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Relative valuation and analyst target price forecasts ☆

Zhi Da[a,1], Ernst Schaumburg[b,*]

[a]239 Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556, United States
[b]Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045, United States

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Abstract

We document that within industry relative valuations implicit in analyst target prices do provide investors with valuable information although the implied absolute valuations themselves are much less informative. Importantly, our findings are not merely a small stock phenomenon but apply to the sample of S&P 500 stocks and do not rely on trading at the exact time of announcement. Using a large database of target price announcements from 1997 to 2004, we construct a simple strategy based on target price implied relative valuations and show that the resulting abnormal return is both economically and statistically significant and not easily explained by transaction costs alone.

JEL classification: G12

Keywords: Target price; Relative valuation; Return reversal

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*Corresponding author. Tel.: +1 212 720 2744.
E-mail addresses: zda@nd.edu (Z. Da), Ernst.Schaumburg@ny.frb.org (E. Schaumburg).
[1]Tel.: +1 574 631 0354.

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1. Introduction

A key question in the finance and accounting literatures on equity analysts is whether forecasts and recommendations provide investors with information not already reflected in prevailing market prices, as suggested by the efficient market hypothesis. In other words, do analysts add value? And if so, how? In this paper, we approach this question using a large database of equity analyst target price forecasts between 1997 and 2004.

Analyst target prices are arguably both noisy and potentially biased measures of fundamental values and it is unclear what, if any, information target prices convey in addition to other announcements such as earnings forecasts and buy/sell recommendations. In fact, most studies have found little evidence of investors being able to earn abnormal returns based on the level of analysts' buy/sell recommendations or price targets unless trading takes place at the time of announcement (e.g., Barber, Lehavy, McNichols, and Trueman, 2001; Brav and Lehavy, 2003). Although there is evidence of profitability from trading on buy/sell recommendation changes, once a realistic measure of transaction costs has been accounted for, there is no clear evidence of any abnormal profits surviving the implementation shortfall.[1] By contrast, we show that there is substantial short-term information in the within industry *relative* valuations implied by analyst target price forecasts. This is true even after controlling for announcement effects and other concurrent information releases and after accounting for measures of transaction costs.

The fact that relative target prices are more informative than absolute target prices is not too surprising given that equity analysts tend to rely on relative valuation models and specialize in a handful of stocks within a single sector/industry. Analysts are therefore well situated to rank the *relative* strength of each stock going forward, although they may have significantly less insight into forecasting macrovariables which affect the performance of each sector or the economy as a whole. A similar conclusion is reached by Boni and Womack (2006), in the context of analyst stock recommendations, who show that investment strategies based on recommendation revisions improve significantly if sorting is done within industries rather than unconditionally.[2]

In order to quantify the short-term target price informativeness, we implement a sector-neutral long–short strategy in the following manner: at the end of every month, we consider the subset of S&P 500 stocks for which at least one analyst has announced a target price during the first 25 calendar days of the month.[3] *Within* each sector we sort the stocks according to their *target price implied expected return* (*TPER*) defined as the return implied by the equity analysts' 12-month-ahead price target and the current market price, or, $TPER = TP/P - 1$. We then construct an equally weighted portfolio that is long the

[1] Black's (1973) original ValueLine analysis found that a simple (long only) portfolio constructed based on ValueLine rankings significantly outperformed the market over a five-year period. Due to the way the ValueLine rankings are constructed, this amounted to a relative strength strategy. The ValueLine Centurion fund was created to exploit this finding, but ex post turned out to suffer from a significant implementation shortfall due to the strategy's high turnover and the fund is no longer in existence.

[2] The short-term informativeness of target prices documented in this paper, however, differs substantially from the results in Boni and Womack (2006). In particular, their recommendation-based strategies lead to momentum in returns, whereas strategies based on target price implied relative valuations result in short-run reversal.

[3] The average five-day lag between the portfolio formation and the beginning of the one-month holding period eliminates the announcement pronounced effect documented in Brav and Lehavy (2003). Without this gap our results are strengthened.

highest *TPER* stocks from each sector and short the lowest *TPER* stocks from each sector. Since the portfolio is equally weighted, it is by construction sector neutral, thereby isolating the relative strength information contained in analysts' price targets. Over the period 1999–2004, this strategy has yielded a substantial abnormal return of 203 bp/month (134 bp for the long portfolio and 69 bp for the short portfolio).

This result is remarkable because the abnormal profit stems from trading in S&P 500 stocks as opposed to frequent trading in small stocks.

We show that the significant abnormal return to the TPER strategy is robust to various models of risk adjustment and survives a battery of robustness checks. While 200 bp/month is large for a S&P 500 strategy, we show that the strategy's inherently high turnover reduces the abnormal return to approximately 148 bp/month (106 bp/month on the long side and 42 bp/month on the short side) after accounting for direct transaction costs and a measure of price impact.

We investigate a number of possible sources of the abnormal returns on the *TPER*-sorted portfolios. By definition, TPER has the current stock price in the denominator, leading one to suspect that our results may simply be driven by a sort on price or price ratios. However, we find that neither a sort on 1/P nor any other commonly used accounting price ratio (e.g., B/P, E/P, etc.) is able to produce any risk-adjusted profits in our sample. We also examine several types of forecasts issued by the analysts and show that the profit is not entirely explained by: (1) delayed reaction to stock recommendations (cf., Womack, 1996); (2) reaction to target price revisions (cf., Brav and Lehavy, 2003; Asquith, Mikhail, and Au, 2005); nor (3) earnings announcement effects or post-earning-announcement drift (PEAD).

The TPER strategy involves buying recent losers and selling recent winners. The resulting abnormal return is therefore related to the short-term return reversal phenomenon of Jegadeesh (1990) and Lehmann (1990). The short-run reversal effect has been linked to the occurrence of liquidity events both theoretically (e.g., Campbell, Grossman, and Wang, 1993), and empirically (e.g., Conrad, Hameed, and Niden, 1994; Avramov, Chordia, and Goyal, 2006). Consistent with these studies, we find that stocks tend to be particularly illiquid in months when they enter our extreme TPER portfolios. However, we are not simply rediscovering short-term return reversal: our risk adjustment explicitly includes a reversal factor designed to capture the standard short-term return reversal effect and, moreover, implementing the standard reversal strategy fails to produce significant profits if restricted to the S&P 500 universe.

Our main results extend beyond the S&P 500 universe to the set of all stocks in the First Call database that receive regular analyst coverage over the extended sample period from 1997 to 2004. Within this larger sample, we show that the strategy works better when the industry classification is refined from 9 sectors to 24 industries, consistent with the relative valuation interpretation of TPER. We also investigate the performance of the strategy across various subsamples and find more significant results within the value stock segment. We attribute the effect of the book-to-market ratio to the fact that analysts' estimates for value firms (with a higher fraction of tangible assets) may be less noisy than for growth firms, thus providing a more precise control for fundamental value. Interestingly, we find that the performance of the strategy is weaker in the post 2001 subsample, coinciding with a market-wide improvement in liquidity due to decimalization in early 2001 and consistent with target prices being less informative after regulation FD (Fair Disclosure) which took effect in October 2000.

The remainder of the paper is structured as follows: Section 2 discusses data sources and the key TPER variable. The portfolio construction and the main results for the S&P

500 sample are given in Section 3. Section 4 analyzes potential sources to the profit of our TPER strategy. Section 5 describes the full sample results and Section 6 concludes.

2. Data description

The First Call database, which covers our sample period from December 1996 through December 2004, provides the target prices used in this study. At the end of each month from December 1996 to December 2004, we consider stocks that trade above a price of $5 and receive at least one (12 months ahead) target price announcement during the first 25 calendar days of the month. The $5 price filter helps to alleviate any possible impact from the bid–ask bounce and other market microstructure related noise. To ensure that our results are not driven by an immediate market reaction to target price announcements studied in Brav and Lehavy (2003), we discard target prices issued during the last five calendar days of the month. We do not fill in the blanks using older target prices in order to avoid introducing an upward bias in the target prices, which arises because analysts are more likely to issue a target price when they are in favor of a stock, as documented by Brav and Lehavy (2003).

Table 1 presents a summary of the resulting full sample containing approximately 1,700 stocks each month, increasing from 1,095 in 1,996 to 1796 in 2004. For each stock, we have on average 2.5 target prices per month. The sample on average covers 76% of the CRSP stock universe in terms of market capitalization, increasing from 55.5% in 1996 to 83% in 2004. Our sample also covers most of the "representative" stocks, which are constituents of the major equity indices. For instance, in 2004, our sample covers 496 of the S&P 500 stocks, 980 of the Russell 1000 stocks, and 2,780 of the Russell 3000 stocks. On average, 54% of the stocks in our sample are listed on the NYSE, 43% are listed on NASDAQ, and the remaining 3% are listed on the AMEX. The median market capitalization of stocks in our sample, averaging over the sampling period, is 919*M*—much larger than that of all NASDAQ stocks (85*M*), but slightly smaller than that of all NYSE stocks (963*M*).

The target price implied expected return (TPER) is computed as the consensus target price (split adjusted) divided by the end of month stock price: $TPER_t = \overline{TP}_t/P_t - 1$, where the consensus target price $\overline{TP}_t$ is the simple average of all target prices received during the first 25 calendar days of month t. We do not make use of analyst identities in constructing the consensus forecast since several studies, including Bradshaw and Brown (2005) and Bonini, Zanetti, Bianchini, and Salvi (2010), have found no systematic difference in analyst target price forecasting abilities. We note that defining the consensus target price as the median or employing various schemes for over-weighting more recent target prices and down-weighting target prices announced at the beginning of the month does not alter our results significantly. As shown in Panel A of Table 1, the mean *TPER* during this sampling period is 40% (the median is 24%), substantially higher than one would expect for the market as a whole. The mean *TPER* was as high as 64% (median 36%) in 2000 during the final stages of the NASDAQ bubble.

We break down our sample into sectors according to the first two digits of Standard and Poor's GICS (Global Industry Classification Standard).[4] Using IBES data, Boni

[4]The four- or six-digit GICS would, in principle, yield better sector control, but the number of stocks in each sector would drop dramatically, making the results too noisy. For example, using the four-digit GICS would leave us with, on average, less than 15 stocks in each industry group per month for our benchmark S&P 500 stock sample, making it nonsensical to sort within each industry group. For the full sample with more stocks, we do use the finer 24 industries classification.

Table 1

First Call target price data description.

From December 1996 to December 2004, at the end of each month, we include stocks which had at least one (1 year ahead) target price announcement during the first 25 calendar days of the month. Panel A summarizes basic sample characteristics across the sampling period. Panel B presents the coverage of the component stocks of three major equity indices in the U.S. in 2004. Panel C breaks down our sample into sectors according to Standard and Poor's GICS (Global Industry Classification Standard). Since there are too few stocks in the Telecommunications Services sector, we group them with the Information Technology sector to form a combined "Technology" sector. This classification is consistent with the way sector ETFs (SPDRs) are constructed after 1999.

Panel A: Basic sample characteristics

Year	Number of stocks per month	Number of target prices per stock per month	Mean TPER	Median TPER	Median mkt-cap (in million $)	NYSE	AMEX	NASDAQ	% of all stocks in terms of mkt-cap-
1996	1095	1.75	39.10%	23.10%	754	56.00%	3.30%	40.70%	55.50%
1997	1205	2.02	35.70%	21.50%	799	57.60%	3.50%	38.90%	58.20%
1998	1641	2.37	45.60%	28.80%	718	55.70%	3.50%	40.80%	68.60%
1999	1675	2.45	44.70%	28.60%	795	54.90%	3.10%	42.00%	73.60%
2000	1759	2.59	63.70%	36.40%	983	51.50%	2.60%	45.90%	78.50%
2001	1761	2.72	50.50%	26.40%	920	50.90%	2.30%	46.80%	80.50%
2002	1738	2.84	39.90%	23.20%	916	53.30%	2.30%	44.50%	83.10%
2003	1677	2.49	19.70%	13.40%	1,022	54.90%	2.60%	42.50%	82.80%
2004	1796	2.51	18.40%	13.20%	1,216	53.20%	2.80%	44.00%	83.00%

Panel B: Index coverage in 2004

	S&P 500	Russell 1000	Russell 3000
Number of stocks included	496	980	2782
Percentage	99.20%	98.00%	92.70%

Panel C: Sector breakdown

Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Technology*	Utilities
In terms of number of stocks								
4.9%	5.7%	12.6%	18.0%	4.5%	10.7%	17.9%	22.5%	3.3%
In terms of mktcap								
5.2%	3.6%	10.5%	14.0%	8.3%	12.7%	18.0%	25.2%	2.4%
S&P 500 in terms of mktcap								
6.1%	3.4%	11.1%	13.1%	8.8%	13.6%	18.5%	21.5%	3.8%

*We combine Information Technology sector and Telecommunication Services sector to form the Technology sector, consistent with the grouping of sector ETF.

and Womack (2006) show that the GICS sector and industry definitions match well with the areas of expertise of most analysts, as defined by the set of stocks covered by each analyst. The GICS is therefore a natural choice of sector definition. The GICS used in this paper are obtained from various sources: Standard and Poor's publishes the GICS classification of S&P 500 stocks on its website. Historical GICS for some companies are available in Compustat starting in December 1994, however, all GICS classifications prior to 1999 are backfilled. Consistent with the way sector ETFs are formed, we group Telecommunications Services with Information Technology to form a combined Technology sector. The resulting nine sectors are: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Technology and Utilities. Panel C of Table 1 shows the sector break down of our sample both in terms of number of stocks and in terms of market capitalization. The sector break down of our sample is in line with that of the broad market as proxied by the S&P 500 index. Across time, we observe the dominance of the Technology sector in 2000 due to the NASDAQ bubble and the recent increase of the Energy sector due to the surge in oil prices.

The S&P 500 universe, which is the main focus of this paper, distinguishes itself in several respects: First, S&P 500 stocks receive the most attention and coverage by analysts. On average, analysts issue target prices for around 350 of the S&P 500 stocks each month and the average number of target prices per stock each month is 4—significantly higher than that of the average stock in the First Call database (2.5). Therefore, the consensus target price used to compute *TPER* for S&P 500 stocks is less prone to outliers and presumably more accurate. Second, S&P 500 stocks are on average more liquid and cheaper to trade, which makes it easier to bound the potential impact of transaction costs. Since the GICS was officially launched by Standard & Poor's and Morgan Stanley Capital International (MSCI) in 1999, we focus on the sample period starting in January 1999 to avoid issues with backfilling.

Throughout the study, we obtain daily stock prices and returns from CRSP and high frequency data from the NYSE TAQ database, stock recommendations and earning announcement data from the First Call database, and accounting variables from Compustat. All remaining analyst forecasts are from IBES.

3. A relative value strategy based on analyst target price forecasts

In this section, we describe the construction and performance of a sector-neutral long–short portfolio of S&P 500 stocks that exploits the signal about relative valuations contained in the analyst target price forecasts and in particular the 12 month ahead target price implied expected return (TPER).

The TPER is likely to be an imperfect predictor of future returns for a number of reasons. First, the consensus analyst target price itself is known to be imprecise due to disagreement among analysts, the lack of a commonly agreed upon absolute valuation model, and the presence of analyst biases [see Michaely and Womack (2005) for example]. Second, the target price itself is not a direct measure of fundamental value since it contains a substantial forward-looking systematic risk component, and thus TPER for two stocks with different risk characteristics are not immediately comparable. To illustrate this, consider the analyst's target price forecast within a factor model framework. The TPER can be decomposed into three components:

$$TPER = E^A[\alpha] + \beta_M E^A[Mkt] + \sum_{i=1}^{n-1} \beta_i' E^A[\lambda_i].$$

The first component, the analyst's estimated alpha, measures the current deviation between price and fundamentals as perceived by the analysts. The second and third terms reflect the familiar forward-looking systematic risk components consisting of market risk and "other" risk factors. $E^A[\cdot]$ denotes analysts' expectations, which are liable to be contaminated by noise due to differences of opinion, modeling error, and behavioral biases. In many cases, the first term will be swamped by the latter two components, which contain no information about fundamental values. Moreover, these two components will contain considerable noise when analysts have limited ability to forecast factor loadings and/or factor risk premia. Figs. 1 and 2 provide evidence that analysts cannot forecast market return nor the relative performance of different sectors. In this case, a naïve sort on TPER will implicitly be a sort on beta.

Sorting on TPER within groups of "similar" stocks (i.e., stocks with "similar" risk characteristics) will serve to eliminate much of the noise from the systematic risk component and isolate the "relative value" identified by the analyst. Our proxy for groups of "similar" stocks is the two-digit GICS sectors, a choice which, as in Boni and Womack (2006), can be motivated by the fact that analysts specialize in a sector (rather than being generalists) and typically cover at least half a dozen stocks within the same industry. By analyzing the specifics of a handful of similar firms, it is reasonable to assume that the analyst is well situated to rank the *relative* strength of each stock going forward, although he may have significantly less insight into the forecasting of macrofactors that affect the performance of the sector as a whole.

The portfolio construction proceeds in the following manner: Within each sector we rank stocks into nine groups according to their current month TPERs and form nine equal-weighted portfolios: Portfolio 1 comprises the highest TPER stocks from each sector, Portfolio 2 the second highest, and so on up to Portfolio 9, which comprises the lowest TPER stocks from each sector. We choose nine portfolios, rather than 10, so that we can compare the portfolios with various 3 by 3 double-sorting schemes. Near identical results are obtained by sorting into deciles.

In their study of analyst buy/sell recommendations, Jegadeesh, Kim, Krische, and Lee (2004) consider a set of 12 accounting and performance characteristics and conclude that analysts tend to chase "glamour" stocks. Panel A of Table 2 reports the average value of each of these 12 characteristics, along with the average price, average return during the month of portfolio formation, and the average TPER for each of the nine portfolios. Consistent with the Jegadeesh, Kim, Krische, and Lee (2004) finding, we see that TPER in general increases with growth indicators (i.e., if a firm has experienced high sales growth (*SG*) over the past year or if its long-term growth rate (*LTG*) is expected to be high, then its stock is more likely to be associated with a higher TPER). We also see that the TPER sort is related to a sort on price and past return by virtue of the end-of-month stock price appearing in the denominator of the TPER definition. High (low) TPER stocks tend to have a lower (higher) price and a lower (higher) past return at the one-to-six month horizon, as can be seen from the *Price*, *RET1M*, and *RETP* columns in Panel A of Table 2.

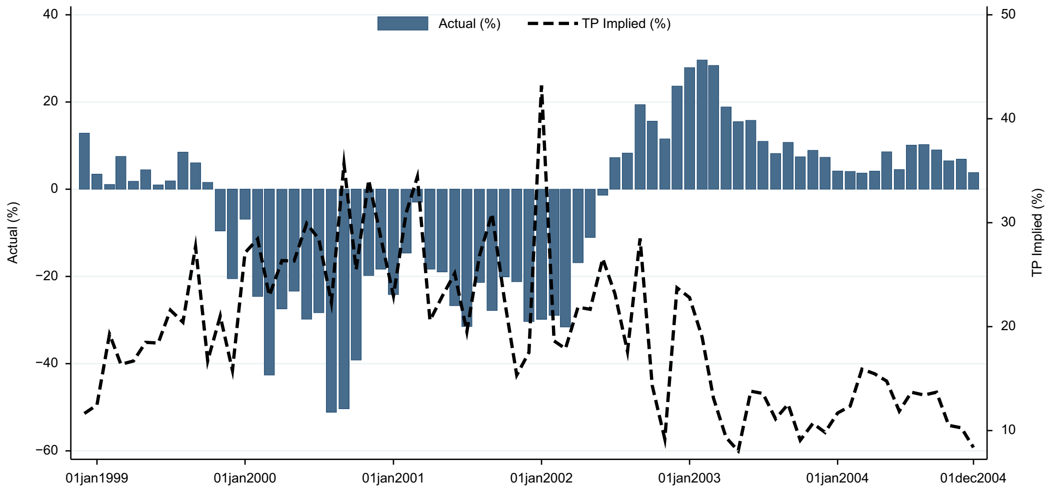

Fig. 1. Target price implied one-year-ahead expected return (TPER) versus actual one-year return. At the end of each month from December 1998 to December 2004, we compute the equity analysts' implied return forecast for the value-weighted portfolio of S&P500 stocks with analyst coverage that month (dashed line). We compare this to the ex post realized 12-month return of the portfolio (solid bars). The graph confirms the finding of Bradshaw and Brown (2005) that analysts on average are unable to forecast the market risk-premium.

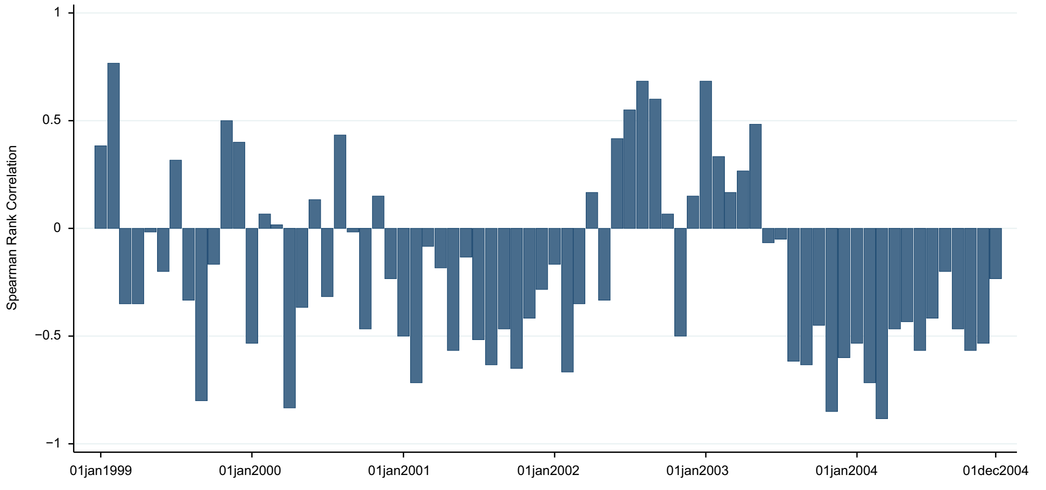

Fig. 2. Rank correlation between target price implied and actual sector returns across nine GICS (Global Industry Classification System) sectors. At the end of each month from December 1998 to December 2004, we create nine value-weighted GICS sector portfolios from the set of S&P 500 stocks with analyst coverage that month. We then compute the 12-month return forecast for each sector implied by target prices and compute the Spearman rank correlation with the ex post realization of the sector returns. If analysts were able to predict relative sector performance, then the rank correlation should be consistently positive. This is clearly not the case and we conclude that analysts have no such skill on average.

The relation between changes in target price and the TPER is shown in Panel B of Table 2. The S&P 500 stocks receive frequent target price coverage: less than 1.5% of these stocks have a target price during the current month and none during the previous two months. The percentage of target price upgrades increases monotonically with TPER. In Portfolio 1, which has the highest TPER, the recent target price changes are dominated by upgrades (percentage upgrades and downgrades are 55% and 22%, respectively). The reverse is true for Portfolio 9, in which the majority of the stocks suffer recent downgrades (percentage upgrades and downgrades are 19.7% and 56.7%, respectively). Panel B also reports various liquidity-related portfolio characteristics, which include the price impact of Breen, Hodrick, and Korajczyk (2002) (Pimpact), the percentage bid–ask spread (Pspread), and the Amihud measure of Amihud (2002).[5]

Table 3 shows that the first post-formation month excess returns (in excess of the risk-free rate) in general are increasing in TPER. Portfolio 1, which has the stocks with the highest TPER relative to all S&P 500 stocks within a sector, earns the highest first month

[5]The percentage spread is calculated as the ask minus bid scaled by the bid/ask midpoint. The Amihud (2002) measure, calculated as the ratio between the absolute return on a stock and the dollar trading volume (both daily) is

$$\text{Amihud} = |\text{daily return}|/(\text{daily \$ volume}).$$

Breen, Hodrick, and Korajczyk (2002) propose a direct measure of price impact using high frequency tick-by-tick data. Each trade is categorized as either buyer or seller initiated using the Lee and Ready (1991) methodology (i.e., depending on whether the transaction price is closer to the bid or ask and in case of tied comparing to the last observed trade). The price impact measure is then calculated by regressing observed price changes on signed volumes each day and assuming an average trading speed of $1 million per hour.

Table 2
Characteristics of TPER-sorted portfolios.
Panel A: The Jegadeesh, Kim, Krische, and Lee (2004) characteristics. RETP is the cumulative market-adjusted return in months −6 through −1 preceding the month of portfolio formation; RET2P is the cumulative market-adjusted return in months −12 through −7 preceding the month of portfolio formation; FREV is the analyst earnings forecast revision; SUE is the most recent quarter's unexpected earnings; TURN is the average daily volume turnover in the six months preceding the month of portfolio formation; EP is the earnings-to-price ratio; BP is the book-to-price ratio; LTG is the mean analyst forecast of expected long-term growth in earnings; SG is the rate of growth in sales over the past year; SIZE is the natural log of a firm's market capitalization; TA is total accruals divided by total assets; CAPEX is the capital expenditures divided by total assets; Price is the closing price at the end of the month of portfolio formation; and RET1M is the return during the month of portfolio formation. Panel B: We report the percentage of upgrades, downgrades, reiterations, and missing stocks for each portfolio during the three months prior to portfolio formation. If the current target price exceeds $1.05\times$ last target price, we classify the change as an upgrade; if the current target price is smaller than $0.95\times$ last target price, we classify the change as a downgrade; otherwise, we classify it as a reiteration. If there is no target price announcement in the third and second month preceding the current month, we classify it as missing. We also report various liquidity characteristics: the percentage bid–ask spread (Pspread, in bp), the price impact (Pimpact, in bp) and the Amihud measure ($\times 10^7$).

Panel A: Characteristics studied in Jegadeesh, Kim, Krische, and Lee (2004)

Portfolio	Momentum and trading volume					Valuation multipliers		Growth indicators		Firm	Fundamental indicators		Others		
	RETP	RET2P	FREV (bp)	SUE	TURN	EP	BP	LTG	SG	Size SIZE	CAPEX	TA	Price	RET1M	TPER
1	−3.39%	4.00%	−12.3	0.39	0.74	0.013	0.45	15.27	1.156	16.3	3.87%	−2.31%	31.8	−5.31%	67.90%
2	0.80%	4.33%	7.68	0.57	0.7	0.036	0.4	15.21	1.151	16.37	4.24%	−2.05%	37.2	−3.22%	36.40%
3	2.76%	4.45%	14.71	0.57	0.68	0.033	0.39	14.95	1.141	16.41	4.04%	−1.97%	39.5	−1.13%	28.40%
4	4.65%	5.29%	15.19	0.61	0.68	0.04	0.38	14.28	1.13	16.37	4.12%	−1.90%	42.8	−0.03%	23.00%
5	5.68%	4.94%	12.17	0.6	0.67	0.037	0.38	14.63	1.119	16.38	4.04%	−1.59%	44.9	1.62%	18.80%
6	7.02%	4.81%	19.83	0.63	0.66	0.037	0.38	13.94	1.127	16.32	4.09%	−2.13%	45.2	2.79%	14.80%
7	6.61%	5.26%	7.29	0.65	0.66	0.04	0.38	13.37	1.111	16.3	3.93%	−1.86%	46.8	3.97%	10.70%

8	7.59%	5.22%	5.46	0.66	0.66	0.033	0.39	13.5	1.107	16.24	3.94%	−2.25%	46.5	5.22%	5.10%
9	6.60%	4.44%	−6.69	0.46	0.69	0.037	0.43	13.03	1.096	16.19	4.00%	−1.60%	45.1	6.04%	−9.00%

Panel B: Target price changes and liquidity measures

	Target price changes				Liquidity measures		
Portf.	% missing	% upgrade	% downgrade	% reiteration	Pimpact	Pspread	Amihud
1	2.03%	55.35%	21.96%	20.70%	18.3	20.2	8.02
2	1.34%	46.18%	22.35%	30.10%	14.4	17.5	6.34
3	1.10%	39.46%	26.55%	32.90%	12.9	17.3	5.52
4	1.25%	38.90%	25.57%	34.30%	12.4	15.6	5.33
5	1.32%	36.90%	25.36%	36.40%	12.2	15.1	5.29
6	0.96%	34.13%	28.21%	36.70%	12	14.3	5.04
7	1.56%	30.93%	32.00%	35.50%	12.6	14.2	5.34
8	1.56%	25.52%	39.93%	33.00%	12.8	14.8	5.50
9	1.87%	19.74%	56.73%	21.70%	14.6	15.2	6.18

Table 3
Returns on within-sector TPER-sorted portfolios of S&P500 stocks.
At the end of each month from December 1998 to December 2004 and within each sector, we rank S&P500 stocks in our sample into nine portfolios according to the current month TPERs and label them from 1 to 9 (1 with the highest TPER and 9 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 six months after portfolio formation and risk-adjusted alphas using a five-factor model. The five factors are the three Fama-French factors, a momentum factor (UMD), and a reversal factor (DMU). All returns and alphas are monthly. *t*-values are reported in the square brackets.

	First mth excess return	Five-factor model						Future excess return				
		alpha	MKT	SMB	HML	UMD	DMU	Month 2	Month 3	Month 4	Month 5	Month 6
1	1.58%	1.34%	1.367	0.039	0.470	−0.334	0.027	1.19%	0.68%	1.13%	0.53%	1.00%
	[1.77]	[3.47]	[14.04]	[0.43]	[4.37]	[−5.75]	[0.40]	[1.34]	[0.78]	[1.28]	[0.60]	[1.06]
2	0.91%	0.58%	1.232	0.057	0.445	−0.267	0.105	0.54%	0.64%	0.79%	0.57%	0.49%
	[1.17]	[2.10]	[17.72]	[0.89]	[5.79]	[−6.42]	[2.18]	[0.72]	[0.88]	[1.06]	[0.80]	[0.64]
3	0.60%	0.35%	1.057	−0.014	0.439	−0.207	0.037	0.20%	0.42%	0.55%	0.44%	0.64%
	[0.90]	[1.13]	[13.59]	[−0.20]	[5.12]	[−4.45]	[0.69]	[0.34]	[0.59]	[0.81]	[0.64]	[0.96]
4	0.95%	0.72%	1.082	−0.014	0.401	−0.128	−0.059	0.67%	0.89%	0.47%	0.56%	0.37%
	[1.56]	[3.01]	[17.78]	[−0.24]	[5.96]	[−3.52]	[−1.41]	[1.13]	[1.50]	[0.71]	[0.89]	[0.60]
5	0.77%	0.57%	1.000	−0.078	0.412	−0.095	−0.043	0.40%	0.68%	0.43%	0.69%	1.01%
	[1.36]	[2.12]	[14.77]	[−1.25]	[5.51]	[−2.34]	[−0.92]	[0.67]	[1.08]	[0.68]	[1.16]	[1.61]
6	0.57%	0.37%	0.954	−0.012	0.426	−0.132	−0.107	0.52%	0.82%	0.88%	0.63%	0.15%
	[1.06]	[1.74]	[17.80]	[−0.23]	[7.20]	[−4.14]	[−2.88]	[0.92]	[1.58]	[1.55]	[1.04]	[0.23]
7	0.48%	0.38%	0.955	−0.107	0.300	−0.076	−0.064	0.69%	0.60%	0.68%	0.52%	0.83%
	[0.92]	[1.88]	[18.66]	[−2.28]	[5.30]	[−2.49]	[−1.79]	[1.33]	[1.09]	[1.25]	[0.87]	[1.47]
8	0.46%	0.32%	0.980	−0.075	0.290	−0.078	−0.041	0.44%	0.84%	0.90%	0.42%	0.53%
	[0.83]	[1.33]	[16.27]	[−1.35]	[4.37]	[−2.16]	[−0.98]	[0.80]	[1.43]	[1.54]	[0.72]	[0.92]
9	−0.19%	−0.69%	1.084	0.154	0.583	−0.092	−0.083	0.55%	0.38%	0.33%	0.56%	0.88%
	[−0.33]	[−3.00]	[18.49]	[2.85]	[9.00]	[−2.63]	[−2.05]	[0.85]	[0.64]	[0.51]	[0.86]	[1.31]
1−9	1.77%	2.03%	0.283	−0.115	−0.113	−0.242	0.110	0.63%	0.30%	0.79%	−0.03%	0.12%
	[3.55]	[5.06]	[2.79]	[−1.23]	[−1.00]	[−3.99]	[1.57]	[1.37]	[0.58]	[1.73]	[−0.07]	[0.27]

excess return (158 bp/month) and Portfolio 9, which has the stocks with the lowest relative TPER, earns the lowest first month excess return (−19 bp/month). The return on the spread Portfolio 1–9, 177 bp/month (*t*-value 3.55), is the return to a portfolio of long–short sector strategies or relative value strategies (long stocks with the highest TPERs and short stocks with the lowest TPERs within each sector). Panel A also shows that the excess returns to the spread portfolio are not significantly different from zero beyond the first month after portfolio formation. A closer inspection reveals that approximately two-thirds of the first month profit (110 bp) accrues during the first two weeks.

To account for the fact that the significant first month excess returns on the spread Portfolio 1–9 may be the result of systematic risk exposures, we risk adjust the return using a five-factor model that includes both the Fama and French (1993) three factors and the Carhart (1997) momentum factor. To investigate whether the excess return is related to but different from the standard short-run reversal effect in small stocks, we also include the a short-run reversal factor as a fifth factor. The explicit inclusion of a short-run reversal factor is particularly relevant given the strong relation between TPER and recent past returns. Throughout the paper, we continue to use this five-factor model as our benchmark for computing risk-adjusted returns, although we stress that none of our qualitative findings depend on the choice of a three-, four-, or five-factor model, or on the choice of a characteristics-based model of risk adjustment.

The results in Table 3 show that the five-factor risk-adjusted returns are even higher and more significant than the excess returns themselves. The spread Portfolio 1–9 yields a highly significant five-factor alpha of 203 bp/month (*t*-statistic of 5.06). The reported factor loadings in Table 3 clearly show that the sector neutrality of the long-short strategy helps to reduce, but not eliminate, the systematic risk exposures. The spread portfolio only loads significantly on the market and the momentum factor and its market exposure is much smaller than that of any one of the nine portfolios. The remaining positive loading on the MKT factor is intuitive since, ceteris paribus, high beta stocks will receive higher target prices relative to their current market price. The highly significant negative loading on the momentum factor confirms the spread portfolio's tendency to load up on intermediate-term losers and short intermediate-term winners. In fact, all nine portfolios load significantly and negatively on the UMD factor, although the result is strongest for Portfolio 9. This may appear counterintuitive, but it occurs because relative winners and losers within the S&P 500 sectors do not map into the overall winners and losers as defined in a standard momentum strategy, which involves a broad universe of traded stocks. For the same reason the loading on the short-run reversal factor (DMU), albeit positive, is not significant despite the fact that the spread portfolio is long short-term losers and short short-term winners, as seen in Table 2.

Fig. 3 shows the monthly time series of five-factor risk-adjusted returns to our trading strategy compared to the market excess return. During the period from January 1999 to January 2005, the sector-neutral long–short strategy has had a much better risk-return trade-off than the overall market portfolio. The monthly Sharpe ratio of the spread return and the five-factor alpha are 0.41 and 0.67, respectively, and are all clearly better than that of the market, which is only 0.01 during the same period due to the burst of tech bubble and a recession in the United States during 2001. In Fig. 3, the time period prior to 1999 is shaded to highlight the fact that the GICS assignments are backfilled and that the long–short strategy was not feasible ex ante prior to 1999. For this reason, we focus on the

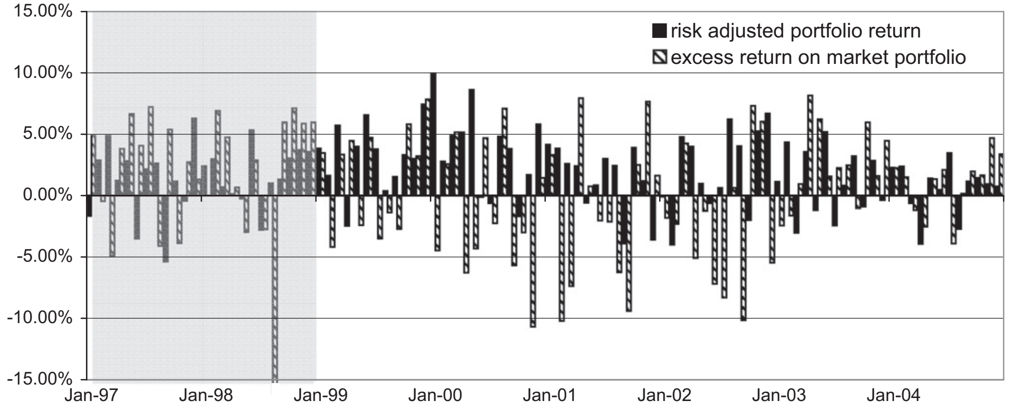

Fig. 3. Time series of the excess returns on the market portfolio and the risk-adjusted benchmark portfolio returns. The monthly (five-factor) risk-adjusted returns of the benchmark long–short strategy using S&P500 stocks (black bars) versus the market excess return over the risk-free (striped bars) between January 1997 and January 2005 are plotted. The shaded pre-1999 period indicates the subsample where the GICS classification is backfilled. This period is excluded from the main analysis although all results remain qualitatively similar if it is included.

sampling period from 1999 to 2004. However, when we extend the analysis to the period from 1997 to 2004, the performance of our long–short strategy remains qualitatively unchanged although the risk-adjusted return to the spread Portfolio 1–9 is slightly reduced (the five-factor alpha drops to 162 bp/month, *t*-value 4.2).

We stress the crucial role played by sector control. If we instead form portfolios based on ranking the TPER across all stocks rather than within each sector, and compute the first month post-formation portfolio excess returns, they lose their significance. The spread Portfolio 1–9 returns only 79 bp/month (*t*-value of 0.86), much smaller than the spread of 177 bp/month when the long-short position is constructed within sector. This is an indication of the fact that it is relative and not absolute valuations that convey the most information to investors.[6]

3.1. Robustness of the benchmark specification

To investigate the robustness of our findings, we examine the effect of various alternative portfolio formation strategies in Table 4. When we compare the results in Panels A and B, we see that on average, the equal-weighted strategies do better than value-weighted strategies. It is also evident that allowing target-price collection during the last five days of the portfolio formation month strengthens the profitability of the spread portfolio, a reflection of the announcement effect documented in Brav and Lehavy (2003).

[6]Brav and Lehavy (2003) find abnormal profits even when they globally rank stocks. There are two reasons behind such abnormal profits. First, they examine a much larger sample while we focus on the larger S&P stocks. Second, such abnormal profits are obtained over the period beginning two days prior and ending two days subsequent to the target price announcement while we keep at least five days between the target price announcement and portfolio formation. If we allow target-price collection during the last five days of the portfolio formation, ranking TPER across all stocks would produce a larger spread Portfolio 1–9 return of 115 bp/month.

Table 4
Robustness to alternative portfolio formation strategies.
We examine the robustness of the average excess and five-factor risk-adjusted returns to changes in our benchmark portfolio formation strategy. All returns and alphas are monthly averages over the period January 1999–January 2005 (72 months). In Panel A, we show the equal-weighted portfolios with and without a five-day gap between the target price collection period and the portfolio formation date. The "GICS," "SIC," and "FF Sectors" columns correspond to three different choices of sector classification schemes: the GICS (our benchmark, numbers in bold), one-digit SIC Codes, and the Fama-French sector definitions, respectively. The column "$\geq$3 TP/mth" displays results from using the GICS sector specification but requiring that stocks have at least three target price announcements during the portfolio formation period. The column "Ex-Jan" displays the result from using the GICS sector classification but excluding January months from the sample. Finally, the column "ATPER" displays the result of using as an alternative definition of TPER, the average of announced target prices divided by the respective market price on the day of the announcement, rather than the average of announced target prices divided by the market price on the portfolio formation date. In Panel B, we show the value-weighted portfolio results. We weight the portfolios separately within each sector so that each sector position remains equally weighted, ensuring the sector neutrality of the long–short portfolio. *t*-values are reported in the square brackets.

Panel A: Excess returns and 5-factor alphas for equal weighted portfolios

	5 day gap						No gap					
	GICS	SIC	FF Sectors	§3 TP/mth	Ex-Jan	ATPER	GICS	SIC	FF Sectors	§3 TP/mth	Ex-Jan	ATPER
Portf 1 (α)	0.0134	0.0102	0.0103	0.0186	0.0125	0.0095	0.0141	0.0114	0.0106	0.0161	0.0131	0.0095
t-stat	[3.47]	[2.59]	[2.65]	[3.21]	[3.06]	[2.98]	[3.65]	[2.72]	[2.73]	[3.32]	[3.23]	[2.92]
Portf 9 (α)	−0.0069	−0.0024	−0.0043	−0.0006	−0.0058	−0.0005	−0.0075	−0.0038	−0.0050	−0.0005	−0.0063	−0.0018
t-stat	[−3.00]	[−1.03]	[−1.92]	[−0.14]	[−2.41]	[−0.22]	[−3.01]	[−1.59]	[−2.04]	[−0.13]	[−2.43]	[−0.73]
1–9 (excess ret)	0.0177	0.0094	0.0140	0.0164	0.0155	0.0077	0.0189	0.0123	0.0150	0.0152	0.0164	0.0105
t-stat	[3.55]	[1.30]	[2.53]	[2.28]	[3.07]	[1.68]	[3.55]	[1.72]	[2.66]	[2.32]	[3.06]	[2.25]
1–9 (α)	0.0203	0.0126	0.0146	0.0192	0.0183	0.0101	0.0215	0.0152	0.0156	0.0165	0.0194	0.0114
t-stat	[5.06]	[2.93]	[3.47]	[3.00]	[4.43]	[2.82]	[5.08]	[3.45]	[3.77]	[2.91]	[4.52]	[3.10]

Panel B: Excess returns and 5-factor alphas for value weighted portfolios

	GICS	SIC	FF Sectors	§3 TP/mth	Ex-Jan	ATPER	GICS	SIC	FF Sectors	§3 TP/mth	Ex-Jan	ATPER
Portf 1 (α)	0.0069	0.0064	0.0048	0.0166	0.0068	0.0045	0.0079	0.0078	0.0054	0.0120	0.0076	0.0046
t-stat	[1.84]	[1.79]	[1.24]	[3.04]	[1.73]	[1.28]	[2.11]	[2.06]	[1.38]	[2.60]	[1.96]	[1.32]
Portf 9 (α)	−0.0089	−0.0054	−0.0037	−0.0025	−0.0082	0.0000	−0.0084	−0.0052	−0.0049	−0.0030	−0.0075	−0.0016
t-stat	[−3.29]	[−2.30]	[−1.45]	[−0.60]	[−3.03]	[0.00]	[−2.94]	[−2.00]	[−1.75]	[−0.76]	[−2.59]	[−0.54]
1–9 (excess ret)	0.0132	0.0076	0.0055	0.0165	0.0114	0.0019	0.0136	0.0091	0.0064	0.0131	0.0113	0.0050
t-stat	[2.56]	[1.14]	[0.99]	[2.35]	[2.22]	[0.41]	[2.49]	[1.35]	[1.06]	[1.99]	[2.08]	[1.02]
1–9 (α)	0.0158	0.0118	0.0085	0.0191	0.0149	0.0045	0.0163	0.0131	0.0103	0.0150	0.0151	0.0062
t-stat	[3.56]	[2.61]	[1.78]	[3.04]	[3.41]	[0.98]	[3.58]	[2.90]	[2.14]	[2.65]	[3.40]	[1.39]

We also investigate the effect of using alternative sector specifications. Except in the no-gap, equal-weighted scenario, the naïve one-digit SIC sector definition does poorly. While the Fama-French 10 sector specification does much better than the one-digit SIC, it is still strictly dominated by the nine sector GICS. This finding is consistent with the "relative value" interpretation since the nine sector GICS arguably provides the better proxy for the analysts' areas of specialization.

Our benchmark definition of TPER is only one of many possibilities. In Table 4 we consider the alternative specification ATPER = average (TP_t/P_t), (i.e., the average of each analyst's target price divided by the market price on the announcement date), rather than the average target price divided by the market price on the portfolio formation date. The alternative TPER specification performs significantly worse than our benchmark specification, indicating that the spread between the consensus target price and the end-of-month stock price is more informative than is the average of (stale) spreads. Consensus target prices are necessarily time averages given the low frequency with which target prices are issued. Market prices on the other hand are directly observable. In this sense our TPER definition uses the most current information and it is not surprising that TPER does better than ATPER. We also check the effect of imposing a stricter requirement on the minimum number of target prices required in a given month. Requiring at least three target prices does not in general reduce the alpha, but the t-value, although still significant, deteriorates due to the reduction in sample size. We conclude that our qualitative results are robust to minor changes in the specifics of the portfolio formation strategy.

Fig. 3 shows that a few particularly large risk-adjusted returns fall during January, especially in 2000 and 2001. To ensure that our results are not driven by the January Effect, we report in Table 4 the excess returns and five-factor alpha of the spread portfolio excluding the month of January. After excluding January, the return and alpha of our long–short strategy (Portfolio 1–9) in the benchmark scenario drop in magnitude to 155 and 183 bp/month, respectively, with modest reductions in the levels of significance (given a loss of 8.3% of the data). Therefore, we conclude that the January Effect does not significantly drive our results.

Around 87% of the S&P 500 stocks are listed on the NYSE (NASDAQ accounting for 12% and AMEX accounting for less than 1%). We verify that our results are not driven by the NASDAQ stocks in our S&P 500 stock sample and the associated "tech bubble" during the late 1990s. Excluding NASDAQ stocks yields negligible changes in the results: the profit in Portfolio 1–9 is 174 bp (t-value of 3.5) and the five-factor alpha is 195 bp (t-value of 4.42).

Table 5 shows that the abnormal return is robust to various models of risk adjustment. When we risk adjust by using a standard three-factor Fama-French model, we find an alpha of 196 bp/month with a t-value of 4.34. When we add the fourth momentum factor, UMD, the alpha increases to 212 bp/month with a t-value of 5.27. Therefore, the negative momentum exposure contributes to part of the large benchmark five-factor-alpha but it does not drive it.

In addition, if the cross-sectional dispersion of TPER partly reflects differences in liquidity, then the profitability of the spread portfolio could result from exposure to an aggregate liquidity risk factor. To investigate this, we add the Pastor and Stambaugh (2003) value-weighted liquidity factor as a sixth pricing factor. The resulting six-factor alpha of the spread portfolio is virtually unchanged (201 bp/month, t-value of 4.95) and the market and momentum factors remain the only factors with significant loadings.

Table 5
Risk-adjusted returns on within-sector TPER-sorted portfolios of S&P500 stocks.
The table reports the average risk-adjusted excess returns on the extreme TPER-sorted portfolios and the spread portfolio. We consider the Fama-French (1993) three-factor model, the Carhart's four-factor model with the momentum factor and our benchmark five-factor model augmented with the Pastor and Stambaugh (2003) value-weighted aggregate liquidity factor (LIQ). We also report the characteristics-adjusted returns. The benchmark characteristics portfolios are either the five by five book-to-market and size double-sorted portfolios or the three by three by three book-to-market, size, and momentum triple-sorted portfolios. All returns and alphas are monthly. t-values are reported in the square brackets.

Model	Portfolio	Risk-adjusted return	MKT	SMB	HML	UMD	DMU	LIQ
Three-factor	1	1.15%	1.595	−0.098	0.542			
		[2.47]	[14.59]	[−0.92]	[4.15]			
	9	−0.81%	1.124	0.123	0.601			
		[−3.36]	[19.85]	[2.25]	[8.88]			
	1–9	1.96%	0.472	−0.221	−0.059			
		[4.34]	[4.45]	[−2.15]	[−0.46]			
Four-factor	1	1.36%	1.371	0.039	0.470	−0.339		
		[3.58]	[14.23]	[0.44]	[4.40]	[−6.01]		
	9	−0.76%	1.073	0.154	0.585	−0.077		
		[−3.24]	[17.95]	[2.80]	[8.82]	[−2.20]		
	1–9	2.12%	0.298	−0.116	−0.115	−0.262		
		[5.27]	[2.92]	[−1.22]	[−1.01]	[−4.38]		
Six-factor	1	1.29%	1.407	0.106	0.462	−0.283	0.026	−0.092
		[3.33]	[13.69]	[1]	[4.3]	[−3.92]	[0.39]	[−1.18]
	9	−0.72%	1.107	0.192	0.578	−0.063	−0.084	−0.052
		[−3.11]	[17.86]	[3.01]	[8.93]	[−1.45]	[−2.06]	[−1.12]
	1–9	2.01%	0.300	−0.086	−0.116	−0.220	0.110	−0.040
		[4.95]	[2.77]	[−0.77]	[−1.03]	[−2.9]	[1.55]	[−0.48]
Char-adj BM/Size 5 × 5	1	1.64%						
		[1.13]						
	9	−0.46%						
		[−0.4]						
	1–9	2.10%						
		[2.72]						
Char-adj BM/Size/ Mom 3 × 3 × 3	1	1.36%						
		[3.54]						
	9	−0.37%						
		[−1.39]						
	1–9	1.74%						
		[4.2]						

Alternatively, if we risk adjust the spread portfolio excess return using the returns on characteristics matched Size- and B/M-sorted portfolios as in Daniel and Titman (1997), the alpha increases to 210 bp with a t-value of 2.72. Characteristic-based risk adjustment using returns on Size, B/M and past return triple-sorted portfolios yields qualitatively similar results (alpha of 174 bp/month with a t-value of 4.2).

3.2. Transaction costs

The liquidity variables reported in Panel B of Table 2 answer the question of whether the profit of our long–short strategy can overcome the implementation shortfall. On the one hand, we expect transaction costs to be low since we are trading stocks in the S&P 500 index. On the other hand, our long–short strategy involves monthly portfolio rebalancing, which amplifies the transaction costs and could wipe out any profits.

To gauge the magnitude of the transaction costs, we focus on Portfolios 1 and 9. On average, in each month there are 33 stocks in each of the two portfolios and the monthly portfolio turnover ratios are 73.7% and 80.4% for Portfolios 1 and 9, respectively. We estimate the average percentage spread to be 20.2 bp (Portfolio 1) and 15.2 bp (Portfolio 9). Our estimates of the average price impact [Pimpact calculated as in Breen, Hodrick, and Korajczyk (2002) and assuming $1million traded per hour] are 18.3 bp for Portfolio 1 and 14.6 bp for Portfolio 9, respectively. The magnitudes of the price impacts are smaller than those documented in Keim and Madhavan (1996) since we are only considering S&P 500 stocks and since liquidity has improved substantially over time. The total transaction costs are then for Portfolio 1: $73.7\% \times (20.2\,\text{bp}+18.3\,\text{bp}) = 28.4\,\text{bp}$; and for Portfolio 9: $80.4\% \times (15.2\,\text{bp}+14.6\,\text{bp}) = 26.6\,\text{bp}$. These transaction cost estimates are considerably smaller than the five-factor alphas of 134 and 69 bp/month, but depend crucially on the amount of trading in the strategy. Under this assumption, the sector-neutral long–short strategy (Portfolio 1–9) yields a risk-adjusted profit net of transaction costs of 148 bp/month ($203-28.4-26.6$) per month (*t*-value 3.67), or 17.8% per year. Therefore, our findings are unlikely to be explained by transaction costs alone. In practice, the transaction cost can likely be reduced by over-weighing more liquid stocks and under-weighing less liquid stocks, as suggested by Korajczyk and Sadka (2004).

4. Potential sources of the profit

In this section, we examine several possible drivers of the risk-adjusted return to our TPER strategy.

4.1. Size-related anomalies

The definition of TPER involves dividing by the current stock price, which raises the question of whether our results are simply driven by size-related anomalies. To investigate this possibility, within each sector, we sort stocks into nine portfolios according to the inverse end of month stock price (1/P). This strategy produces an insignificant risk-adjusted return of only 76 bp/month (118 bp before risk adjustment), as shown in column 2 of Table 6. This result is not surprising, because low-priced stocks tend to be small stocks, so a sort on 1/P is in part a sort on size. Therefore, controlling for the SMB factor eliminates much of the profit. Qualitatively similar results hold when we sort on other price ratios, such as book-to-price ratio, earnings price, or sales price ratios.

4.2. Short-term price reversal and reaction to target price announcement

Because we define TPER as a ratio between target price and market price, its current level is influenced by both its past return and past revisions in the target price. Can either of these effects explain the returns to the benchmark strategy?

Table 6
Profits to alternative sector-neutral long–short strategies in the S&P sample.
At the end of each month from December 1998 to December 2004, we construct various sector-neutral long–short strategies using S&P500 stocks for our sample. For each strategy, we report the equal-weighted first-month excess return (in excess of the risk-free rate) for the long and short portfolios, the profit to the overall long–short strategy, and its associated five-factor alpha. All returns and alphas are monthly. *t*-values are reported in the square brackets.

TPER: Within each sector, we sort stocks into nine portfolios according to the current-month TPERs, then long stocks with the highest TPER and short stocks with the lowest TPER.

1/P: Within each sector, we sort stocks into nine portfolios according to the inverse of the stock price (1/P) at the end of the month, then long stocks with the highest 1/P and short stocks with the lowest 1/P.

BP: Within each sector, we sort stocks into nine portfolios according to the book-to-price ratio (BP) at the end of the month, then long stocks with the highest BP and short stocks with the lowest BP.

Ret: Within each sector, we sort stocks into nine portfolios according to the current month returns, then long past losers and short past winners.

DTP: Within each sector, we sort stocks into nine portfolios according to the current month DTP (change in target price), which we define as $\Delta TP_t/TP_{t-1}$, then long stocks with the highest DTP and short stocks with the lowest DTP.

TPER w/o EA: We focus on stocks in nine within-sector TPER-sorted portfolios of S&P500 for which there was no earning announcement during the month of portfolio formation.

Rec: We take the subsample of stocks with at least one recommendation announced during the first 25 calendar days of the current month. Within each sector, we sort stocks into nine portfolios according to the current month average level of analyst stock recommendation (Rec), then long stocks with the highest recommendations and short stocks with the lowest recommendations.

ΔRec : We take the subsample of stocks with at least one recommendation announced during the first 25 calendar days of the portfolio formation month which also had a recommendation during either of the preceding two month. We compute the most recent revision in recommendations (ΔRec) and within each sector, we sort stocks into nine portfolios according to ΔRec, then long stocks with the highest ΔRec and short stocks with the lowest ΔRec.

ΔRec × Ret: Within each sector, we conduct a three by three independent sort based on ΔRec and Ret, then long past losers with high ΔRec and short past winners with low ΔRec.

	TPER	1/P	BP	Ret	DTP	TPER w/o EA	Rec	ΔRec	ΔRec × Ret
Long excess ret	1.58%	1.52%	1.15%	1.36%	0.76%	1.71%	0.41%	0.92%	0.83%
	[1.77]	[1.73]	[1.41]	[1.63]	[1.15]	[1.82]	[0.62]	[1.38]	[1.11]
Short excess ret	−0.19%	0.34%	0.10%	0.15%	0.80%	−0.35%	1.07%	0.43%	0.41%
	[−0.33]	[0.66]	[0.17]	[0.24]	[1.08]	[−0.54]	[1.41]	[0.64]	[0.68]
L-S excess ret	1.77%	1.18%	1.05%	1.22%	−0.04%	2.07%	−0.66%	0.49%	0.42%
	[3.55]	[1.84]	[1.84]	[2.24]	[−0.09]	[3.15]	[−1.55]	[1.37]	[0.94]
L-S alpha	2.03%	0.76%	0.60%	0.62%	0.15%	2.22%	−0.61%	0.32%	0.20%
	[5.06]	[1.80]	[1.63]	[1.48]	[0.38]	[3.30]	[−1.32]	[0.87]	[0.45]

As we have seen, our benchmark long–short Portfolio 1–9 involves a long position in past losers and a short position in past winners, albeit not the extreme winners and losers of a standard reversal strategy. To show that short-term return reversal alone does not drive our results, we construct a sector-neutral long–short strategy based on short-term return reversal. We form portfolios by sorting the S&P 500 stocks within sectors based on the past one-month return alone, and then go long the past losers and short the past winners. Column 4 in Table 6 reports the profits and alphas to the alternative sector-neutral long–short trading strategy. The loser-minus-winner return spread is 122 bp/month and significant with a t-value of 2.24. However, once we adjust for risk by using the five factors, the significance disappears. The five-factor alpha is only 62 bp/month, with a t-value of 1.48. We obtain comparable but weaker results by sorting on the past three-month return. When we sort on past returns without sector control, the profit and alpha are even smaller (108 and 4 bp/month, respectively).

Changes in target prices are positively related to future returns, as has been demonstrated by Brav and Lehavy (2003) and Asquith, Mikhail, and Au (2005). This relation is also evident in our S&P 500 stock sample, as illustrated in Table 2. However, analysts' revision in target price alone does not drive the future return. Column 5 of Table 6 shows that sorting stocks into nine portfolios based on the percentage change in the target price DTP within sectors does not yield any significant portfolio return spread for our S&P 500 stock sample. We note that the computation of DTP restricts us to the subsample of our S&P 500 stocks with target price announcements during the preceding month. We verify that the profit to our benchmark TPER-based strategy hardly changes when restricted to this subsample. Further, the five-day gap introduced between the collection of target prices and the beginning of the holding period guarantees that any announcement effects essentially have dissipated.

To summarize, neither the past return or changes in target price alone can explain the profit to our TPER strategy. The profit comes from exploiting the relative valuation information implied in the TPER, which combines information from both the target price and the market price of a stock.

4.3. Earning announcements and stock recommendations

In addition to target prices, analysts provide investors with information such as earnings forecasts and stock recommendations, which are known to affect future returns. Target prices are also more likely to be revised during periods with significant earnings news. To ensure that our results are not driven entirely by a delayed reaction to earnings announcements, we restrict our attention to stocks in each of the within-sector TPER-sorted portfolios for which there are no earnings announcement, during the portfolio formation period. We obtain the exact time for each earnings announcement from the First Call Historical Database (FCHD).

On average, 58% of the target price coverage occurs during a month with no earning announcement. This percentage is stable across all TPER-sorted portfolios for our S&P 500 stock sample. We report the excess return and the five-factor alpha for the subsample with no earnings announcements in Column 6 of Table 6. In the subsample with no earning-announcements during the month of portfolio formation, the profit and five-factor alpha not only do not disappear, but become even higher (207 and 222 bp/month, respectively). Therefore, our results do not seem to be driven by any delayed reaction to earnings announcements such as a post-earnings announcement drift.

To show that our results are not driven by stock recommendations alone, we construct an alternative sector-neutral long–short strategy based on the level of stock recommendations and revisions to stock recommendations. From December 1998 to December 2004, we focus on stocks in our S&P 500 sample for which there is at least one stock recommendation announcement during the first 25 calendar days of the portfolio month. We construct nine portfolios sorted on the level of recommendations within sectors.

Sorting on the level of recommendation does not seem to work. Column 7 of Table 6 shows that the long-high-recommendation/short-low-recommendation strategy produces a loss, consistent with the findings in Boni and Womack (2006).

We investigate the subsample of stocks for which there are also stock recommendation announcements during the second or third month preceding the current month. This procedure makes it possible for us to compute the most recent revision in recommendations during the past three months prior to portfolio formation. We construct nine portfolios sorted on revision in recommendation within sectors in this subsample. Although we can see from Column 8 in Table 6 that on average the long-upgrade–short-downgrade portfolio produces a profit, the profit and alpha are not significant. Again, we verify that the profitability of our TPER-based strategy hardly changes when we move to these two subsamples where we apply filters based on the availabilities of past recommendations. Finally, we examine a strategy based on both past return and recommendation revision. Within each sector, we conduct a three by three independent sort based on past one-month returns and the most recent revisions in recommendation. We then go long past losers with upgrades and short past winners with downgrades. Column 9 of Table 6 shows that this long–short strategy generates neither a significant profit nor alpha.

4.4. *Cross-sectional regression results*

The portfolio-sorting methodology has the advantage that it is non-parametric but has the drawback that it is not possible to simultaneously control for multiple characteristics due to the limited sample size. At the cost of assuming linearity, we can examine whether relative TPER has any incremental predictive power for returns after controlling for other stock characteristics in a cross-sectional regression framework.

In Table 7, we look at several alternative model specifications. In Model 1, we run a cross-sectional regression of one-month stock returns on sector-demeaned TPERs and other price-related stock characteristics including the past one-month return (*RET1M*), the book-price ratio (*BP*), earnings-price ratio (*EP*), and *SIZE*. In this case, the relative TPER remains significant, indicating incremental predictive power for short-run returns. In Models 2 and 3, we add two variables related to analyst forecasts: analyst earnings forecast revision (*FREV*) and stock recommendation change. We use two alternative definitions for stock recommendation change: ΔRec measures the most recent revision in the level of recommendations and *AgRecChg* measures the number of recommendation upgrades minus the number of recommendation downgrades within the month. Following Boni and Womack (2006), to reflect relative valuation, we first sector-demean both ΔRec and *AgRecChg*. In the presence of both price-related stock characteristics and other analyst-forecast-related variables, TPER remains the only variable that is significant in forecasting one-month stock returns. Finally, in models 4 and 5, we include the remaining eight stock characteristics *LTG*, *CAPEX*, *SG*, *SUE*, *TA*, *TURN*, *RETP*, and *RET2P*, which Jegadeesh, Kim, Krische, and Lee (2004) show to have predictive power for future stock returns. If we use all 15 stock characteristics, TPER remains significant.[7] The slope

[7]The requirement that all 15 characteristics be available significantly reduces the size of the cross-section. On average, there are only 150 stocks in each cross-section. Consequently, the regression results in models 4 and 5 should be interpreted with some caution.

Table 7
Cross-sectional regressions.
Each month from December 1998 to December 2004, we run cross-sectional regressions of one-month returns on sets of explanatory variables. These include the lagged one-month return (RET1M); book-to-price ratio (BP); the earnings-to-price ratio (EP); log market cap (SIZE); target price implied expected return (TPER); the analyst earnings forecast revision (FREV); the most recent revision in recommendations (ΔRec); a recommendation change variable used in Boni and Womack (2006), which we define as the number of recommendation upgrades minus the number of recommendation downgrades within the month (AgRecChg); and the remaining eight characteristics studied in Jegadeesh, Kim, Krische, and Lee (2004), which are LTG, CAPEX, SG, SUE, TA, TURN, RETP, and RET2P. We first sector-demean TPER, ΔRec, and AgRecChg to reflect relative valuation. All variables are cross-sectionally demeaned and all explanatory variables are also standardized so that the regression slope coefficient can be interpreted as the impact on return of a one standard deviation change. The reported slope coefficients are averaged across time and the robust t value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the square brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5
RET1M	−0.0042	−0.0035	−0.0041	−0.0055	−0.0059
	[−1.91]	[−1.42]	[−1.58]	[−2.71]	[−2.78]
BP	0.0012	0.0026	0.0027	0.0005	0.0001
	[0.66]	[1.33]	[1.46]	[0.17]	[0.04]
EP	0.0001	0.004	0.0037	0.0042	0.0046
	[0.04]	[0.78]	[0.75]	[0.94]	[1.03]
SIZE	−0.0038	−0.0029	−0.003	−0.0055	−0.0054
	[−1.22]	[−0.79]	[−0.84]	[−1.75]	[−1.84]
TPER	0.0031	0.0037	0.0037	0.0039	0.0041
	[2.41]	[2.41]	[2.35]	[2.14]	[2.21]
FREV		−0.0003	−0.0003	0.0014	0.0012
		[−0.22]	[−0.18]	[0.75]	[0.66]
ΔRec		0.0009		0.0022	
		[0.97]		[2.11]	
AgRecChg			0.0022		0.0023
			[1.69]		[1.63]
Other characteristics in Jegadeesh et al.	No	No	No	Yes	Yes
# obs per month	322	215	221	153	157
Avg R-sq	10.90%	13.70%	13.80%	28.50%	28.20%

coefficient on TPER is 41 bp, which measures the change in the next-month return caused by an one standard deviation change in TPER (holding other characteristics constant), and is broadly consistent with what we find with the sorting exercise given that the average TPERs in our extreme portfolios are about two standard deviations away from the average TPER in our sample.

The portfolio sorting and cross-sectional regression results both indicate that relative TPER has predictive power for short-run stock returns and that the predictive power is not entirely driven by any of the previously studied stock characteristics considered here.

4.5. Liquidity events

By the definition of the TPER as the ratio of the consensus target price to the end-of-month stock price, the strategy on average involves buying losers with recent upgrades in consensus target prices and selling winners with recent target price downgrades, as reflected in Table 2. The TPER strategy therefore has similarities to the well-known short-run reversal effect, although it does not necessarily involve trading the most extreme winners and losers, and, as we have seen above, the TPER profits are not driven by the standard short-run reversal effect.

An often cited explanation for the short-run reversal phenomenon is the occurrence of liquidity shocks and it is therefore natural to ask whether the TPER strategy profits are also related to liquidity events.

We provide several pieces of evidence suggesting that this is indeed the case, namely that the pattern of abnormal returns to the TPER strategy is related to the time variation in the liquidity of individual stocks in the portfolio.

First, both Campbell, Grossman, and Wang (1993) and Conrad, Hameed, and Niden (1994) argue that non-information-motivated trades can be detected by abnormal trading volume. Panel A of Table 8 displays the changes in the turnover ratio (defined as trading volume divided by number of share outstanding) across the three months (portfolio pre-formation, formation, and post-formation). For both Portfolios 1 and 9, we see increases in trading volume during the portfolio formation month (although this increase is only statistically significant for Portfolio 1).

Second, Panel B of Table 2 shows that the two extreme portfolios, 1 and 9, display levels of illiquidity that are higher than average. The fact that they experience a larger price reversal is therefore consistent with Campbell, Grossman, and Wang (1993) as liquidity shock usually affects illiquid stocks more as their demand curves are more downward-sloping (Avramov, Chordia, and Goyal, 2006). To ensure that this pattern is not driven by a few illiquid stocks always appearing in Portfolio 1 or 9, we compute the average percentage changes in these measures when a stock enters Portfolio 1 or Portfolio 9. Panel B of Table 8 shows that stocks are more illiquid during periods when they are in Portfolio 1 or 9. It is possible that the higher degree of asymmetric information is driving the lower liquidity of the stocks in Portfolios 1 and 9. To protect themselves against information asymmetries, market makers tend to raise the trading cost of such stocks, making them more illiquid (see Sadka and Scherbina, 2007). Panel B of Table 8 provides supporting evidence for this explanation. For each stock, in each month, we define its target price dispersion measure as the standard deviation of target prices received from different analysts divided by the consensus target price, similar to the dispersion measure used in Diether, Malloy, and Scherbina (2002). For a given stock, the dispersion measure is a lot higher when it enters Portfolio 1 or 9 compared to when it is not in either of the extreme portfolios. The dispersion measure increases by 62% (with a t-value of 6.41) when it enters Portfolio 1 and by 72% (with a t-value of 8.31) when it enters Portfolio 9.

Third, trading by institutional investors is an important source of potential price pressures, especially for large stocks. Gompers and Metrick (2001) find that the largest institutional investors hold a majority of outstanding U.S. large capitalization stocks and in this situation, institution-specific liquidity shocks can result in large block trades. There is ample evidence of the price impact of institutional trades. Obizhaeva (2007), in the context of portfolio transition trades, finds significant liquidity effects lasting several weeks, while Coval and Stafford (2007) document the persistent liquidity effects of asset fire sales (purchases) by mutual funds. Given this scenario, during the month of portfolio formation, we would expect Portfolio 1 to be associated with large institutional selling and Portfolio 9 to be associated with large institutional buying. This pattern is exactly what we find when we use U.S. equity mutual fund holding data from Morningstar. From

Table 8
Liquidity related characteristics and mutual fund turnover of TPER-sorted portfolios in the S&P sample.
Panel A reports the turnover during the months before ($t-1$), during (t) and after ($t+1$) the portfolio formation for our nine within-sector TPER-sorted portfolios (1 being the highest TPER and 9 being the lowest TPER) from December 1998 to December 2004. We define the turnover as the total monthly trading volume divided by the number of share outstanding. In addition, we report the trading pattern of U.S. equity mutual funds across TPER-sorted portfolios. At the end of each month from December 1998 to December 2004 and for each stock in our S&P sample, we compute the change in holdings by mutual funds as a group during the preceding three months. For the subset of mutual funds that report their holdings both at the end of the current month and also three months earlier, we compute the changes in holdings (as a percentage of total number of shares outstanding) of each stock and aggregate them across funds as

$$\text{Mfh\_chg} = \frac{\text{holding}_t - \text{holding}_{t-3}}{\#\text{ shares outstanding}}.$$

We then report the average diff Mfh_chg and the t-value associated with Mfh_chg for each of the nine TPER-sorted portfolios. We winsorize Mfh_chg at the 1st and 99th percentiles. Panel B reports the average percentage change in bid–ask spread (Pspread), price impact measure (Pimpact), Amihud (2002) liquidity measure (Amihud) and dispersion in analyst's target price forecast (Dispersion) when a stock is in Portfolio 1 or Portfolio 9 as compared to when it is not. When we compute the percentage change in Pspread, we adjust for the change in price by multiplying the percentage change by $\sqrt{p_t/p_{t-1}}$.

Panel A: Changes in turnover and mutual fund holdings

Portfolio	Turnover ($t-1$)	Turnover (t)	Turnover ($t+1$)	Change from $t-1$ to t	t-value of the change	Mfh_chg ($\times 10^4$)	t-value
1	18.73%	19.76%	19.53%	1.02%	2.69	−14.7	−5.15
2	16.30%	16.79%	16.47%	0.50%	1.61	−6.15	−1.99
3	15.29%	15.60%	15.51%	0.30%	1.07	−1.38	−0.45
4	14.52%	14.87%	14.68%	0.35%	1.2	−1.75	−0.49
5	14.29%	14.59%	14.37%	0.30%	1	6.98	2.67
6	14.14%	14.27%	14.09%	0.13%	0.5	5.51	1.6
7	13.92%	14.03%	13.81%	0.11%	0.37	9.98	3.13
8	14.95%	15.21%	14.70%	0.27%	0.78	8.54	2.73
9	15.75%	16.13%	15.85%	0.38%	1.1	12.48	3.56

Panel B: Changes in liquidity characteristics upon entering extreme TPER portfolios

	Pimpact	Pspread	Amihud	Dispersion
When stock enters portfolio 1				
Percentage change	11.40%	6.50%	9.90%	61.90%
t-value	3.36	3.42	3.71	6.41
When stock enters portfolio 9				
Percentage change	9.70%	7.00%	7.50%	72.30%
t-value	3.31	3.96	3.5	8.31

December 1998 to December 2004, at the end of each month and for each stock in our S&P sample, we compute the change in holdings by mutual funds as a group during the preceding three months. For the subset of mutual funds that report their holdings at the end of the current month and also for three months earlier, we compute the changes in holdings of each stock and aggregate across funds as a percentage of total number of shares outstanding:

$$\text{Mfh\_chg} = \frac{\text{holding}_t - \text{holding}_{t-3}}{\#\text{ of shares outstanding}}$$

Panel A of Table 8 reports the average Mfh_chg and the t-value associated with Mfh_chg for each of the nine TPER-sorted portfolios. For Portfolio 1, the Mfh_chg is significantly negative, indicating heavier than usual mutual fund selling. For Portfolio 9, the Mfh_chg is significantly positive, indicating unusually heavy mutual fund buying.

4.6. Summary and additional discussion

We have examined several potential factors related to the TPER strategy profit and concluded that none of them alone can explain the profit. These factors includes size, past returns, target price revision, earnings forecasts, and stock recommendations. TPER provides additional predictive power for one-month-ahead stock returns even after we control for these factors, as well as other stock characteristics. The relative valuation implied by analyst target prices therefore appears to be distinct from other investment signals previously identified in the literature.

The price reversal in our TPER strategy does not take place immediately but lasts for a few weeks even for S&P 500 stocks. There could be several explanations for such a delay in price reversal. First, since resolving information asymmetry takes time, the associated higher trading cost may also last for a while. Second, news that comes out during the holding period may push the price in an unwanted direction, thus the profit to the long–short strategy is not guaranteed. Although the profit covers the transaction cost in magnitude on average, its significance level may be reduced after accounting for the transaction cost. There is also downside risk. For instance, the long–short strategy produced a (risk adjusted) loss of almost −4% during September 2001. Third, the liquidity event may produce self-reinforcing externalities as described in Coval and Stafford (2007), where asset fire sales by one mutual fund can trigger subsequent fire sales by others leading to persistence and possibly deepening of the mispricing. Finally, there may be times when the mobility of the financial capital is low (i.e., it takes time for an investor to identify a profitable opportunity and then move capital to that opportunity). All these considerations may prevent risk-averse arbitrageurs from promptly correcting the price.

5. Full sample results

In order to further examine the performance of our benchmark strategy over time and across subsamples, we extend the preceding analysis to the full sample of all stocks receiving regular analyst target price coverage between December 1996 and December 2004.[8] The larger sample allows us to control for stocks characteristics in our sorting procedure, as well as to examine the effect of finer sector control. Consistent with the relative valuation interpretation of the *TPER* sort and the finding in Boni and Womack (2006), going from a nine sector classification (two-digit GICS) to a 24 industry classification (three-digit GICS) does indeed improve our results, producing a larger and

[8]Stocks trading below \$5 (about 6% of the sample) were excluded. Additionally, stocks with extreme *TPER* s were dropped.

more significant profit. Table 9 shows that, with the finer industry classification, the full sample results are qualitatively similar to those of the S&P 500 sample. The first-month excess return is monotonically increasing in TPER and the resulting benchmark industry-neutral long–short strategy yields an excess return of 139 bp/month (t-value of 4.39) and a five-factor alpha of 125 bp/month (t-value of 4.97).

5.1. Performance in sub-periods

We split the sampling-period into two, 1997–2000 and 2001–2004, and examine the performance of the benchmark sector-neutral long–short strategy in each of the sub-periods for both the S&P 500 sample and the full sample. Since the full sample contains more stocks, we move from a nine sector classification (two-digit GICS) to a 24 industry classification (three-digit GICS). The results based on a single regression using data from 1997 to 2004 are reported in Table 9.

Table 9
Returns on within-sector/industry TPER-sorted portfolios in sub-periods.
At the end of each month from December 1996 to December 2004 and within each sector (for S&P 500 stocks)/ industry (for the full sample), we rank stocks into 9 groups according to the current month TPERs and label them from 1 to 9 (1 with the highest TPER and 9 with the lowest TPER). The sector classification is based on the first two digits of GICS (9 sectors in total). The industry classification is based on the first three digits of the GICS (24 industries in total). For each stock, we compute its next one-month excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks within each portfolio. We report the average excess returns and risk-adjusted alphas (using the five- and four-factor models) for portfolios 1, 9 and 1–9. All returns and alphas are monthly. * highlights the fact that the GICS is backfilled and the long–short strategy was infeasible ex ante prior to 1999. t-values are reported in the square brackets.

Panel A: S&P500 sample						
	1997–2000*			2001–2004		
Portfolio	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha
1	1.87%	1.30%	1.29%	1.27%	0.88%	0.78%
	[1.88]	[2.51]	[2.47]	[1.09]	[2.28]	[2.10]
9	0.20%	−0.70%	−0.70%	0.02%	−0.57%	−0.47%
	[0.27]	[−1.97]	[−1.98]	[0.03]	[−2.72]	[−2.27]
1–9	1.66%	2.00%	1.99%	1.25%	1.45%	1.25%
	[2.62]	[3.50]	[3.44]	[2.01]	[3.46]	[3.21]

Panel B: Full sample						
	1997–2000*			2001–2004		
Portfolio	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha
1	1.69%	1.02%	0.99%	1.89%	0.93%	0.62%
	[1.66]	[2.62]	[2.71]	[1.76]	[3.79]	[3.06]
9	0.38%	−0.53%	−0.51%	0.24%	−0.51%	−0.27%
	[0.49]	[−1.55]	[−1.61]	[0.33]	[−2.37]	[−1.31]
1–9	1.59%	1.72%	1.68%	1.19%	1.21%	0.81%
	[3.53]	[4.32]	[4.51]	[2.66]	[3.77]	[3.31]

The long–short strategy produces a significant risk-adjusted return in both sub-periods but the performance is better in the first sub-period although the difference is not statistically significant (see Fig. 3). For the S&P 500 sample, the monthly five-factor risk-adjusted return was 199 bp/month (t-value of 3.44) during 1997–2000 and 125 bp/month (t-value of 3.21) during 2001–2004.[9] For the full sample, the monthly five-factor risk-adjusted return is 168 bp (t-value of 4.51) during the first four years and 81 bp (t-value of 3.31) during the last four years of the sample. Finer sector classification seems to help the performance of the TPER strategy, as the profit becomes more significant in the full sample.

There are several possible explanations for the weaker performance after 2000. In August of 2000, the SEC adopted Regulation FD to curb the practice of selective disclosure of material non-public information. Prior to Regulation FD, equity analysts could have acquired more information than the public, so the target price would be a more informative control for changes to a firm's fundamental values. Therefore, we would expect our benchmark sector neutral long–short strategy to do better during the pre-Regulation FD period. Another important event during our sample period was decimalization, which took place starting in January 2001 for NYSE stocks and March 2001 for NASDAQ stocks, and which significantly reduced most measures of trading costs. If part of the risk-adjusted return does reflect the reward for providing liquidity, then the sudden increase in liquidity after decimalization and gradual increase in liquidity throughout our sample period are both consistent with lower risk-adjusted profits in the post 2000 period.

5.2. *Performance in subsamples*

An important ingredient for the success of the sector-neutral long–short strategy is the availability of an accurate control for significant changes in fundamental value. It is therefore natural to conjecture that the largest risk-adjusted profits are to be found in the subset of stocks with the least noisy analyst forecasts. With this in mind, we turn to investigating the performance of this strategy within subsamples.[10]

Panel A of Table 10 shows the performance for stocks listed on the NYSE and NASDAQ.[11] Although our sector-neutral long–short strategy produces a significant profit and alpha across both exchanges, the alpha is more significant for NYSE stocks (t-value of 4.73) than NASDAQ stocks (t-value of 2.69). Consistent with this, we find that NYSE stocks receive more analyst coverage and are associated with less dispersion of target price forecast across analysts when compared to NASDAQ stocks. This may also be related to the fact that companies listed on NYSE tend to be more mature so that analysts produce less noisy assessments of the relative strength of companies in the same sector, resulting in a better performance of the long–short strategy.

Panel B of Table 10 shows the performance of our sector-neutral long–short strategies within six size and book-to-market sorted portfolios. In general, we find the performance

[9]The average of the alphas from the two sub-periods is not directly comparable to the 203 bp/month alpha in the benchmark case since the latter was based on a regression excluding the period 1997–1998.

[10]We revert to using the nine-sector control in this subsection since the number of stocks in each subsample is significantly reduced.

[11]There are too few AMEX-listed stocks in our sample (less than 3%) to investigate the subsample performance.

Table 10
Performance of sector-neutral long–short strategies in various subsamples.
Panel A reports the results for NYSE and NASDAQ stocks separately. Panel B reports the results across size and book-to-market double-sorted groups. Panel C reports the results within each of our nine sectors. The sampling period is from December 1996 to December 2004. All returns and alphas are monthly. *t*-values are reported in the square brackets.

Panel A: NYSE versus NASDAQ

Exchange	Excess ret.	Alpha	MKT	SMB	HML	UMD	DMU
NYSE	1.28%	1.13%	0.218	0.04	0.073	−0.186	0.195
	[4.07]	[4.73]	[3.76]	[0.71]	[1.02]	[−4.82]	[4.13]
NASDAQ	1.45%	1.15%	0.071	0.29	−0.15	−0.213	0.542
	[2.61]	[2.69]	[0.69]	[2.87]	[−1.16]	[−3.08]	[6.4]

Panel B: Size and book-to-market sorted subsamples

Group	Size	B/M	Excess return	alpha	MKT	SMB	HML	UMD	DMU
Small value	272,647	0.84	2.36%	2.07%	0.104	0.142	0.033	0.041	0.193
			[4.92]	[4.12]	[0.86]	[1.22]	[0.22]	[0.52]	[1.99]
Small Growth	322,905	0.3	1.12%	1.15%	0.08	0.023	−0.325	−0.315	0.515
			[1.33]	[1.48]	[0.43]	[0.13]	[−1.41]	[−2.57]	[3.45]
Medium value	1,263,608	0.68	1.02%	0.95%	0.222	−0.065	0.095	−0.168	0.169
			[2.02]	[1.91]	[1.87]	[−0.56]	[0.65]	[−2.13]	[1.76]
Medium growth	1,285,998	0.24	0.62%	0.56%	0.412	0.081	−0.171	−0.271	0.283
			[0.83]	[0.85]	[2.61]	[0.53]	[−0.87]	[−2.59]	[2.22]
Large value	10,844,724	0.55	0.88%	0.84%	0.109	−0.163	−0.117	−0.139	0.323
			[1.92]	[2.08]	[1.13]	[−1.74]	[−0.97]	[−2.17]	[4.14]
Large growth	25,703,362	0.18	0.65%	0.23%	0.085	0.095	−0.27	−0.132	0.811
			[0.84]	[0.37]	[0.57]	[0.66]	[−1.46]	[−1.34]	[6.76]

Panel C: Sector sorted subsamples

GICS	Sector	Excess ret.	alpha	MKT	SMB	HML	UMD	DMU
10	Energy	1.87%	1.45%	0.479	0.258	0.199	−0.341	0.378
		[2.42]	[2.09]	[2.86]	[1.59]	[0.96]	[−3.07]	[2.77]
15	Materials	1.53%	1.57%	0.109	0.287	−0.197	−0.199	0.093
		[2.5]	[2.57]	[0.74]	[2]	[−1.08]	[−2.02]	[0.78]
20	Industrials	1.82%	1.96%	0.375	0.086	−0.035	−0.281	−0.117
		[3.47]	[4.06]	[3.21]	[0.76]	[−0.24]	[−3.62]	[−1.23]
25	Consumer Discr.	2.36%	2.42%	−0.031	0.125	−0.147	−0.179	0.175
		[5.85]	[6.11]	[−0.32]	[1.34]	[−1.23]	[−2.79]	[2.23]
30	Consumer Staples	1.21%	0.92%	0.221	0.316	−0.046	−0.131	0.267
		[1.59]	[1.18]	[1.17]	[1.72]	[−0.2]	[−1.04]	[1.73]
35	Health Care	−0.29%	−0.33%	0.081	0.164	−0.461	−0.315	0.582
		[−0.3]	[−0.36]	[0.37]	[0.77]	[−1.71]	[−2.17]	[3.27]
40	Financials	1.13%	0.69%	0.312	−0.032	0.258	0.077	0.128
		[3.12]	[1.89]	[3.56]	[−0.38]	[2.37]	[1.31]	[1.79]
45 & 50	Technology	1.11%	0.49%	0.174	0.347	−0.351	−0.134	0.909
		[1.29]	[0.73]	[1.08]	[2.23]	[−1.76]	[−1.26]	[6.96]
55	Utilities	0.86%	0.77%	0.148	0.223	0.131	−0.296	0.17
		[1.29]	[1.13]	[0.9]	[1.39]	[0.64]	[−2.69]	[1.26]

to be much better for value stocks (with high book-to-market ratios) than growth stocks (with low book-to-market ratios). We attribute the effect of the book-to-market ratio to the fact that analysts' estimates for value firms with a higher fraction of tangible assets will be less noisy (e.g., fewer outliers) than for growth firms. We also find that the performance is somewhat better for small stocks than large stocks. To the extent that liquidity plays a role, this is consistent with the fact that small stocks are more illiquid in general, although the size effect is likely tempered by the more noisy and less frequent analyst forecasts. The small-value stock portfolio produces a highly significant profit of 236 bp/month and, since it only loads on DMU, produces a large alpha of 207 bp/month, with comparable level of significance (t-value of 4.12).[12]

Panel C of Table 10 shows the performance across nine sectors. In general, the sector-neutral long–short strategy works reasonably well except in the Consumer Staples, Health Care, Technology and Utilities sectors. The relative performance across sectors is consistent with the book-to-market ratio effect as the Consumer Staples, Health Care, and Technology sectors are the only three sectors that contain more growth than value stocks.[13] In addition, the target prices are arguably more noisy for technology stocks during our sampling period as they are associated with the largest dispersion across different analysts.

6. Conclusion

Most existing studies of equity analysts have found little if any evidence of investors being able to earn abnormal profits (net of transaction costs) based on analyst information, unless trading takes place at the time of announcement. In this paper, we have reexamined the issue using a large database of analyst target price forecasts. We have chosen to focus on target prices because they, as opposed to recommendation or earnings forecasts, represent a direct measure of the fundamental value perceived by analysts. The key result from our analysis is that the informativeness of analysts' target price forecasts mainly derives from the implied within sector/industry relative valuations and not from the level of the individual forecasts themselves. Moreover, the predictive power of target prices for subsequent returns is economically and statistically significant even after explicitly skipping the first week post announcement. A simple, yet very effective, way of exploiting the information in target prices is to form portfolios of stocks based on their target price implied return (TPER) among stocks in the same S&P GICS sector. Applying this approach to the set of S&P 500 stocks, a simple sector-neutral long–short strategy earns a statistically significant average risk-adjusted profit of almost 200 bp per month during the period from 1999 to 2004, much higher than most transaction cost estimates.

Our results are remarkably robust to changes in the specifics of the portfolio construction strategy, choice of sampling period, alternative risk-adjustment models, and sector definitions. We have also shown that the information contained in the TPER variable is not subsumed by other analyst forecasts, earnings announcements, other stock

[12]A closer examination of the big stock subsample shows that large non-S&P 500 stocks have significantly lower analyst coverage and book-to-market ratios but significantly more uncertain target prices than the average S&P 500 stock. This finding partly explains why the strategy does not work as well for large stocks not in the S&P 500.

[13]Although the Utilities sector also contains more value stocks, it is relatively small. Utility stocks only account for 3.3% of the our sample. As a result, the number of stocks in the long–short portfolio is only around five, making the resulting portfolio return very noisy.

level characteristics commonly used to predict returns. Interestingly, we find some evidence that the TPER strategy profit is correlated over time with mutual fund trading patterns, as well as changes in a number of popular cross-sectional measures of individual stock level liquidity such as turnover, the bid–ask spread, price impact, and the Amihud liquidity measure. Finally, we have confirmed that our findings extend to the larger full sample of all stocks receiving regular analyst coverage over the sampling period from 1997 to 2004.

Few equity analysts are true generalists and most specialize in a handful of stocks within a single industry or, less often, a sector. It is therefore natural to think that analysts will do a better job at judging the relative performance of stocks within their area of specialization rather than the performance of the industry or economy as a whole. This intuition is supported by the findings in our paper using analyst target price forecasts, as well as those in Boni and Womack (2006) using analyst stock recommendations, and suggest that future research on analyst forecasts would benefit from focusing on comparing forecasts across stocks within the same industry. This approach helps in reducing the noise associated with analyst forecast and isolating the relative value component that contains most of the information valuable to investors.

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