returns subsequent to target price adjustments. The study finds that target price revisions contain information regarding future abnormal stock returns far beyond what is conveyed in stock price alone. The study finds an abnormal return of 2.69% when sorting on the target price to stock price ratio and an abnormal return of 7.17% when sorting on the change in target price to stock price ratio. These findings suggest that investors perceive a change in target price as an informative signal about a stock's valuation.

Da and Schaumburg (2011) further investigate the relationship between target price and stock price. Da and Schaumburg build on the previous literature by developing Brav and Lehavy's (2003) target price to price ratio into a target price implied return (TPER). The paper investigates a trading strategy involving purchasing stocks with the highest TPER and shorting those with the lowest TPER. The study finds that the strategy can yield statistically significant abnormal returns but only in 1 month post announcement and only if the stocks are sorted within industries.

More recently, Palley et al. (2021) examine how the amount of dispersion in the individual target prices comprising the consensus affects the predictive relationship between the consensus target price and future returns. They find some evidence that when dispersion is low, returns predicted by consensus target prices are more positively associated with realised future returns. However, they document a strong negative association between predicted and realised returns for stocks with high target price dispersion.

Target price formation

We next examine the prevailing literature regarding analysts' target price formation. Bandyopadhyay et al. (1995) find that the short-term earnings forecasts explain just 30% of the variations in the short-term target prices. This suggests that analysts take more information into account than simply the earnings forecasts when formulating a target price.

Asquith et al. (2005) investigate the methodology used by analysts to compute target prices and compare the effectiveness of these models. The paper reports that the methodologies used vary significantly among analysts. Nevertheless, they can fall into one of three categories: earnings multiples, discounted cash flow, or asset multiples. Comparing the ex-post returns shows that the market price reactions to forecast announcements across the three models are not significantly different. Additionally, the study finds no relationship between the methodology used and the probability of a target price being reached.

Da et al. (2016) attempts to decompose target prices into two main drivers, 1-year-ahead earnings forecasts and 1-year price-to-earnings ratio forecasts. They argue that while the models used by individual analysts differ, the model in their paper captures the majority of indicators that analysts tend to use. Using cross-sectional regressions, the paper finds that over longer horizons, earnings forecasts are the main driver of target prices. On the contrary, the target prices at short-term horizons rely far more on sentiment and factors unrelated to firm fundamentals.

More recently, Dechow and You (2020) investigate the determinants of analysts' target price implied returns. They identify four broad sets of factors that help explain the cross-sectional variation in target price implied returns: future realised stock returns, errors in forecasting fundamentals, errors in forecasting the expected return to risk, and biases relating to analysts' incentives. They find that errors in forecasting the expected return to empirical risk proxies have the greatest impact. The also find that investors make similar valuation errors to analysts and/or do not perfectly back out the predicted bias in target prices.

International studies on analyst forecasts

Finally, analyst forecasts in economies other than the U.S. have also been covered in a few international studies. Bilinski et al. (2013) and Bradshaw et al. (2019) examine how the institutions of the firm-country and analyst-country affect the accuracy and optimism, respectively, of analyst target prices around the world. Bilinski and Bradshaw (2021) find that analyst dividend forecasts are available for most dividend-paying firms and are more accurate than alternative proxies based on extrapolations of past dividends around the world. Brown et al. (2008) examines the link between the accuracy of analysts' dividend forecasts, earnings predictability and dividend policies of firms around the world.

Data description

Target price

The monthly consensus (median) target prices for individual stocks are used as the first component in constructing our TDER predictor.[3] The data are sourced from the International Brokers Estimate System (IBES) database. The consensus target prices are for the 1-year horizon and are calculated from target prices issued by individual analysts in the last 105 days. Our sample of consensus target prices in IBES is from March 1999 to December 2020.

[3] Da and Schaumburg (2011) and Da et al. (2016) use the target prices from individual analysts within a month to calculate a median target price by themselves rather than using the consensus target price in IBES, which is used by this paper and, for example, Palley et al. (2021). Moreover, Da and Schaumburg (2011) skip the target prices issued in the last 5 calendar days. As in Da et al. (2016), we do not skip 5 days after the release of consensus forecasts as the predictability of target prices is concentrated in the first few weeks anyway.

Dividend per share

The monthly consensus (median) dividend per share forecasts are used as the second component in constructing our TDER predictor. The data are also sourced from the IBES database. The IBES dividend per share forecasts are available for different quarter or fiscal year ends. We approximate the consensus dividend per share at the 1-year horizon by interpolating two data points at the nearest horizons. The complete consensus dividend per share data is available from May 2002. Hence, our data sample is from May 2002 to December 2020.

The dividend per share forecasts are then matched with target prices based on the date on which the consensus estimates are calculated and the IBES company Tickers, resulting in a sample consisting of firms' monthly target prices and dividend per share forecasts for the 1-year horizon. For each stock and in each month, the expected return implied by the target price and dividend per share and the expected return implied by the target price alone are calculated according to (3) and (2), respectively.

Stock data

Daily stock price data are sourced from the Center for Research in Security Prices (CRSP) database. The stock SIC code is also obtained from CRSP. The Fama and French five-factor data, including the risk-free rate, and their 10-sector classification of industries are downloaded from Kenneth French's website.

Future realised returns

Since the consensus target prices and dividend forecasts are released on the third Thursday each month, in order to calculate the first-month returns of stocks after the announcements, we compound the daily returns within the following month immediately after the announcements. We calculate the second-month returns and the monthly returns for risk factors similarly.

Summary statistics

Table 1 reports the summary statistics of the sample. For each sample for a given month, we compute the statistics of the TDER, TPER, and dividend yield (DY) across the stocks and count the number of stocks in the sample. The table reports the averages of these statistics over the months. The second column shows that the stocks on average have an expected total return of 18.75%, an expected capital gains of 15.15%, and an expected dividend yield of 3.60% over the next year. The fourth column shows that the standard

deviations across the stocks of the expected total return, capital gains, and dividend yield are on average 32.23%, 31.00%, and 4.28%, respectively. The last two columns show that on average the 95% percentile of the expected dividend yield is 10.14%, while the 5% percentile is 0.50%.

The last row reports the statistics of the number of stocks in the sample. We have on average 1413 stocks in the sample each month over time. We start with 397 stocks in May 2002, and this number increases to more than 1600 after March 2013.

Table 1 Summary statistics

	Mean	Median	SD	95% percentile	5% percentile
TDER (%)	18.75	15.13	32.33	49.88	− 3.80
TPER (%)	15.15	11.86	31.00	45.06	− 6.94
DY (%)	3.60	2.58	4.28	10.14	0.50
Number of firms	1413	1436	298	1779	797

The table reports the summary statistics of the sample. For each month, we calculate across the firms the mean, median, standard deviation, 95% percentile, and 5% percentile of the expected total returns implied by the 1-year target price and dividend forecasts (TDER), and the expected capital gains implied by the 1-year target price forecasts only (TPER), and the expected dividend yields implied by the 1-year dividend forecasts (DY). We then take the averages of these statistics over time and report them in the first three rows of the table. The last row reports the mean, median, standard deviation, 95% percentile, and 5% percentile over time of the number of firms in the sample each month.

Methodology

For each month between May 2002 and November 2020 the stocks in our sample are sorted based on the expected returns implied by their consensus target prices and dividend forecasts over the next year. The stocks are then placed into decile portfolios. The stocks with the highest consensus expected returns are placed into the decile 1 portfolio and the stocks with the lowest expected returns are placed into the decile 10 portfolio.

Once assigned into a portfolio, the stocks are matched with their realised returns over different horizons. We focus on the 1-month horizon as the predictability of TPER is shown to be concentrated at this horizon in Da and Schaumburg (2011). These realised returns are then averaged within each decile portfolio to give an equally weighted average return of the portfolio.

Finally, we report the total return of a long-short trading strategy in which we buy the decile 1 portfolio of stocks with the highest implied expected returns and sell the decile 10 portfolio of stocks with the lowest implied expected returns.

In addition, we test if the portfolio mean returns are statistically different from zero using the Newey-West t-statistic. Furthermore, a risk-adjusted alpha is constructed using the Fama-French five-factor model. We again use the Newey-West t-statistic to test for the statistical significance of the alpha. The risk-adjusted alpha is estimated using the following time-series regression:

$$R_t^e = \alpha + a\left(R_t^m - R_t^f\right) + s\left(SMB_t\right) + h\left(HML_t\right) + r\left(RMW_t\right) + c\left(CMA_t\right) + \epsilon_t, \tag{4}$$

where R_t^e is the excess return of a portfolio or the return of the long-short portfolio. The regressors on the right-hand side are the five factors, respectively.

Results

Portfolios sorted universally based on TDER

Table 2 reports the results when stocks are sorted into ten decile portfolios universally based on TDER. First, the strategy of buying the decile 1 portfolio of stocks with the highest TDER and selling the decile 10 portfolio of stocks with the lowest TDER generates a spread of 1.18% in the first month, which is statistically significant at the 5% level (column 2).

To investigate whether the positive first-month returns of the strategy are due to systematic risks, we adjust for the risk using the Fama-French five-factor model. Column 3 reports that after adjusting the risk, the strategy still generates an abnormal return of 0.88% (10.56% annualized) in the first month, which is still statistically significant at the 5% level. This result is to the contrary of Da and Schaumburg (2011), which stress that analyst forecasts are valuable only in terms of relative valuation when they are sorted within industries and report that they were unable to generate a statistically significant alpha when stocks are sorted universally using TPER.

The strategy has positive exposures to the market (MKT), size (SMB), and value (HML) factors but negative exposures to the profitability (RMW) and investment (CMA) factors (columns 4–8). Note that the market beta of the long-short portfolio is much smaller than that of each individual portfolio. Da and Schaumburg (2011) explain that this positive

Table 2 Returns on universally TDER-sorted portfolios

Portfolio	First-month	Five-factor model						Second-month	Twelve-month
	Excess return	alpha	MKT	SMB	HML	RMW	CMA	Excess return	Excess return
1	1.62%	0.55%	1.27	0.73	0.96	− 0.14	− 0.64	0.78%	10.69%
	[2.34]	[1.56]	[9.91]	[3.75]	[3.78]	[− 0.69]	[− 1.96]	[1.15]	[1.69]
2	1.17%	0.15%	1.15	0.51	0.54	0.12	− 0.36	0.76%	9.90%
	[2.33]	[0.94]	[18.93]	[5.60]	[4.54]	[1.15]	[− 2.03]	[1.55]	[2.23]
3	1.09%	0.15%	1.07	0.36	0.44	0.16	− 0.22	0.77%	10.1%
	[2.54]	[1.28]	[26.36]	[5.59]	[5.04]	[1.79]	[− 1.60]	[1.80]	[2.60]
4	1.11%	0.20%	1.01	0.37	0.45	0.23	− 0.18	0.70%	10.18%
	[2.75]	[2.17]	[32.78]	[7.29]	[6.95]	[3.66]	[− 1.76]	[1.79]	[2.87]
5	1.09%	0.20%	0.99	0.33	0.39	0.24	− 0.20	0.80%	10.29%
	[2.83]	[2.23]	[34.21]	[7.35]	[6.61]	[3.86]	[− 1.89]	[2.14]	[2.99]
6	0.94%	0.07%	0.95	0.33	0.31	0.27	− 0.07	0.75%	9.71%
	[2.61]	[0.94]	[45.16]	[8.48]	[8.16]	[6.01]	[− 1.17]	[2.11]	[3.00]
7	0.78%	− 0.11%	0.94	0.31	0.25	0.37	0.04	0.78%	9.59%
	[2.25]	[− 1.30]	[35.67]	[8.07]	[5.56]	[7.41]	[0.75]	[2.32]	[3.06]
8	0.80%	0.00%	0.87	0.32	0.28	0.29	− 0.01	0.67%	9.31%
	[2.42]	[− 0.07]	[48.48]	[8.63]	[8.34]	[6.41]	[− 0.18]	[1.99]	[3.00]
9	0.69%	− 0.08%	0.83	0.27	0.25	0.29	0.10	0.63%	8.91%
	[2.17]	[− 0.95]	[28.09]	[5.55]	[6.05]	[5.13]	[1.70]	[1.89]	[2.85]
10	0.44%	− 0.32%	0.82	0.35	0.30	0.21	0.12	0.50%	8.06%
	[1.27]	[− 2.72]	[21.05]	[5.29]	[4.75]	[3.09]	[1.41]	[1.37]	[2.44]
1–10	1.18%	0.88%	0.45	0.38	0.66	− 0.35	− 0.76	0.28%	2.62%
	[2.44]	[2.36]	[3.10]	[1.70]	[2.57]	[− 1.72]	[− 2.29]	[0.64]	[0.64]

Immediately after the consensus target prices and DPS forecasts are released in each month from May 2002 to December 2020, we rank all stocks in our sample into ten portfolios according to the current month TDERs and label them from 1 to 10 (1 with the highest TDER and 10 with the lowest TDER). For each stock, we compute the first-month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during each of the first 2 months after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

loading on the market risk factor is intuitive as high beta stocks will receive higher target prices relative to their current market prices.

The last two columns report the results for the portfolio returns in the second month and in the next 12 months after the portfolio formation.

Consistent with Da and Schaumburg (2011), we find that the long-short strategy based on TDER is unable to generate a statistically positive return in either the second month or the next 12 months after the portfolio formation.

Portfolios sorted within sectors based on TDER

In order to test whether the relative rankings of expected returns implied by analyst forecasts are more meaningful within industries because of analyst specialised industry expertise, as suggested by Da and Schaumburg (2011) when they use TPER, we now implement the strategy by sorting stocks based on TDER within industries. Instead of using the industries defined by the SIC code, we use the Fama-French 10-sector classification. Da and Schaumburg (2011) show that this classification of sectors performs better than the single-digit SIC classification.[4] Specifically, the stocks within each sector are first separately sorted into decile portfolios, and the portfolios for each decile across the sectors are then pooled together to form the decile portfolio for the whole market.

Table 3 reports the first-month portfolio returns and the risk-adjusted alpha of the portfolios. First, the strategy of buying the decile 1 portfolio of stocks with the highest TDER within each sector and selling the decile 10 portfolio of stocks with the lowest TDER within each sector generates a spread of 1.29% in the first month, which is 11 basis points

[4] Da and Schaumburg (2011) suggest that the GICS classification of industries matches the expertise of analysts better and the long-short strategy based on TPER using GICS performs better that using the Fama-French 10 sectors or the single-digit SIC. Unfortunately, we do not have the data for the GICS of stocks.

Table 3 Returns on within-sector TDER-sorted portfolios

Portfolio	First-month	Five-factor model						Second-month	Twelve-month
	Excess return	Alpha	MKT	SMB	HML	RMW	CMA	Excess return	Excess return
1	1.79%	0.73%	1.26	0.68	0.83	− 0.09	− 0.58	0.82%	11.55%
	[2.73]	[2.21]	[9.99]	[3.72]	[3.39]	[− 0.42]	[− 1.80]	[1.30]	[1.90]
2	1.12%	0.14%	1.11	0.52	0.58	0.11	− 0.40	0.85%	10.51%
	[2.28]	[0.87]	[19.91]	[5.86]	[4.79]	[0.99]	[− 2.13]	[1.74]	[2.38]
3	1.14%	0.21%	1.07	0.35	0.47	0.14	− 0.29	0.77%	10.21%
	[2.63]	[1.80]	[25.99]	[5.46]	[5.71]	[1.81]	[− 2.38]	[1.79]	[2.67]
4	1.05%	0.11%	1.04	0.36	0.40	0.21	− 0.15	0.72%	9.77%
	[2.56]	[1.11]	[29.23]	[6.22]	[5.96]	[3.02]	[− 1.33]	[1.80]	[2.68]
5	1.03%	0.15%	1.00	0.31	0.41	0.19	− 0.17	0.72%	9.71%
	[2.67]	[1.88]	[39.93]	[6.68]	[7.52]	[2.94]	[− 1.81]	[1.91]	[2.80]
6	0.93%	0.04%	0.96	0.33	0.31	0.31	− 0.02	0.74%	9.71%
	[2.55]	[0.53]	[46.07]	[9.66]	[7.43]	[7.21]	[− 0.41]	[2.04]	[2.94]
7	0.79%	− 0.07%	0.92	0.35	0.30	0.32	− 0.01	0.74%	9.30%
	[2.25]	[− 0.87]	[41.54]	[9.34]	[7.59]	[6.87]	[− 0.21]	[2.09]	[2.90]
8	0.79%	− 0.03%	0.89	0.33	0.32	0.30	− 0.04	0.65%	8.90%
	[2.34]	[− 0.43]	[42.49]	[8.34]	[10.86]	[5.83]	[− 0.66]	[1.90]	[2.81]
9	0.65%	− 0.13%	0.84	0.31	0.25	0.27	0.08	0.64%	9.04%
	[1.99]	[− 1.72]	[32.60]	[7.26]	[6.28]	[6.03]	[1.37]	[1.91]	[2.82]
10	0.50%	− 0.28%	0.83	0.36	0.30	0.26	0.13	0.52%	8.29%
	[1.46]	[− 2.72]	[20.60]	[6.01]	[5.38]	[4.78]	[2.08]	[1.47]	[2.58]
1–10	1.29%	1.00%	0.42	0.32	0.53	− 0.35	− 0.71	0.30%	3.26%
	[2.98]	[3.03]	[2.95]	[1.55]	[2.06]	[− 1.68]	[− 2.17]	[0.78]	[0.87]

Immediately after the consensus target prices and DPS forecasts are released in each month from May 2002 to December 2020, we rank stocks within each sector in our sample into ten portfolios according to the current month TDERs and label them from 1 to 10 (1 with the highest TDER and 10 with the lowest TDER). For each stock, we compute the first-month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during the first month after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

(1.32% annualised) higher than that when stocks are sorted universally and is also more statistically significant at the 1% level (column 2).

After adjusting for risk, the abnormal return on the long-short strategy is 1.00% in the first month, which is 12 basis points (1.44% annualised) higher than that when stocks are sorted universally and is also more statistically significant at the 1% level (column 3). Surprisingly, the exposure of the strategy to the market risk factor only changes slightly when we switch to the within-sector sorted portfolios. This contradicts the intuition that sorting stocks within sectors should help to eliminate systematic risk because stocks within each sector should have similar risk profiles. This is likely because our classification of ten sectors is broader than that of industries with specific risk profiles.

The last two columns show that sorting stock within sectors based on TDER does not generate a statistically significant spread in either the second month or the next 12 months.

Portfolios sorted universally based on TPER

In order to evaluate whether including dividend forecasts in TDER improves upon the performance of the strategy based on TPER in Da and Schaumburg (2011), which only considers target prices, we now examine the portfolio performance when sorting stocks universally based on TPER in our sample.

Table 4 reports the portfolio returns and the risk-adjusted alpha. First, the strategy of buying the decile 1 portfolio of stocks with the highest TPER and selling the decile 10 portfolio of stocks with the lowest TPER generates a positive return of 1.17% in the first month, which is only one basis point lower than that when stocks are sorted universally based on TDER and is also statistically significant at the 5% level (column 2). After adjusting for risk, the abnormal return on the long-short strategy is 0.84% in the first month, which is only four basis points (0.48% annualised) lower than that when stocks are sorted universally based on TDER and is also statistically significant at

Table 4 Returns on universally TPER-sorted portfolios

Portfolio	First-month	Five-factor model						Second-month	Twelve-month
	Excess return	Alpha	MKT	SMB	HML	RMW	CMA	Excess return	Excess return
1	1.61%	0.52%	1.30	0.69	0.92	− 0.11	− 0.61	0.80%	10.96%
	[2.38]	[1.55]	[10.17]	[3.59]	[3.81]	[− 0.58]	[− 2.01]	[1.20]	[1.80]
2	1.27%	0.24%	1.17	0.49	0.52	0.07	− 0.37	0.76%	10.17%
	[2.51]	[1.51]	[19.80]	[5.31]	[4.12]	[0.63]	[− 1.94]	[1.55]	[2.33]
3	1.02%	0.07%	1.06	0.44	0.46	0.15	− 0.27	0.78%	10.27%
	[2.32]	[0.65]	[25.29]	[7.11]	[5.44]	[1.61]	[− 1.93]	[1.83]	[2.70]
4	1.11%	0.19%	1.03	0.34	0.42	0.23	− 0.19	0.79%	10.49%
	[2.75]	[2.08]	[34.07]	[6.75]	[6.46]	[3.75]	[− 2.08]	[2.04]	[2.96]
5	1.04%	0.17%	0.97	0.34	0.35	0.23	− 0.18	0.80%	10.18%
	[2.80]	[1.96]	[35.78]	[8.22]	[5.85]	[4.00]	[− 1.82]	[2.17]	[2.97]
6	0.91%	0.02%	0.97	0.32	0.27	0.29	− 0.01	0.71%	9.55%
	[2.54]	[0.22]	[42.67]	[8.21]	[6.38]	[5.89]	[− 0.15]	[2.01]	[2.91]
7	0.86%	0.03%	0.90	0.29	0.28	0.32	− 0.02	0.77%	9.65%
	[2.55]	[0.40]	[48.31]	[8.28]	[7.87]	[8.67]	[− 0.47]	[2.26]	[3.03]
8	0.77%	− 0.05%	0.88	0.31	0.29	0.32	0.02	0.71%	9.19%
	[2.30]	[− 0.59]	[35.39]	[6.82]	[7.58]	[5.87]	[0.34]	[2.08]	[2.90]
9	0.69%	− 0.07%	0.82	0.28	0.29	0.28	0.12	0.60%	8.69%
	[2.13]	[− 0.81]	[31.56]	[5.76]	[6.15]	[5.29]	[1.91]	[1.77]	[2.74]
10	0.43%	− 0.32%	0.81	0.38	0.36	0.26	0.10	0.43%	7.60%
	[1.23]	[− 2.53]	[21.31]	[5.55]	[5.47]	[3.69]	[1.07]	[1.16]	[2.24]
1–10	1.17%	0.84%	0.49	0.31	0.56	− 0.38	− 0.71	0.37%	3.36%
	[2.55]	[2.39]	[3.36]	[1.43]	[2.31]	[− 1.94]	[− 2.27]	[0.89]	[0.91]

Immediately after the consensus target prices are released in each month from May 2002 to December 2020, we rank all stocks in our sample into ten portfolios according to the current month TPERs and label them from 1 to 10 (1 with the highest TPER and 10 with the lowest TPER). For each stock, we compute the first month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during each of the first 2 months after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

the 5% level (column 3). The last two columns show that sorting stock universally based on TPER does not generate a statistically significant spread in either the second month or the next 12 months.

Table 6 in the Appendix reports that when stocks are sorted within sectors based on TPER, both the raw return and the risk-adjust return of the long-short portfolio at the 1-month horizon are only three basis points worse than those when stocks are sorted within sectors based on TDER.

Therefore, when stocks are sorted universally, including dividend forecasts only slightly improves the portfolio performance.

Portfolios sorted universally based on the expected dividend yield

To investigate why the improvement of TDER over TPER in terms of the portfolio performance is small at the 1-month horizon, we now examine separately the return predictability of the expected dividend yield implied by analyst DPS forecasts. We look at the performance of a strategy where stocks are sorted universally based on the expected dividend yield, the ratio of the 1-year forecast of DPS over the current price (DY).

Table 5 reports the portfolio returns and the risk-adjusted alpha. It can be seen that the strategy of buying the decile 1 portfolio of stocks with the highest DY and selling the decile 10 portfolio of stocks with the lowest DY generates a return of 0.24% in the first month, but it is not statistically significant (column 2). After adjusting for risk, the abnormal return on the long-short strategy is 0.29% in the first month, which is also not statistically significant (column 3). The last column shows that the strategy does not generate a significant return in the second month either. Table 7 in the Appendix reports similar results when the stocks are sorted within sectors based on the expected dividend yield implied by analyst DPS forecasts.

Therefore, the return predictability of the expected dividend yield is weak at the 1-month horizon, which explains

Table 5 Returns on universally dividend yield-sorted portfolios

Portfolio	First-month	Five-factor model						Second-month
	Excess return	alpha	MKT	SMB	HML	RMW	CMA	Excess return
1	1.21%	0.27%	1.06	0.67	0.80	0.17	− 0.56	0.55%
	[2.10]	[0.88]	[9.48]	[4.00]	[3.72]	[0.84]	[− 1.74]	[0.93]
2	0.95%	0.08%	0.98	0.36	0.54	0.27	− 0.17	0.67%
	[2.24]	[0.48]	[14.13]	[3.50]	[5.01]	[2.49]	[− 1.11]	[1.48]
3	1.04%	0.22%	0.96	0.23	0.54	0.19	− 0.16	0.73%
	[2.66]	[1.55]	[18.19]	[2.87]	[5.64]	[2.00]	[− 1.04]	[1.81]
4	0.90%	0.07%	0.92	0.32	0.43	0.27	− 0.03	0.65%
	[2.42]	[0.72]	[31.37]	[5.71]	[7.72]	[4.05]	[− 0.35]	[1.80]
5	0.98%	0.12%	0.94	0.35	0.40	0.26	− 0.04	0.79%
	[2.61]	[1.64]	[33.35]	[7.16]	[9.21]	[4.74]	[− 0.55]	[2.16]
6	0.81%	− 0.07%	0.96	0.39	0.33	0.22	− 0.04	0.66%
	[2.15]	[− 1.10]	[35.33]	[10.26]	[9.18]	[5.50]	[− 0.70]	[1.76]
7	0.97%	0.07%	0.99	0.39	0.35	0.20	− 0.07	0.69%
	[2.49]	[0.99]	[30.94]	[11.42]	[8.12]	[4.84]	[− 1.35]	[1.82]
8	0.87%	− 0.01%	0.97	0.39	0.36	0.16	− 0.16	0.78%
	[2.25]	[− 0.17]	[54.59]	[11.47]	[11.17]	[4.21]	[− 2.89]	[2.04]
9	1.03%	0.08%	1.04	0.33	0.23	0.17	− 0.15	0.77%
	[2.66]	[0.99]	[38.6]	[7.10]	[4.98]	[2.82]	[− 1.97]	[2.08]
10	0.97%	− 0.02%	1.07	0.43	0.19	0.15	− 0.03	0.87%
	[2.28]	[− 0.17]	[29.03]	[6.55]	[2.68]	[1.82]	[− 0.37]	[2.04]
1–10	0.24%	0.29%	− 0.01	0.24	0.61	0.02	− 0.53	− 0.33%
	[0.71]	[0.90]	[− 0.07]	[1.39]	[2.84]	[0.08]	[− 1.62]	[− 1.03]

Immediately after the consensus DPS forecasts are released in each month from May 2002 to December 2020, we rank all stocks in our sample into ten portfolios according to the current month DYs and label them from 1 to 10 (1 with the highest DY and 10 with the lowest DY). For each stock, we compute the first month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during each of the first 2 months after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

why the improvement of TDER over TPER in the portfolio performance is small at the 1-month horizon.

Discussion

The value of dividend forecasts

The first finding of this study is that the addition of the expected dividend yield to the TPER predictor appears to only slightly improves the effectiveness of the strategy. A hypothesis of this paper is that the inclusion of expected dividend should improve the accuracy of analyst return forecasts and, therefore, result in a more profitable trading strategy. The results, however, have suggested that this benefit is small at the 1-month horizon. The portfolio alpha increases by only 0.48% on an annual basis when expected dividends are included. The possible reason for this finding is that the expected dividend yield is correlated with the current dividend-price ratio, which captures the value/growth characteristic of stocks. However, the return predictability of dividend-price ratio is usually at the longer horizons of 1–5 years, while the return predictability of target prices is only at the shorter horizons within a month. This mismatch in horizons between the return predictability of dividend forecasts and target prices may explain why including dividends does not improve the predictability much at the 1-month horizon.

The absolute and relative valuation

The second finding of this study is that the trading strategy based on TDER or TPER can be effective even when stocks are sorted universally, although sorting stocks within sectors improves the performance of the strategy. Da and Schaumburg (2011) emphasise the relative valuation and argue that

analysts have expertise in identifying the derivations from fundamental values for stocks within the industries they cover but do not have much knowledge about the industry systematic risk or factor risk premium. However, there is evidence that analysts have industry expertise, and their industry recommendations also contain valuable information of portfolio strategy. Kadan et al. (2012) show that portfolios based on industry recommendations generate abnormal returns and industry recommendations contain information which is orthogonal to that included in firm recommendations. They suggest that the investment value of analysts' recommendations is enhanced when both industry and firm recommendations are used. This suggests a strategy of sorting industries in addition to sorting stocks within industries, which can be even more informative than sorting stocks universally.

Extensions

Our findings suggest possible extensions and areas of interest for future study of this topic. The finding that the inclusion of dividends does not improve the effectiveness of the strategy much raises questions about the intuition behind TPER as a return predictor. If high TPER stocks earn higher returns because analysts have forecasted accurately, the prediction should be significant up to the target price forecast ending date, and the accuracy could be improved more by the inclusion of dividend forecasts.

It is possible that the positive abnormal returns associated with TPER are not related to the expected return forecasted by analysts but instead to the forecast revisions. Da and Schaumburg (2011) note in their study that within their portfolios the percentage of stocks with a recent upwards price target revision is monotonically increasing along their decile portfolios. It is possible that the positive abnormal returns associated TPER are instead driven by positive target price revisions hidden in the TPER predictor. A possible extension of this study would be to sort stocks based on target price revisions (ΔTP/TP) rather than TPER.

Conclusion

This paper finds that taking into account the analyst dividend forecasts slightly improves the cross-sectional return predictability of stocks at the 1-month horizon compared with the expected capital gains implied by only analyst target prices. This is irrespective of whether the stocks are sorted universally or within industries. The possible reason is that the return predictability of the expected dividend yield implied by dividend forecasts captures the value effect, for which the return predictability is usually at the long term, while the return predictability of target prices is only at the short-term 1-month horizon.

This paper also finds that using analyst consensus target price and dividend forecasts, there is cross-sectional return predictability at the 1-month horizon even when stocks are sorted universally, although sorting stocks within industries improves the return predictability.

Future research on this topic should focus on examining whether the return predictability of target prices at the short term is due to the information content of target prices or the short-term market reaction after the announcement of a target price revision. It would be interesting to examine the return predictability of target price revisions instead of just expected returns implied by target price and dividend forecasts. It is also worth investigating whether sorting industries according to analyst recommendations in addition to sorting stocks within industries will improve the strategy performance.

Appendix

See Tables 6 and 7.

Table 6 Returns on within-sector TPER-sorted portfolios

Portfolio	First-month	Five-factor model					
	Excess return	Alpha	MKT	SMB	HML	RMW	CMA
1	1.74%	0.67%	1.27	0.63	0.82	− 0.11	− 0.59
	[2.69]	[2.12]	[10.38]	[3.58]	[3.48]	[− 0.56]	[− 1.88]
2	1.20%	0.22%	1.11	0.53	0.57	0.10	− 0.42
	[2.44]	[1.45]	[20.83]	[6.35]	[4.72]	[0.89]	[− 2.34]
3	1.10%	0.16%	1.07	0.37	0.44	0.14	− 0.29
	[2.55]	[1.51]	[27.45]	[6.03]	[5.54]	[1.83]	[− 2.37]
4	1.05%	0.13%	1.04	0.32	0.42	0.19	− 0.17
	[2.61]	[1.34]	[29.8]	[5.64]	[6.54]	[2.83]	[− 1.64]
5	1.02%	0.12%	1.00	0.34	0.36	0.25	− 0.15
	[2.68]	[1.53]	[36.66]	[7.87]	[6.29]	[4.07]	[− 1.6]
6	0.86%	0.00%	0.95	0.33	0.34	0.23	− 0.04
	[2.35]	[− 0.06]	[41.86]	[9.02]	[7.75]	[4.99]	[− 0.62]
7	0.83%	− 0.01%	0.91	0.33	0.30	0.34	0.00
	[2.40]	[− 0.17]	[42.75]	[8.31]	[7.92]	[7.28]	[0.07]
8	0.78%	− 0.05%	0.90	0.32	0.31	0.32	− 0.01
	[2.29]	[− 0.70]	[44.60]	[8.13]	[9.24]	[7.00]	[− 0.24]
9	0.70%	− 0.08%	0.85	0.31	0.28	0.26	0.10
	[2.11]	[− 1.02]	[35.25]	[7.02]	[6.80]	[5.35]	[1.87]
10	0.48%	− 0.30%	0.83	0.40	0.35	0.31	0.10
	[1.38]	[− 2.78]	[22.22]	[6.61]	[5.70]	[5.35]	[1.32]
1–10	1.26%	0.97%	0.45	0.24	0.47	− 0.42	− 0.69
	[3.03]	[3.03]	[3.18]	[1.21]	[1.95]	[− 2.14]	[− 2.15]

Immediately after the consensus target prices are released in each month from May 2002 to December 2020, we rank stocks within each sector in our sample into ten portfolios according to the current month TPERs and label them from 1 to 10 (1 with the highest TPER and 10 with the lowest TPER). For each stock, we compute the first month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during the first month after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

Table 7 Returns on within-sector dividend yield-sorted portfolio

Portfolio	First-month	Five-factor model					
	Excess return	Alpha	MKT	SMB	HML	RMW	CMA
1	1.29%	0.36%	1.07	0.63	0.77	0.07	− 0.48
	[2.30]	[1.29]	[10.54]	[4.20]	[3.92]	[0.39]	[− 1.63]
2	1.07%	0.14%	1.02	0.47	0.47	0.25	− 0.13
	[2.42]	[0.90]	[18.01]	[5.48]	[4.53]	[2.41]	[− 0.77]
3	1.06%	0.18%	0.99	0.32	0.47	0.25	− 0.11
	[2.63]	[1.40]	[19.77]	[3.77]	[4.97]	[2.60]	[− 0.72]
4	0.94%	0.07%	0.98	0.30	0.40	0.21	− 0.09
	[2.47]	[0.66]	[23.84]	[4.64]	[5.38]	[2.49]	[− 0.69]
5	0.81%	− 0.04%	0.94	0.33	0.40	0.24	− 0.11
	[2.18]	[− 0.45]	[35.15]	[6.27]	[8.50]	[4.29]	[− 1.41]
6	0.85%	− 0.02%	0.95	0.35	0.38	0.26	− 0.10
	[2.29]	[− 0.29]	[57.68]	[9.70]	[10.80]	[7.47]	[− 2.11]
7	0.88%	0.02%	0.95	0.37	0.36	0.21	− 0.09
	[2.34]	[0.27]	[29.61]	[9.71]	[8.97]	[5.51]	[− 1.74]
8	0.92%	0.05%	0.95	0.38	0.35	0.23	− 0.10
	[2.48]	[0.83]	[53.03]	[12.88]	[11.69]	[6.04]	[− 2.02]
9	0.96%	0.07%	0.99	0.35	0.35	0.16	− 0.21
	[2.50]	[1.10]	[38.9]	[7.78]	[10.12]	[3.10]	[− 3.42]
10	0.96%	0.00%	1.05	0.40	0.23	0.16	− 0.03
	[2.33]	[− 0.01]	[35.62]	[6.51]	[3.55]	[2.19]	[− 0.43]
1–10	0.33%	0.36%	0.02	0.23	0.54	− 0.09	− 0.45
	[1.11]	[1.26]	[0.23]	[1.52]	[2.78]	[− 0.45]	[− 1.54]

Immediately after the consensus DPS forecasts are released in each month from May 2002 to December 2020, we rank stocks within each sector in our sample into ten portfolios according to the current month DYs and label them from 1 to 10 (1 with the highest DY and 10 with the lowest DY). For each stock, we compute the first month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks in the same portfolio. The table reports the average excess returns during the first month after portfolio formation and risk-adjusted alphas using the Fama-French five-factor model. All returns and alphas are monthly. *t*-values are reported in the square brackets.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Declarations

Conflict of interest The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

References

Asquith, Paul, Michael B. Mikhail, and SAu. Andrea. 2005. Information Content of Equity Analyst Reports. *Journal of Financial Economics* 75 (2): 245–282.

Bandyopadhyay, Sati P., Lawrence D. Brown, and Gordon D. Richardson. 1995. Analysts' Use of Earnings Forecasts in Predicting Stock Returns: Forecast Horizon Effects. *International Journal of Forecasting* 11 (3): 429445.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman. 2001. Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *Journal of Finance* 56 (2): 531–563.

Bilinski, Pawel, Danielle Lyssimachou, and Martin Walker. 2013. Target Price Accuracy: International Evidence. *The Accounting Review* 88 (3): 825–851.

Bilinski, Pawel, and Mark T. Bradshaw. 2021. Analyst Dividend Forecasts and Their Usefulness to Investors. *The Accounting Review* (forthcoming).

Boni, Leslie, and Kent L. Womack. 2006. Analysts, Industries, and Price Momentum. *Journal of Financial and Qualitative Analysis* 41 (1): 85–109.

Bradshaw, Mark T., Alan G. Huang, and Hongping Tan. 2019. The Effects of Analyst-Country Institutions on Biased Research: Evidence from Target Prices. *Journal of Accounting Research* 57 (1): 85–120.

Brav, Alon, and Reuven Lehavy. 2003. An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics. *Journal of Finance* 58 (5): 1933–1967.

Brown, Philip, Janice C.Y.. How, and Peter Verhoeven. 2008. The Accuracy of Analysts' Dividend Forecasts around the World. *Pacific-Basin Finance Journal* 16 (4): 411–435.

Cowles, Alfred. 1933. Can Stock Market Forecasters Forecast?. *Econometrica* 1 (3): 309–324.

Da, Zhi, and Ernst Schaumburg. 2011. Relative Valuation and Analyst Target Price Forecasts. *Journal of Financial Markets* 14: 161–192.

Da, Zhi, Keejae Hong, and Sangwoo Lee. 2016. What Drives Target Price Forecasts and Their Investment Value?. *Journal of Business Finance and Accounting* 43 (3): 487–510.

Dechow, Patricia M., and Haifeng You. 2020. Understanding the Determinants of Analyst Target Price Implied Returns. *The Accounting Review* 95 (6): 125–149.

Grossman, Sanford J., and Joseph E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. *American Economic Review* 70 (3): 393–408.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach. 2012. Analysts' Industry Expertise. *Journal of Accounting and Economics* 54 (23): 95–120.

Palley, Asa B., Thomas D. Steffen, and X. Frank Zhang. 2021. The Effect of Dispersion on the Informativeness of Analyst Target Prices. Working Paper, Yale University.

Stickel, Scott E. 1995. The Anatomy of the Performance of Buy and Sell Recommendations. *Financial Analysts Journal* 51 (5): 25–39.

Womack, Kent L. 1996. Do Brokerage Analysts' Recommendations Have Investment Value?. *Journal of Finance* 51 (1): 137–167.

Jinji Hao graduated with a Bachelor of Science in mathematics from the Fudan University, China, in 2005. He received the Master of Arts in economics from the Peking University, China, and the Master of Finance from the University of Hong Kong in 2010. He received the Ph.D. degree in economics from Washington University in St. Louis in 2017. Since then, he has been a Lecturer in Finance at the Victoria University of Wellington. His research activities are focused on financial economics, banking, and derivatives.

Jonathon Skinner received the Bachelor of Commerce in economics and finance from the Victoria University of Wellington in 2021. He graduated with the Bachelor of Commerce (Honours) in finance at the Victoria University of Wellington in 2022. Since then, he has been a Market Operations Analyst at the New Zealand's Exchange (NZX).