The Value of Equity Analysts' Target Prices

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Abstract

We document that short-run deviations between prices and fundamentals can be identified in real time using equity analysts' target price forecasts. The deviations are economically and statistically significant and of a magnitude not easily explained by transaction costs alone. Our benchmark portfolio of S&P500 stocks, for instance, earned an average risk-adjusted return of 195bps per month during the period 1999-2004. We show that the abnormal return is in part a premium required by investors for providing liquidity and is highly correlated with standard cross-sectional measures of liquidity such as the bid-ask spread, price impact and changes in trading volume. Our results contribute to the existing literature on analysts' forecasts by pointing out that, while the target price itself need not provide an accurate estimate of true fundamental values, relative valuations of firms within an industry tend to be more precise. This finding is consistent with analysts having skill in analyzing the specifics of individual firms but limited ability to forecast systematic factors driving returns at the sector level.

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1 Introduction

A key question in the finance literature dealing with equity analysts' recommendations, is whether analysts provide investors with information not already reflected in prevailing market prices, as required by the efficient market hypothesis. In other words, do analysts add value? In this paper, we approach this question using equity analysts' target price forecasts.

The analyst target price is arguably a noisy measure of the true fundamental value of a stock. It contains a forward-looking systematic risk component as well as a firm specific risk component which includes potential analyst biases. Most previous studies, going back to Cowles (1933), have found limited or no evidence of analysts providing investors with valuable information in the form of buy/sell recommendations or price targets.[1] In this paper, we show that analysts on average get relative valuations right even if they fail to assess fundamental values themselves with any degree of precision. This finding can be motivated by the fact that most 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 macro factors which affect the performance of the sector as a whole. In order to identify potential deviations of prices from fundamentals, we therefore focus on relative price forecasts *within* the same narrowly defined sector, thereby eliminating much of the effect of systematic risk factors while preserving the relative strength information contained in analysts' price targets.[2]

Based on these observations, we construct a sector-neutral long-short portfolio in the

[1]A prominent exception is Fisher Black's original ValueLine analysis Black (1973) in which the author found that a simple (long only) portfolio constructed based on ValueLine rankings significantly outperformed the market over a five year period. Due 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 transaction costs. In fact the fund is no longer in existence.

[2]Moskowitz and Grinblatt (1999) show that industry wide return patterns are a main driver of individual stock returns in the context of momentum strategies. In the current study, which relies on reversal rather than momentum, we explicitly cancel out industry effects in order to focus on the relative value identified by analysts. A recent paper by Boni and Womack (2005) also shows investment strategy based on stock recommendation revision in the same industry improves the return significantly.

following manner: at the end of every month, we consider the set of S&P500 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 into 9 portfolios according to their *target price expected return* ($TPER$) defined as the return implied by the equity analysts' 12-month-ahead price target and the current market price, or, $TPER = TP/P - 1$. Finally we construct an equal weighted portfolio which is long the highest $TPER$ stocks in each sector (portfolio 1) and short the lowest $TPER$ stocks in each sector (portfolio 9). Since the portfolio is equal weighted, it is by construction sector neutral. Over the period 1999-2004, this strategy has yielded a Fama-French 3-factor alpha of 195bps per month.[4]

The importance of sorting stocks on $TPER$ *within* sector can be further illustrated by decomposing $TPER$ into two components:

$$TPER = E^A[\alpha] + \beta' E^A[F].$$

The first component represents the alpha predicted by analysts, which stems from the value of management expertise, the competitive advantage of the firm, its growth potential, and other sources that are not yet fully reflected in the current stock price. Analysts mainly add value by estimating $E^A[\alpha]$ across stocks in the same industry. The second term is the familiar forward-looking systematic risk component which can be expressed using a linear factor model. This component is considerably more noisy given the inability of analysts to forecast the factor risk premium $E^A[F]$, as documented in Bradshaw and Brown (2005). However, to the extent that stocks in the same sector have similar systematic risks (similar β), sorting on $TPER$ *within* a sector controls for the systematic risk component and generates a spread in the alpha which is where the analysts' value-added mainly lies. Moreover, the sector neutral long-short strategy considered in this paper helps to explicitly eliminate most of the systematic risk exposure.

Our findings contribute to the recent research on analyst's target prices. Brav and Lehavy (2003) and Asquith, Mikhail, and Au (2005) document a significant market reaction to target price revisions controlling for the arrival of other information, providing evidence that investors on average consider target prices to be informative. Bradshaw and Brown (2005) show that analysts do not appear to exhibit persistent differential abil-

[3]The average 5-day lag between the portfolio formation and the beginning of the one month holding period eliminates announcement effects.

[4]As discussed in detail below, the choice of sampling period is dictated by the ex-ante availability of the detailed Standard & Poors sector classification used.

ities in forecasting target prices. In this paper we show that the information embedded in the level of target prices, if properly exploited, can lead to superior investment results. Several previous studies have examined investment strategies based on information provided by analysts – mainly stock recommendations.[5] However, most of these investment strategies have only produced risk-adjusted paper profits which disappear after accounting for transaction costs due to high portfolio turnover. In contrast, we propose a sector-neutral long-short strategy involving only S&P 500 stocks which produces a risk-adjusted alpha of around 100bp per month after accounting for direct transaction costs and price impact.[6]

Jegadeesh, Kim, Krische, and Lee (2004) consider the relationship between analysts' buy/sell recommendations and a set of 12 stock characteristics which help forecast future stock returns. They find that the change in analyst's recommendations (although not the level of recommendations) has additional explanatory power for future return over and above the 12 characteristics. In a similar cross-sectional regression, we show that the $TPER$ implied by analysts' target prices has significant predictive power for one-month ahead stock returns after controlling for the other 12 stock characteristics.

We study the source of the abnormal returns on the $TPER$ sorted portfolios and show that the profit is not likely driven by: (1) delayed reaction to stock recommendation (c.f. Womack (1996)); (2) reaction to target price revisions (c.f. Brav and Lehavy (2003) and Asquith, Mikhail, and Au (2005)); (3) post-earning-announcement drift (PEAD); (4) pure short-term return reversal (c.f. Jegadeesh (1990) and Lehman (1990)). Instead we find strong evidence suggesting that only the combined information conveyed by price target and current market price drives the profit in our portfolio. One interpretation of this finding is that the analyst target price provides a way of assessing whether a recent change in price was mainly driven by changing fundamentals, and therefore likely permanent, or mainly driven by investor sentiment or liquidity, and therefore likely temporary in nature. In other words, we argue that the $TPER$ is a direct, albeit noisy, measure of the discrepancy between price and fundamental value for each individual stock. A very large or very small $TPER$ (relative to other stocks in the sector) is unlikely purely due to fun-

[5]Two examples are Dimson and Marsh (1984) and Barber, Lehavy, McNichols, and Trueman (2001). Michaely and Womack (2002) provides and excellent survey of related papers.

[6]The abnormal returns derive equally from the long and short side of the portfolio and it is possible to implement a version where the shorting of individual stocks is replaced by shorting S&P index futures or sector ETFs.

damentals. It is likely driven in part by investor sentiment or liquidity, making a future price correction more probable.

A temporary divergence between the market price and fundamental can be seen as an indication of the degree of illiquidity of the asset. The common presumption is that the price effects of liquidity motivated trades will dissipate quickly while information motivated trades will have a permanent effect thereby impounding new information in market prices.[7] Pastor and Stambaugh (2003), for instance, in their study of an aggregate liquidity factor, focus on liquidity effects that play out within one day.[8] It is far from clear, however, what duration in general should be attributed to liquidity induced price movements. As has been argued in the "limits of arbitrage" literature, liquidity effects, albeit temporary, could be of a considerably longer duration (c.f. Shleifer and Vishny (1997) and more recent empirical papers by Gabaix, Krishnamurthy, and Vigneron (2005) and Sadka and Scherbina (2004)). Liquidity effects may also persist due to either self-reinforcing externalities, as has been suggested by Coval and Stafford (2005) in the context of asset fire sales by equity mutual funds, or capital immobility as has been argued in Berndt, Douglas, Duffie, Ferguson, and Schranzk (2005). It is therefore not surprising to observe that the price corrections, which generate the sector neutral long-short strategy's abnormal profits in our paper, on average last several weeks up to a month.[9]

Consistent with the liquidity interpretation, we document that a stock which enters our long-short portfolio in a given month experiences a significant increase in its bid-ask spread, its price impact measure (Breen, Hodrick, and Korajczyk (2002)) as well as its

[7] In financial economics the somewhat vague term "liquidity of an asset" is related to the question: How much will prices move if an investor trades a given quantity of the asset within a short period of time. When the liquidity level associated with an asset is low, an investor wishing to trade a significant quantity of it must pay a premium to do so and, conversely, an investor ready to provide the liquidity will be rewarded, as in the model of Campbell, Grossman, and Wang (1993). This definition of liquidity is symmetric with respect to buying and selling of an asset. An investor desiring to buy an asset is equally demanding "liquidity" from the market maker who holds the inventory.

[8] In their study of block trades Keim and Madhavan (1996) find that the price impact of a sell order on lasts on average one day. Buy orders on the other hand tend to have a more permanent effect, much of which accrues during the first day.

[9] The $TPER$ relates to liquidity events at the individual stock level in a cross section rather than the aggregate level of liquidity in the economy (c.f. Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Chordia, Roll, and Subrahmanyam (2001) and Eisfeldt (2004)) or the co-movement of liquidity among stocks (c.f. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001)).

Amihud illiquidity measure (Amihud (2002)). Moreover, the profits are highly correlated with these liquidity measures across time. In line with Campbell, Grossman, and Wang (1993) and Conrad, Hameed, and Niden (1994), we also document an increase in turnover for stocks entering our portfolio as well as a significant change in the order imbalance between seller and buyer initiated trades. In addition, we also observe a substantial increase in the dispersion of analysts' target price forecasts for stocks entering our portfolio, consistent with market makers decreasing liquidity of individual stocks in response to an increased degree of information asymmetry as in Sadka and Scherbina (2004).

While conventional liquidity measures must disentangle information and liquidity based trades ex-post, the $TPER$ sort directly controls for changes in fundamental values (which should equally affect price targets and market prices) and can be conducted in real-time and therefore can be used as the basis for constructing a trading strategy. We do not, however, attempt to identify the fundamental reasons for the observed cross sectional variation in $TPER$. Potential reasons include institutional buying/selling pressures as in Coval and Stafford (2005) or changing market sentiment as in Baker and Wurgler (2005) and Baker and Stein (2004).

We show that our results extend beyond the S&P500 universe to the set of all stocks in the FirstCall database with regular analyst coverage over a slightly longer sample period from 1997 to 2004. In the larger sample we show that the strategy works best for small stocks and especially value stocks. 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. Small stocks, on the other hand, tend to more illiquid, so the reward for liquidity provision is higher, which may explain the better performance of our long-short strategy for small stocks. Interestingly, we also find that the strategy performs significantly better in certain industries such as consumer discretionary and industrials.

The remainder of the paper is structured as follows. Section 2 provides a description of data sources. The main result for the S&P500 sample are given in section 3 while section 4 contains the results for the full sample. Section 5 concludes.

2 Data Description

The target price data is provided by First Call. A distinguishing feature of the First Call Database is that it ensures accurate dating of analysts' reports.[10] At the end of each month from Dec 1996 to Dec 2004, we include only stocks for which there is at least one (1-year-ahead) target price announcement during the first 25 calendar days of the month. It is important to note that, as a result, our sample includes almost no extremely small stocks since these do not receive regular analyst coverage. We do not "fill in the blanks" using older target prices in order to avoid introducing a bias in the target prices. The bias arises because analysts are more likely to issue target price when they are in favor of a stock, as documented in Brav and Lehavy (2003). This endogenous data censoring process creates an upward bias in the observed target prices.[11] To see this, consider a world with zero drift in target price and assume we observe a target price of 100 for a stock at time t ($TP_t = 100$), but nothing at time $t+1$, the expected target price at $t+1$ conditional on no observation at $t+1$ will be smaller than 100. Therefore simply assuming that $TP_{t+1} = 100$ or $\Delta TP_{t+1} = TP_{t+1} - TP_t = 0$, results in an upward bias. To minimize this bias, we only keep the most recent one month target price announcements. In addition, we only keep target price announcements during the first 25 calendar days of the month for two reasons. First, we want to make sure that our results are not purely driven by an immediate market reaction to target price announcements, a phenomenon considered in Brav and Lehavy (2003). Second, this makes our portfolio trading strategies easier to implement since investors, on average, are given 5 days to collect and digest target price information.

Table 1 presents a summary of the resulting sample containing approximately 1700 stocks each month, increasing from 1095 in 1996 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

[10]"most of the analysts' estimates in FCHD (First Call Historical Database) have the date that they were published by the broker. This cannot be said of any other historic estimates database." *First Call Historical Database User Guide*.

[11]Specifically, BL shows about 90% of buy / strong buy recommendations are issued with target prices while only 61% of sell / strong sell recommendations are issued with target prices. Furthermore, sell / strong sell recommendations only account for less than 5% of all recommendations as documented in Jegadeesh et. al (2004).

2004. Our sample also covers most of the "representative" stocks, which are constituents of the major equity indices. For instance, for 2004, our sample covers 496 of the S&P 500 stocks, 980 of the Russell 1000 stocks and 2780 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 919M – much larger than that of all NASDAQ stocks (85M), but slightly smaller than that of all NYSE stocks (963M).

A key variable of interest in this paper is the target price implied expected return one-year-ahead ($TPER$), which is defined as the consensus target price (split adjusted) divided by the end of month stock price minus one, or $TPER_t = TP_t/P_t - 1$, where the consensus target price TP_t is the simple average of all target prices received during the first 25 calendar days of the month.[12] The mean $TPER$ during this sampling period is 40% (the median is 24%) higher than one would expect for the market as a whole. Again, this is partly due to the fact that analysts are far more likely to issue target prices when they are in favor of a stock. In addition, the target price may reflect deliberate optimism of the analyst as proposed in Bradshaw and Brown (2005). This provides another rationale for focusing on the relative $TPER$ in the same sector. 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).[13] The GICS was first introduced in 1999 by Standard & Poor's and Morgan Stanley Capital International (MSCI) to provide one complete, consistent set of global sector and industry definitions which reflects the modern economy. Bhojraj, Lee, and Oler (2003) show GICS to be superior for many financial and accounting research applications.[14] The GICS used in this paper are

[12]Defining the consensus target price using median does not alter the results in any significant way.

[13]In principle, using the 4-digit or the 6-digit GICS gives better sector control. The tradeoff is that the number of stocks in each sector will drop, making the results noisier. For example, we could have 23 industry groups by using the 4-digit GICS, but then we would have, on average, less than 15 stocks in each industry group per month for our benchmark S&P 500 stock sample and further sorting within each industry group becomes less sensible. We show that the nine-sector classification based on the 2-digit GICS works reasonably well for our purpose in this study.

[14]Specifically, they compare GICS to the Standard Industrial Classification (SIC), the North American Industry Classification System (NAICS) and Fama-French (1997) grouping. They show that GICS classifications are significantly better at explaining stock return co-movements, as well as cross-sectional variations in valuation-multiples, forecasted and realized growth rates, R&D expenditures, and various key financial

obtained from various sources: Standard and Poor's publishes the GICS classification of S&P500 stocks on its website. Historical GICS for some companies are available in COMPUSTAT starting from Dec 1994. but the GICS classifications prior to 1999 are backfilled. For stocks in our sample whose GICS are not available from the above two sources, we assign the GICS according to the first three digits of its Industry Classification Code (the *dnum* variable in COMPUSTAT).[15] 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. The resulting 9 sectors are: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Technology and Utilities. This classification is also consistent with the way sector ETFs are formed. Panel C of Table 1 shows the sector break down of our sample both in terms of number of stocks or in terms of market capitalization. The three largest sectors are Consumer Discretionary, Financials and Technology, which together account for almost 60% of the entire sample. 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.

Throughout the study, we obtain prices and returns from CRSP. In computing various portfolio characteristics, we make use of data from COMPUSTAT and TAQ. Finally, we also use stock recommendation and earning announcement data obtained from First Call.

3 The profitability of sector-neutral long-short strategies using S&P 500 stocks

In this section we construct sector neutral long-short portfolio of S&P500 stocks which exploits temporary deviations between the prevailing market prices and fundamentals as measured using information contained in analysts target prices. We choose to focus on the component stocks of the S&P 500 for several reasons: first, S&P 500 stocks receive

ratios.

[15]Specifically, for stocks whose GICS are available from the first two sources, we can observe their *dnum*s and can infer the mapping from *dnum* to sector for these stocks. Making use of this mapping, we can assign a large portion of our sample stocks into sectors. We establish the remaining 150 *dnum*-to-sector mappings by hand based on a detailed sector description provided by Standard and Poor's.

relatively more attention and coverage from analysts. On average, analysts issue target prices for around 350 out of the 500 stocks each month and the average number of target prices per stock each month for S&P500 stocks is 4 – significantly higher than that of the average stock in our sample (2.5). Therefore the consensus target price used to compute $TPER$ for S&P500 stocks is less prone to outliers and presumably more accurate. Second, S&P 500 stocks are more liquid and cheaper to trade which makes the potential implementation shortfall of a trading strategy using S&P 500 stocks less severe, and the result is not likely to be affected by the extremely illiquid stock. Third, the sector assignment of the S&P500 stocks is done by Standard & Poor's and does not rely on a sometimes arbitrary mapping from SIC codes, allowing us more precise sector control. Finally, a variety of S&P 500 index products, such as sector ETFs and futures, are available and allow for exact and cost efficient ways of controlling market and sector risk exposures. Since the GICS (Global Industry Classification Standard) was officially launched by Standard & Poor's and Morgan Stanley Capital International (MSCI) in 1999, we examine the performance of our long-short strategies using S&P 500 stocks from January 1999, a period which also coincides with the beginning of trading for sector ETFs.

3.1 Excess returns and alphas

At the end of each month from Jan 1999 to Nov 2004 and within each sector, we rank the S&P 500 stocks into 9 portfolios according to the current month $TPER$s and label them from 1 to 9 (1 with the highest $TPER$ and 9 with the lowest $TPER$). In line with common practice in the empirical asset pricing literature, we exclude stocks with share prices below five dollars in order to ensure that the results are not driven by small, illiquid stocks or unduly influenced by bid-ask bounce.[16] For each stock, we compute the first month post-formation excess returns (in excess of the equally weighted S&P 500 index return obtained from CRSP). Finally, we equally-weigh the excess returns of all stocks within the same portfolio. These excess returns can be regarded as returns to a portfolio of long-short strategies (long the stocks and short the market). Forming long-short strategies within sectors has two advantages: first, analysts usually specialize in covering stocks by sectors and are presumably more capable of forecasting the relative performance of stocks within the same sector. A long-short strategy within each sector should therefore

[16] As one would expect, this price filter has little impact on S&P 500 stocks. It removes less than 1% of S&P 500 stocks in our sample and hardly changes the results.

directly pick up this skill. Second, to the extent that stocks in the same sector have similar systematic risk (factor risk), a within-sector long-short strategy serves to reduce the exposure to systematic risks which it is not the analysts' comparative advantage to forecast. The results of the analysis are summarized in Table 2.

Panel A reports the average excess returns and risk-adjusted alphas. As one would expect, the excess returns are in general increasing in $TPER$. In portfolio 1 where analysts predict the highest expected one-year-ahead return (relative to all S&P 500 stocks within the same sector), the first month actual excess return is also the highest (90 bps with a t-value of 2.32). On the other hand, portfolio 9 where analysts predict the lowest expected one-year-ahead return (relative to all stocks within the same sector), the first month actual excess return is also the lowest (-87 bps) and more significant (with a t-value of -4.09). The difference between the excess returns of these two extreme portfolios (1 and 9) can be regarded as the return to a portfolio of long-short strategies (within the same sector, long stocks with the highest TPERs and short stocks with the lowest TPERs).[17] The return to the spread portfolio 1-9 is as high as 177 bps with a t-value of 3.55.[18] All the action appears to take place during this first month:[19] If we look at the returns of portfolio 1-9 during the second to sixth month after portfolio formation, none of them are significantly different from zero. Figure 1 contains a graphic representation of this result. Therefore, the first month profit to our long-short strategies is unlikely to be driven by price pressure since it does not reverse in the next 5 months.

However, the significant first month excess return of portfolio 1, 9 and 1-9 might simply result from systematic risk not fully accounted for by our sector controls. We regress the monthly excess returns on the Fama-French (1993) three factors.[20] It turns out that the

[17]This is because we equally weigh the excess returns of stocks in both portfolio 1 and 9. When we compute the difference in these two excess returns, the sector return components get canceled out exactly. This is not true if the excess returns are value-weighted.

[18]About 87% of the S&P 500 stocks are listed in NYSE (NASDAQ accounts for 12% and AMEX accounts for less than 1%). We verify that our results are not driven by NASDAQ stocks in our S&P 500 stock sample. The results hardly changes if we exclude the NASDAQ stocks. For example, the profit in portfolio 1-9 is 174 bp (t-value of 3.50) and the three-factor alpha is 188 bp (t-value of 3.94).

[19]Most of the profit to the long-short strategy (portfolio 1-9) happens in the first of two weeks (110 bp out of 177 bp).

[20]The three factors are: MKT, SMB and HML. MKT is the market return minus risk free rate. SMB is the return to a zero-investment portfolio of longing small stocks and shorting big stocks. HML is the return to a zero-investment portfolio of longing high book-to-market stocks and shorting low book-to-market stocks.

risk-adjusted returns (also known as alpha and defined as the intercept in the regression) are even higher and more significant. In particular, our sector neutral long-short strategy (portfolio 1-9) yields a highly significant (with a t-value of 4.34) three-factor alpha of almost 196 bps. In addition, our long-short strategy within sector helps in reducing the systematic risk. None of the three excess returns load significantly on HML. The factor loadings on MKT and SMB, although significant, are relatively small in magnitude.[21]

To account for momentum risk, we also add in a fourth factor – UMD – in the regression and the results are reported in Panel B of Table 2. The alphas of the three portfolios are higher and more significant (in absolute terms).[22] In particular, the four-factor-alpha of portfolio 1-9 now exceeds 210 bps with a t-value greater than 5, driven mainly by a significant negative loading on the momentum factor. As we shall later see, portfolio 1-9 involves significant long position in recent losers and short position in recent winners – the exact opposite of momentum strategy. For this reason it is not appropriate to include the momentum factor for purposes of risk-adjustment, and we will instead use the conventional Fama-French three factor model throughout the remainder of the paper. This is a conservative treatment in the sense that whenever the three-factor alpha is large and significant, the four-factor-alpha accounting for momentum "risk" will be even larger and more significant.

Figure 2 summarizes our results so far. It shows the monthly time series of the risk-adjusted return to our trading strategy (or the three-factor alpha) and the market excess return. During our sampling period from Jan 1999 to Dec 2004, it is clear that the sector-neutral long-short strategy has a better risk-return tradeoff than the overall market portfolio. The monthly Sharpe ratios of the spread return, the three factor and four factor alphas are 0.41, 0.55 and 0.67, respectively, and are all clearly better than that of the market (0.01) during the same period.[23] [24] A close observation of Figure 2 also shows that

Monthly returns of these three factors are downloaded from Ken French's website.

[21]The 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.

[22]UMD is the return to a zero-investment portfolio of longing past winners and shorting past losers. Monthly returns of the UMD factor are downloaded from Ken French's website.

[23]The factor-model-alpha can be thought of as the excess return to a trading strategy since factors are also excess returns.

[24]¿From Figure 2, it can also be seen that the average annualized alpha increases from 1999 to 2000 and then drops off over the subsequent years until 2004. This is pattern is similar to the investor sentiment factor derived in Baker and Wurgler (2005) and may be an indication that investor sentiment is partly driving the

the alphas usually are higher during January, especially in 2000 and 2001. To ensure that our results are not driven by the "January effect", we also report the excess returns and three-factor-alphas excluding the month of January in Panel B of Table 1. After excluding January, the return and alpha of our long-short strategy (portfolio 1-9) drops in magnitude to 155 bps and 166 bps respectively. However, the standard derivations decrease even more, resulting in higher statistical significance. The t-values of the excess return and alpha now increase to 5.35 and 6.82, respectively. The monthly Sharpe ratios of the spread return, the three factor and four factor alphas excluding January also jump to 0.63, 0.80 and 0.95 respectively. Finally, the time series before 1999 is shaded to highlight the fact that the GICS is backfilled and the long-short strategy was infeasible ex-ante prior to 1999. The performance of our long-short strategy (portfolio 1-9) is slightly reduced (the average alpha drops to 124 bps), partly because of the noise introduced by backfilling the GICS.

It is important to note that sector control is crucial. 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, as shown in Table 3. The long-short portfolio 1-9 (long stocks with the highest $TPER$ and short stocks with the lowest $TPER$) produce a spread of only 79 bps, much smaller than the spread of 177 bps when the long-short position is constructed within sector. In addition, without sector control, the profit becomes more volatile due to its exposure to systematic risk factors, resulting in an insignificant three factor alpha (with a t-value of 1.65).

3.2 Portfolio characteristics and profit after transaction costs

Table 4 reports various portfolio characteristics. The first 12 characteristics are those studied in Jegadeesh, Kim, Krische, and Lee (2004), which have been identified in the previous literature as having predictive power for future stock returns. These 12 characteristics are categorized into 5 groups. The first group contains momentum and trading volume variables including RETP (cumulative market-adjusted return in months -6 through -1 preceding the month of portfolio formation), RET2P (cumulative market-adjusted return in months -12 through -7 preceding the month of portfolio formation), FREV (analysts' earnings forecast revisions), SUE (the most recent quarter's unexpected earnings) and TURN

liquidity events that we identify.

(average daily volume turnover in the six months preceding the month of portfolio formation). The second group contains valuation multiples such as EP (the earnings-to-price ratio) and BP (the book-to-price ratio). The third group contains growth indicators such as LTG (mean analyst forecast of expected long-term growth in earnings) and SG (the rate of growth in sales over the past year). The fourth group contains a firm-size variable – SIZE defined as the natural log of a firm's market capitalization. The fifth group contains fundamental indicators such as TA (total accruals divided by total assets) and CAPEX (capital expenditures divided by total assets). Detailed descriptions of each of the 12 characteristics and their construction can be found in Jegadeesh, Kim, Krische, and Lee (2004).

Apart from these 12 characteristics, we also compute three liquidity-related variables. The first variable is a price impact measure – Pimpact – which measures the average percentage change in price caused by round-trip-trade of 1 million dollar worth of the stock within an hour. It is constructed following the technique described in Breen, Hodrick, and Korajczyk (2002). The second variable is a bid-ask spread measure – Pspread – defined as the average difference between current ask and bid divided by the midpoint. Both Pimpact and Pspread are computed using intraday data from TAQ during the month of portfolio formation (i.e. the month immediately prior to the holding period). The third variable is liquidity measure – Amihud, as discussed in Amihud (2002).[25] Finally, we also report Price (the closing price at the end of the month of portfolio formation), RET1M (the return during the month of portfolio formation) and $TPER$.

Table 4 shows that $TPER$ in general increases with growth indicators. If a firm has experienced high sales growth (SG) over the past year or if its long term growth rate is expected to be high (as captured by LTG), its stock is more likely to be associated with a higher $TPER$. This is consistent with Jegadeesh et. al. (2004)'s finding that analysts generally prefer "glamour" stocks with higher growth potential. In addition, $TPER$ is generally decreasing in past returns (RETP, RET2P and RET1M), not too surprising since recent losers (winners) are likely to trade at lower (higher) prices and price enters denominator when computing $TPER$. Consistent with this explanation, the average trading price for stocks in portfolio 1 is about $32 – much lower than that of stocks in portfolio

[25]To compute the Amihud measure, on each trading day, we first compute the ratio between absolute daily return and the daily dollar trading volume. This ratio is then averaged during the month to get the Amihud liquidity measure.

9 which is \$45. Finally, the SIZE and BP of portfolio 1 and 9 are similar, which explains why our long-short strategy (portfolio 1-9) has small factor loadings on SMB and HML.

In general, the two extreme portfolios have higher than average transaction cost measure, which means they are more illiquid than the average stock. The liquidity variables in Table 4 also allow us to answer a more interesting question: whether the profit of our long-short strategy can overcome the transaction costs? On one hand, we expect low average transaction costs since we are focusing on stocks in the S&P 500 index and we have excluded penny stocks. On the other hand, our long-short strategies involve portfolio rebalancing each month, which potentially could amplify the transaction costs and quickly wipe out any "paper" profits. To gauge the magnitude of the transaction costs, we focus our attention on portfolio 1 and 9. On average, there are 33 stocks in each of the two portfolios each month and the monthly portfolio turnover ratio is 73.7% and 80.4% for portfolio 1 and 9 respectively. Therefore, an estimate of transaction cost (bid-ask spread + price impact) for portfolio1 is: 73.7% $\times$ $(48.3 + 18.3) = 49.1$ bps. For portfolio 9, it is 80.4% $\times$ $(37 + 14.6) = 41.5$ bps.[26] The transaction costs are considerably smaller than the three-factor alphas of 93 bps and 103 bps. Altogether, the sector neutral long-short strategy (portfolio 1-9) yields a risk-adjusted profit net of transaction costs of 105 bps $(196 - 49.1 - 41.5)$ per month, or 12.6% per year which is both statistically and economically significant. In addition, the transaction cost can be further reduced by over-weighing more liquid stocks and under-weighing less liquid stocks as in Korajczyk and Sadka (2004).

Another interesting question to ask is whether $TPER$ has incremental predictive power over and above other predictive variables, in particular the 12 characteristics that are studied in Jegadeesh, Kim, Krische, and Lee (2004). We examine this question using cross-sectional regressions. During each month from Feb 1999 to Dec 2004, we run a cross-sectional regression of the S&P500 stocks' returns on the 12 characteristics studied in Jegadeesh et.al. (2004) and $TPER$. There are on average 250 S&P 500 stocks in each cross-section with the complete 13 characteristics. All variables are cross-sectionally demeaned so the intercept term is zero. In addition, the 13 RHS variables are also standardized so the regression slope coefficient can be interpreted as the impact on return of a one standard deviation change in the variable. The slope coefficients are then averaged across

[26]The implicit assumption behind this calculation is that we trade 1 million dollar worth of each stock within an hour

time and are reported in Panel A Table 5. The robust t-value is computed using Newey-West autocorrelation adjusted standard error with 12 lags. Clearly, $TPER$ has incremental explanatory power even in the presence of other predictive variables. In addition, if we apply sector control by first demeaning all variables within sector, $TPER$ becomes even more significant as can be seen in Panel B. Similar results are obtained in the larger full sample.

3.3 Are the profits driven by past returns or past target price changes alone?

$TPER$ is defined as a ratio between target price and market price; therefore, its current level is determined jointly by past return and past revision in target price. Both variables have been documented to be related to future return, so we want to examine whether past return or past target price revision alone drives our results.

Previous studies have shown that a change in market price (past return) or change in target price alone is associated with future return. For example, Jegadeesh (1990) has documented strong short-run stock return reversal in at horizons of 1 month or less. This is consistent with our finding as our long-short portfolio 1-9 involves long position in past losers and short position in past winners. However, short-term return reversal alone does not drive our results. Table 6 reports the profits and alphas to alternative sector-neutral long-short trading strategies based on the same S&P500 stock sample. For the purpose of comparison, the results of our long-short strategy based on $TPER$ are reproduced in column 2. Column 3 shows the results to a long-short strategy based on the short-term return reversal. Specifically, we form portfolios by sorting the S&P 500 stocks within sectors based on the past 1 month return alone, and then long the past losers and short the past winners. The loser-minus-winner return spread is 122 bps and significant (t-value of 2.24). However, once adjusted for risk using the Fama-French three factors, the significance disappears. The three-factor-alpha is only 90 bps with a t-value of 1.62.[27] This result differs from the previous literature on reversal effects mainly because we here restrict attention to the set of stocks receiving analyst coverage so that very few extremely small stocks are in our sample.

[27] We get comparable but weaker results by sorting on the past 3 month return. In addition, the profit and alpha are even smaller (108 bps and 75 bps per month) if there is no sector control.

Changes in target prices are known to be positively related to future returns (Brav and Lehavy 2003, Asquith, Mikhail and Au 2005). This relationship is also evident in our S&P 500 stock sample. We examine the most recent target price change in the past-three-month period for each stock in our 9 within-sector $TPER$-sorted portfolios. If the current target price exceeds 1.05× last target price, we classify the change as an upgrade; if the current target price is smaller than 0.95× 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 3rd and 2nd month preceding the current month, we classify it as missing. We then report the percentage of upgrade, downgrade, reiteration and missing for each portfolio in Table 7. As one would expect, S&P 500 stocks receive frequent target price coverage: less than 1.5% of these stocks have a target price during the current month but none during the previous two months. The percentage of upgrade in target price increases monotonically with $TPER$. In portfolio 1, which has the highest $TPER$ and first one month return, the recent target price changes are dominated by upgrades (percentage of upgrade and downgrade are 55.4% and 22.0% respectively). The reverse is true for portfolio 9 where the majority of the stocks suffered recent downgrades (percentage of upgrade and downgrade are 19.7% and 56.7%, respectively). However, analysts' revision in target price alone does not drive the future return. Defining the change in the target price DTP_t as $\Delta TP_t / TP_{t-1}$ and sorting stocks into 9 portfolios based on DTP within sectors does not yield any significant portfolio return spread for our S&P 500 stock sample. The results are provided in Column 4 in Table 6.[28]

Finally, we examine a strategy based on both past return and target price revision. Within each sector, we conduct a 3 by 3 independent sort based on DTP and the past one month return. We then go long past losers with high DTP and short past winners with low DTP. This long-short strategy now generates a significant profit of 156 bps per month (t-value of 3.00) and a significant alpha of 142 bps per month (t-value of 2.59), (see Column 5 in Table 6).

In summary, long-short strategy based on price change or target price revision alone does not produce a significant risk-adjusted profit even after controlling systematic risk at the sector level. To make the strategy profitable, we need to combine the information

[28]The computation of DTP restricts us to a subsample of our S&P500 stocks where there are target price announcements during the preceding month. We verify that the profit to our $TPER$-based strategy hardly changes when we move to this subsample.

embedded in both price and target price.

3.4 Are the profits driven by earning announcements or stock recommendations?

Analysts provide investors with information in addition to target prices such as earning forecast and stock recommendations, which are known to affect future returns.

To make sure our results are not driven by pure Post-Earning Announcement Drift (PEAD), we examine stocks in each of the within-sector $TPER$-sorted portfolios of S&P 500 stocks for which there was no earning announcement during the portfolio formation period. The exact time for each earning announcement is obtained from First Call Historical Database (FCHD). We report the excess return and the three-factor-alpha for the sub-sample with no earning announcement in Table 8. On average, 58% of the target price coverage occur during a month with no earning announcement. This percentage is quite stable across all $TPER$-sorted portfolios for our S&P 500 stock sample (although it is slightly higher for the extreme portfolio 1 and 9). Our results do not seem to be driven by delayed reaction to earning announcement (or post-earning announcement drift). If we focus on the subsample with no earning-announcement during the month of portfolio formation, the profit and three-factor alpha not only do not disappear, but become even higher (207 bps and 217 bps respectively).

To show that our results are not driven by stock recommendation alone, we construct alternative sector-neutral long-short strategy based on the level of stock recommendations and revisions to stock recommendations. Specifically, from Jan 99 to Dec 04, we focus on stocks in our S&P 500 sample where there was 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 recommendation within sectors.[29] Sorting on the level of recommendation does not seem to work; the long-high-recommendation-short-low-recommendation produces a loss (see Column 6 in Table 6), consistent with the findings in Boni and Womack (2005). We also look at a sub-sample of stocks where there was also stock recommendation announcements during the 3rd or 2nd month preceding

[29] $TPER$ and the level of stock recommendation are clearly positively correlated. The rank correlation between these two variables is about 0.15 for both the S&P 500 sample and the full sample. However, the fact that the correlation is less than one indicates that target price and stock recommendation do not contain the exact same information.

the current month so we can compute the most recent revision in recommendations during the past three month before portfolio formation. We construct nine portfolios sorted on revision in recommendation within sectors in this sub-sample. Although the long-upgrade-short-downgrade portfolio produces a profit on average, the profit and alpha are not significant.[30] Finally, we examine a strategy based on both past return and recommendation revision. Within each sector, we conduct a 3 by 3 independent sort based on past one month return and the most recent revision in recommendation. We then long past losers with upgrades and short past winners with downgrades. This long-short strategy does not generate significant profit and alpha either (see in Column 7 of Table 6).

3.5 A liquidity interpretation

Figure 3 plots the average evolution of market price (solid line) and target price (dashed line) one month prior to (t = -1) and after (t = 1) portfolio formation (t = 0) for each of our nine within-sector $TPER$-sorted portfolios of S&P 500 stocks. Stock price at portfolio formation (t = 0) is normalized at 1. Clearly, for portfolio 1 and 9, where there is significant excess return during the first month, the market price and target price were moving in opposite directions in the recent past. For portfolio 1, the market price drops despite an upward revision in the median analyst's target price, resulting in a larger gap between the target price and market price as captured by a large $TPER$. For portfolio 9, the reverse is true: the market seems to ignore the median analyst's downgrade in target price leading to a negative $TPER$ at portfolio formation.[31] In portfolio 1 and 9, the adjustment in target price during the first month seems to be much larger than that of the market price. However, our results show that the correction in market price, although relatively small in magnitude, is still significant and can be taken advantage of by implementing the appropriate long-short strategies.

We have shown that a change in market price or target price alone does not drive our results. Only when target price and market price changes are combined in the $TPER$ variable can we identify significant future price movements. A recent change in price could

[30]We again verify that the profit to our $TPER$-based strategy hardly changes when we move to these two subsamples where we apply filters based on the availabilities of past recommendations.

[31]Brav and Lehavy (2003) use a cointegration analysis to show that the correction of the short-run deviation from the long-run relation between the two is dominated by revisions to analyst's target prices, as is also evident from Figure 3.

be driven either by changes in fundamentals that are likely to be permanent, or by investor sentiment or liquidity and therefore likely to be temporary in nature. By looking at analysts' target price revision during the same period of time, we are able to distinguish between these two possibilities. If target price and market price were moving in opposite directions, it is more likely that recent changes in market price is driven by liquidity and will be corrected in the near future. This intuition is directly supported by the results of the double-sort based on past return and target price revision (see in Column 4 in Table 6). Past losers who have experienced recent target price upgrades have significant positive excess returns during the first month on average, while past winners who have experienced recent target price downgrades have negative excess returns during the first month on average. Finally, sector control refines the result because it eliminates systematic risks that have a similar impact on all stocks within the same sector and at the same time preserves the relative strength information contained in analyst's price targets.

Consistent with this explanation, the two extreme portfolios (1 and 9) indeed display a higher than average bid-ask spread, price impact measure and Amihud liquidity measure as seen from Table 4. However, in order to make sure this pattern is not driven by a few illiquid stocks always included in portfolio 1 or 9, we compute the average percentage changes in a stock's bid-ask spread (Pspread), price impact measure (Pimpact) and Amihud liquidity measure (Amihud) when the stock enters portfolio 1 or portfolio 9.[32] Panel C of Table 9 clearly shows that stocks are more illiquid during periods when they are in portfolio 1 or 9. In addition, Figure 3 also plots the turnover ratio (defined as trading volume divided by number of share outstanding) across the three months (portfolio pre-formation, formation and post-formation). The numbers are provided in Panel A of Table 9. For both portfolio 1 and 9, we see increases in trading volume during the portfolio formation month (although this increase is only statistically significant for portfolio 1). This is consistent with the liquidity-driven price-fundamental-divergence interpretation as in Campbell, Grossman, and Wang (1993) and the empirical evidence in Conrad, Hameed, and Niden (1994). Finally, the changes in order imbalance measures from the portfolio formation month to the month after provide further supporting evidence for the liquidity-based interpretation. We examine two order imbalance measures. $OIB1$ is the buyer-initiated shares purchased less than the seller-initiated shares sold (daily). $OIB2$ is

[32]When computing the percentage change in Pspread, we adjust for the change in price by multiplying the percentage change by $\sqrt{p_t/p_{t-1}}$.

$OIB1$ scaled by the total number of shares traded. Both measures are calculated from the intraday database TAQ and first averaged within each calendar month and then within each $TPER$ sorted portfolio. The results are provided in Panel B of Table 9. For portfolio 1, there are significant increases in both measures, indicating more buyer-initiated trades during the month after portfolio formation, which is consistent with a initial price depression during portfolio formation and later price recovery. For portfolio 9, the reverse happens, also consistent with its price reversal pattern.

The target price reflects the opinion of the analyst while the market price reflects the opinion of the market. They differ the most in portfolio 1 and 9. It is reasonable to assume that the degree of information asymmetry is also high for stocks in these two extreme portfolios. In order to protect themselves against this information asymmetry, market makers raise the trading cost of these stocks, making them more illiquid. Panel C of Table 9 provides additional supporting evidence for this explanation. For each stock 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).[33] For the same stock, the dispersion measure is a lot higher when it enters portfolio 1 or 9 as compared to when it does not. 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.

If liquidity temporarily drives a wedge between price and fundamental and the near term correction in price results in the profit and alpha of our sector-neutral long-short strategies, we would then expect the size of the alpha to be correlated with the magnitude of illiquidity (as measured by Pimpact, Pspread and Amihud) in the previous month. This is exactly the case in our S&P 500 sample. Figure 4 plots the time series of price impact measure (Pimpact), bid-ask-spread (Pspread), the Amihud liquidity measure (Amihud) and the three-factor-alpha of next-month excess returns from Jan 99 to Nov 04 for portfolio 1 and 9 separately. Evidently, the alpha moves together with liquidity measures across time. The correlation between alpha and Pimpact is around 0.23, the correlation between alpha and Pspread is about 0.36 and the correlation between alpha and Amihud is about 0.26. These correlations are similar across the two portfolios as seen in Table 10.

The divergence between prices and fundamentals in this case is not corrected imme-

[33]We need the stock to have at least two target prices during the first 25 calendar days in order to compute this dispersion measure.

diately but persists for a few weeks even for S&P500 stocks. There could be several explanations for the delay. 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 -6.2% during September 2001. Third, the liquidity event may produce self-reinforcing externalities as described in Coval and Stafford (2005) 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 – 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.

4 Full sample results

We now extend our analysis to the full sample from Dec 1996 to Dec 2004. We apply the same price filter to exclude stocks traded below or at $5, or about 6% of the entire sample. We also filter out stocks whose $TPERs$ are in the top decile each month, which corresponds to an average cutoff level of $TPER = 70\%$.[34] The mean $TPER$ for such stocks is 106.3% and the median is 95%. Such high $TPER$ could be due to either data error or an extremely bullish view on the part of the analyst, which should not be regarded as an accurate measure of "fundamental" value.[35] We manage to obtain sector classification (GICS) from either S&P website or COMPUSTAT for 72% of the stocks in our sample. We have to manually assign GICS for the remaining 28% of the stocks, which may introduce some noise in the results.

At the end of each month from Dec 1996 to Dec 2004 and within each sector, we rank stocks into 9 groups according to the current month $TPER$s and label them from 1 to 9

[34]The top 10% $TPER$ filter is arguably arbitrary. We verify that the results are qualitatively similar even if we do not apply such filter, although the profit becomes smaller and less significant due to the noise embedded in these extremely high $TPER$s.

[35]We also verify that stocks in the highest-$TPER$ decile have the lowest analyst coverage and the highest target price dispersion measure, indicating that they are extremely noisy measures of "fundamental" value.

(1 with the highest $TPER$ and 9 with the lowest $TPER$). For each stock, we compute its future excess returns (in excess of the equally-weighed return of all stocks in the same sector). Finally, we equally-weigh the excess returns of all stocks within the same portfolio. The results are in Table 11. In general, the excess returns and three factor alphas are still increasing with $TPER$. This is especially true for portfolios with $TPER$ less than the average. Our sector-neutral long-short strategies correspond to portfolios 1, 9 and 1-9. The excess returns and three-factor alphas are significant for each portfolio. In particular, the spread portfolio 1-9 yields an excess return of 130 bps (t-value of 3.29) and a three-factor alpha of 109 bps (t-value of 3.11).

We repeat our previous analysis on the S&P 500 stock sample on the full sample and most of the results stay the same. First, all the action seems to happen during this first month: if we look at the returns of portfolio 1-9 during the second to sixth month after portfolio formation, none of them is significant different from zero (Table 12). Second, sector control is crucial. If we rank the $TPER$ across all stocks rather than within each sector for the full sample and compute the first month post-formation portfolio excess return, they are no longer significant (Table 13). Third, our results are not driven by the past return or the change in target price alone. Sorting our full sample stocks based on past 1 month return does not produce a significant return spread (Column 3 in Table 14). Although portfolios with higher $TPER$ experience more upgrade in target price (Table 15), a simple sorting on change in target price DTP does not produce a significant return spread (Column 4 in Table 14). However, a double sort combining past returns and DTP generates comparable profit as in our $TPER$-based long-short strategy (Column 5 in Table 14). Fifth, our results are not driven by post-earning announcement drift. The results hardly change if we restrict ourselves to a sub-sample of stocks where there was no earning-announcement during the month of formation (Table 16). Sixth, our results are not driven by stock recommendation. Although sorting on level of stock recommendation also produces significant spread profit and alpha (Column 6 in Table 14) in the full sample, the profit and alpha are smaller in size than those produced by sorting on $TPER$. In addition, as in the S&P 500 stock sample, sorting on recent revision in stock recommendation or a double sort based on both past return and recommendation revision does not produce significant profit or alpha (Column 6 and 7 in Table 14).

Table 17 reports mean and median of various portfolio characteristics. As before, $TPER$ in general increases with growth indicators (SG and LTG). In addition, $TPER$ is generally decreasing in past returns (RET1M, RETP and RET2P) and in price. The portfolio associated with the highest $TPER$ is also the most illiquid with large price impact measure and bid-ask spread. Table 18 shows $TPER$ has incremental value on top of the other 12 characteristics that are studied in Jegadeesh, Kim, Krische, and Lee (2004). $TPER$ is highly significant (t-value of 3.65) with the presence of other characteristics in the cross-sectional regression. If we run the regression with sector control (first demeaning all variables within sector), $TPER$ becomes more significant (t-value of 5.56). This is consistent with our hypothesis that analysts are more skilled in relative valuation within sector.

Finally, Figure 5 plots the evolution of turnover and prices across the three months (pre-formation, during formation and post-formation) for the full sample. The patterns of target price and market price dynamics for the full sample are almost identical to those in the S&P 500 stock sample (Figure 3). Clearly, there are increases in turnover for portfolio 1 and 9 where price and fundamental diverge the most. In fact, the increase in turnover is the most significant (t-values above 5) for these two portfolios as compared to the remaining 7 portfolios (Panel A of Table 19). In addition, portfolio 1(9) experienced significantly more buyer-initiated(seller-initiated) trades during the month after portfolio formation (Panel B of Table 19). As in the S&P 500 sample, stocks become more illiquid and their target price forecasts become more dispersed when they are in portfolio 1 and 9 (Panel C of Table 19).

4.1 Performance in sub-samples

The most important ingredient needed for the success of the sector-neutral long-short strategy is the availability of an accurate measurement of fundamental value. It is therefore natural to conjecture that the largest profits are to be found in the subset of stocks for which analysts' forecasts are most accurate. Similarly one would expect higher profits for less liquid stocks. With this in mind, we turn to investigating the performance of this strategy within subsamples.

Table 20 shows the performance for stocks listed in NYSE and NASDAQ.[36] Although our sector-neutral long-short strategy produces significant profit and alphas across both exchanges, the alpha is more significant for NYSE stocks (t-value of 3.63) than NASDAQ stocks (t-value of 2.61). One possible explanation is that companies listed in NYSE

[36]There are too few AMEX-listed stocks in our sample. Shown in Panel A of Table 1, AMEX-listed stocks account for only 3% of our sample.

tend to be relatively more mature and exhibit more value than growth so analysts may be more confident of the relative strength of companies in the same sector, resulting in a better performance of the long-short strategy. Another explanation is offered by Glosten and Milgrom (1985) and Glosten (1989) who argue that liquidity effects in the NYSE and NASDAQ markets will differ depending on the degree of asymmetric information based trading. In particular, the NASDAQ's competitive market makers translates into higher liquidity as long as the asymmetric information is not too severe, an explanation consistent with our strategy yielding more profits for NYSE stocks.

Table 21 shows the performance for value and growth stocks separately. Each month, we sort stocks in our sample into three groups according to their book-to-market ratios, we then report the performance of our sector-neutral long-short strategies in the group with the highest book-to-market ratio (value stocks) and the group with the lowest book-to-market ratio (growth stocks). We find the performance much better on the value stocks than the growth stocks. The alpha is 151 bps and very significant (t-value of 3.96) for value stocks, and is smaller (119 bps) and insignificant (t-value of 1.80) for growth stocks. 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 than for growth firms.

Table 22 shows the performance for small and big stocks separately. Each month, we sort stocks in our sample into three groups according to their market capitalizations. We then report the performance of our sector-neutral long-short strategies in the group with the smallest stocks and the group with the largest stocks. We find the performance better on the small stocks than the large stocks. The alpha is 178 bps and very significant (t-value of 3.87) for small stocks, and is smaller (76 bps) and insignificant (t-value of 1.62) for big stocks. This is consistent with our liquidity explanation. Since small stocks are more illiquid in general, the reward for providing liquidity should be higher for small stocks. Close examination of the big stock portfolio show that big non-S&P 500 stocks have significantly lower analyst coverage and book-to-market ratios but significantly more uncertain target prices than the big S&P 500 stocks, partly explaining why the strategy does not work well beyond the S&P500 universe within the large stock category. Since size and book-to-market ratios are empirically negatively correlated, we also examine the performance of our sector-neutral long-short strategies within 6 size and book-to-market doubled sorted portfolios in Table 23. Within each size group, only the value stock subsample produces significant profit and alphas. Not surprisingly, the small-value stock portfolio now produces a highly significant profit of 242bps. In addition, this profit does not load on any of the three factors, resulting in a large alpha of 234bps with comparable level of significance (t-value of 4.61).

Table 24 shows the performance across 9 sectors. In general, the alphas are significant in Energy, Materials, Industrials, Consumer Discretionary and Financials sectors and not significant in the remaining Consumer Staples, Health Care, Technology and Utilities sector.

5 Conclusion

It is well established that analysts' target prices are noisy measures of fundamental values. The key insight of this paper is that one needs to properly control for the systematic risk factors which the analysts may have very little skill in forecasting. A simple, yet remarkably effective, way of accomplishing this is to rank the discrepancy between price and fundamental ($TPER$) among stocks in the same sector classified using the S&P GICS classification. Using only S&P 500 stocks, a simple sector-neutral long-short strategy earned a statistically significant average risk adjusted profit of almost 200 bps per month during the period from 1999 to 2004, much higher than most realistic transaction cost estimates. A close examination shows that the profit is likely a result of a correction of a temporary divergence between prices and fundamentals. Such divergences are usually thought of as an indication of illiquidity. The profit to our long-short strategy can therefore be interpreted as partly being a reward for providing liquidity. Indeed, we find the profit to be highly correlated with a number of popular cross-sectional measures of liquidity such as the bid-ask spread, price impact, the Amihud liquidity measure and increases in turnover. Interestingly the divergence persists for several weeks even in the case of S&P500 stocks. We argue that the delayed price correction can be explained in part by limits to arbitrage and capital immobility as well as, in some cases, self-reinforcing externalities associated with large asset sales.

The results extend to the full sample of stocks with target prices over the sampling period from 1997 to 2004. In the bigger sample, we show that the long-short strategy works particularly well in the value and small value market segments. We argue that this is to be expected because analysts' in general are able to estimate fundamental values for value firms more precisely due to a higher fraction of tangible assets. For small firms, liquidity effects in general are more severe, leading to a higher liquidity premium for the asset class.

The simple long-short strategy can be refined further. In a portfolio optimization framework, Da and Schaumburg (2005) shows the optimal portfolio incorporating target price information consists of the market portfolio plus various refined long-short strategies. The weights on these strategies depend on not only the level of target price, but also the uncertainty associated with it, which can be empirically proxied by the our dispersion measure.

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A Figures and Tables

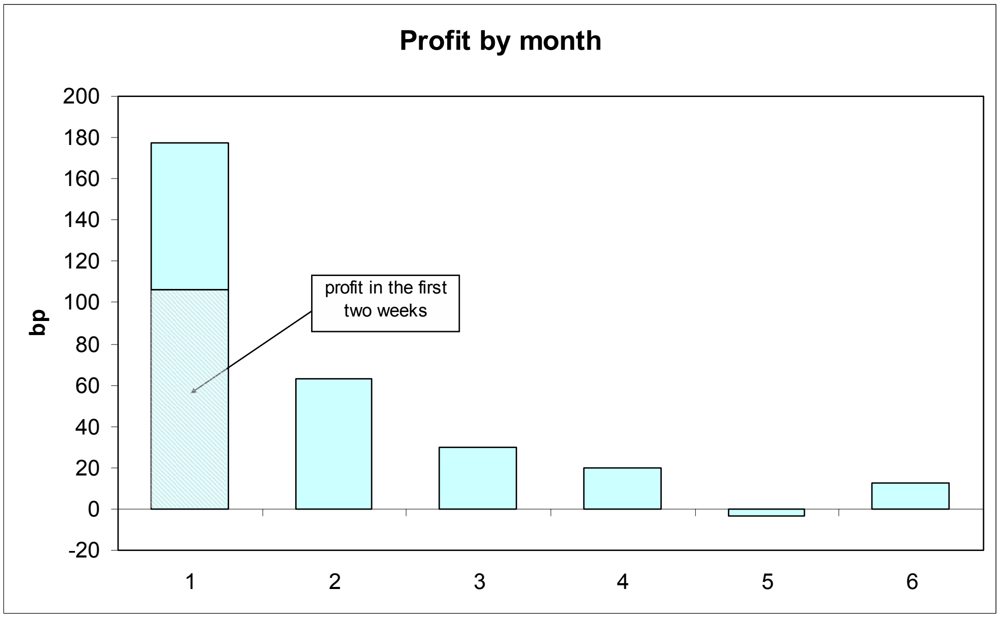

Figure 1: Profit to the sector-neutral long-short strategy (using S&P 500 stocks) over time. We plot the average monthly profit to our sector-neutral long-short strategy (using S&P 500 stocks) during each of the first 6 months after portfolio formation.

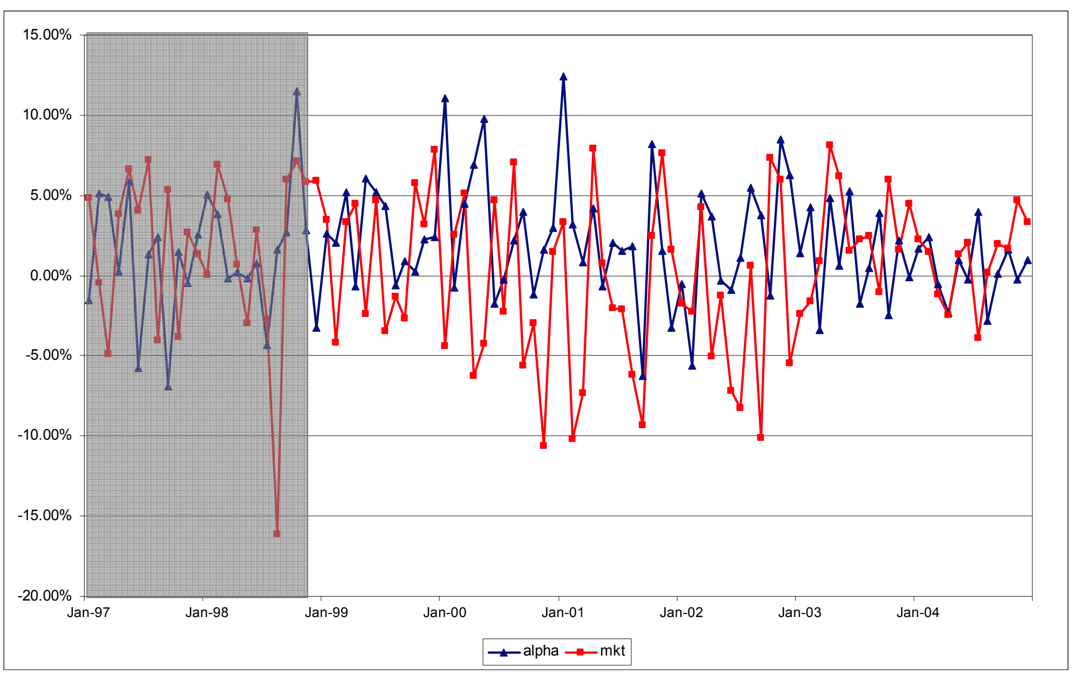

Figure 2: Time series of the market excess returns and the three-factor alphas. We plot the monthly three-factor alphas of long-short strategy using S&P 500 stocks and the market excess return from Feb 1997 to Dec 2004. The time series before 1999 are plotted in shaded area, highlighting the fact that GICS is backfilled before 1999 and the long-short strategy cannot be implemented before 1999.

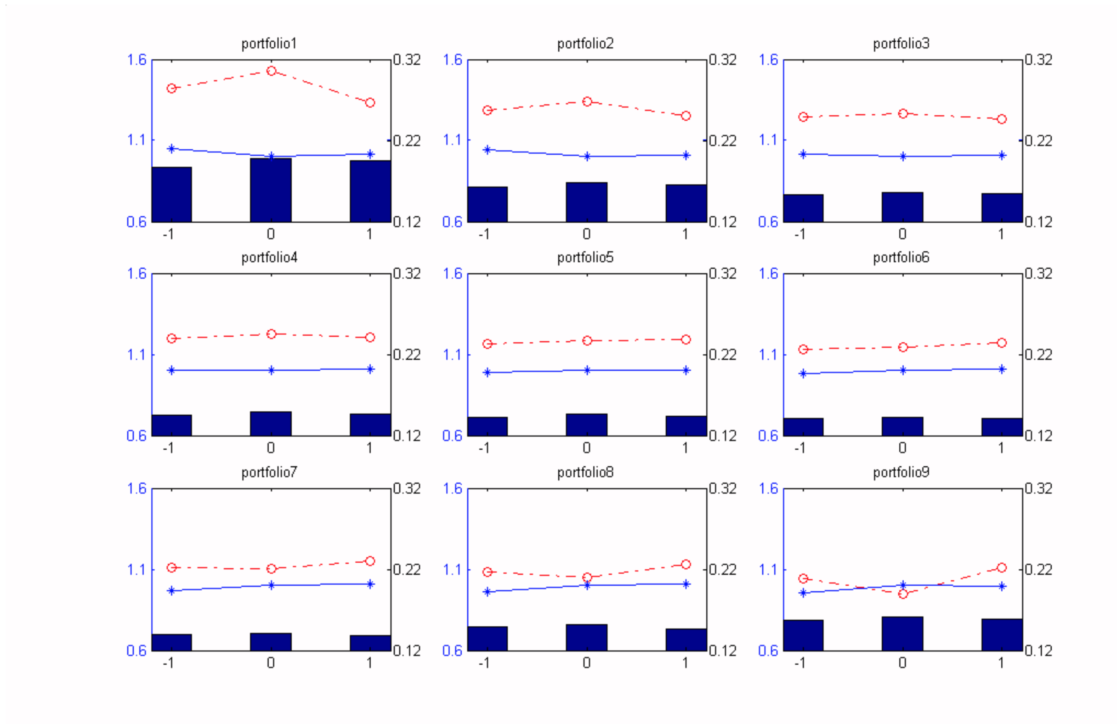

Figure 3: Turnover and price evolution of the 9 TPER-sorted portfolios (S&P 500 stock sample). We plot the evolution of market price (solid line) and target price (dashed line) one month prior to (t = -1) and after (t = 1) portfolio formation (t = 0) for each of our nine portfolios of S&P 500 stocks. Stock price at portfolio formation (t = 0) is normalized at 1. Monthly turnover ratios defined as (trading volume divided by number of share outstanding) are represented by the bars.

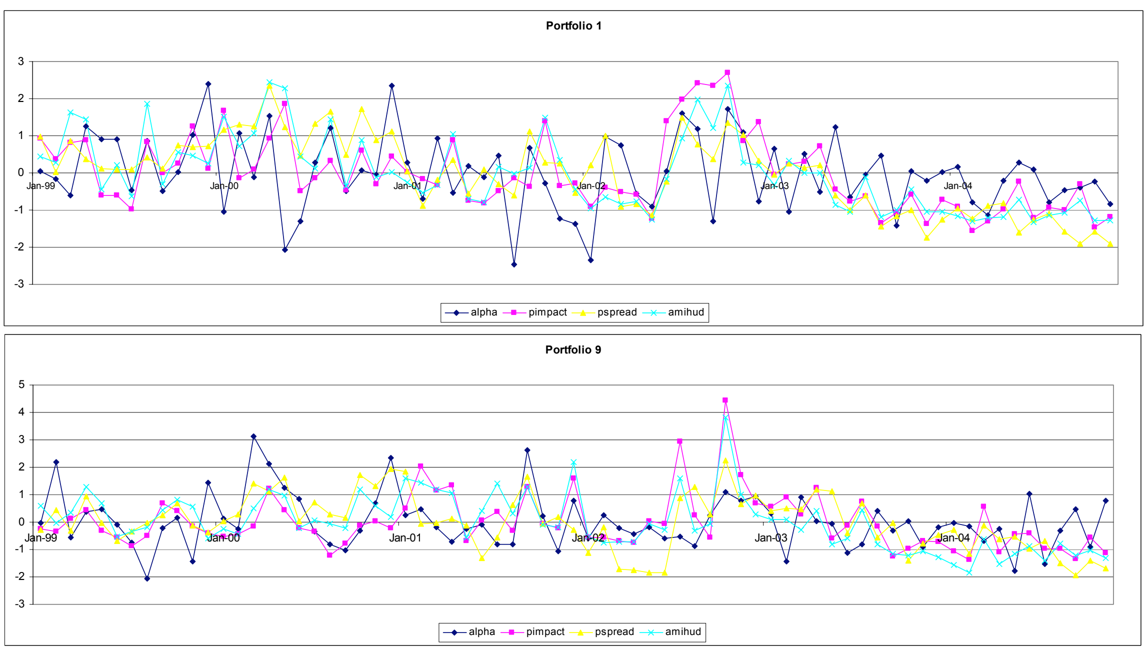

Figure 4: We plot the time series of price impact measure (Pimpact), bid-ask-spread (Pspread), the Amihud liquidity measure and the three-factor-alpha of next-month excess returns to two TPER-sorted portfolios using S&P 500 stocks from Jan 99 to Nov 04. Portfolio 1 is where we long the highest TPER stocks and short the S&P 500 equally-weighted index and portfolio 9 is where we long the S&P 500 equally-weighted index and short the lowest TPER stocks. All time series are standardized to have zero means and unit standard deviations.

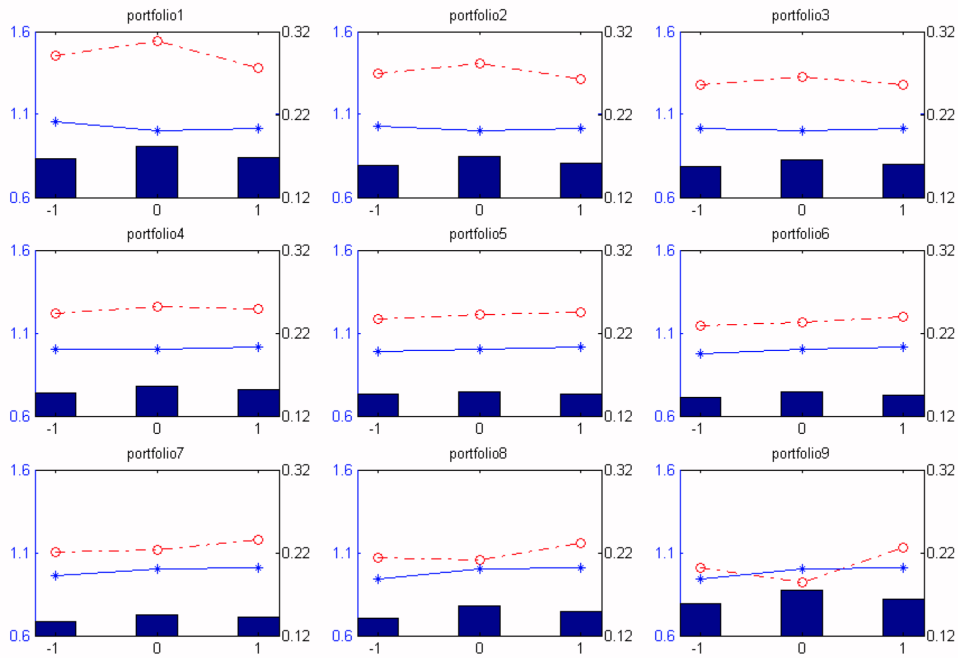

Figure 5: Turnover and price evolution of the 9 TPER-sorted portfolios (full sample). We plot the evolution of market price (solid line) and target price (dashed line) one month prior to (t = -1) and after (t = 1) portfolio formation (t = 0) for each of our nine portfolios of the full sample. Stock price at portfolio formation (t = 0) is normalized at 1. Monthly turnover ratios defined as (trading volume divided by number of share outstanding) are represented by the bars.

Table 1: Data Description

From Dec 1996 to Dec 2004, at the end of each month, we include stocks where there is 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 US 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 also consistent with the way sector SPDRs are formed and traded.

Panel A: Basic sample characteristics

year	number of stocks per month	number of target price per stock per month	Mean TPER	Median TPER	Median mktcap (in million $)	NYSE	AMEX	NASDAQ	% of all stocks in terms of mktcap
1996	1095	1.75	39.1%	23.1%	754	56.0%	3.3%	40.7%	55.5%
1997	1205	2.02	35.7%	21.5%	799	57.6%	3.5%	38.9%	58.2%
1998	1641	2.37	45.6%	28.8%	718	55.7%	3.5%	40.8%	68.6%
1999	1675	2.45	44.7%	28.6%	795	54.9%	3.1%	42.0%	73.6%
2000	1759	2.59	63.7%	36.4%	983	51.5%	2.6%	45.9%	78.5%
2001	1761	2.72	50.5%	26.4%	920	50.9%	2.3%	46.8%	80.5%
2002	1738	2.84	39.9%	23.2%	916	53.3%	2.3%	44.5%	83.1%
2003	1677	2.49	19.7%	13.4%	1,022	54.9%	2.6%	42.5%	82.8%
2004	1796	2.51	18.4%	13.2%	1,216	53.2%	2.8%	44.0%	83.0%

Panel B: Index coverage in 2004

	S&P 500	Russell 1000	Russell 3000
number of stocks included	496	980	2782
percentage	99.2%	98.0%	92.7%

Panel C: Sector breakdown

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Technology *	Utilities
in terms of number of stocks									
1996	5.8%	6.3%	12.9%	19.6%	5.8%	11.9%	14.6%	20.6%	2.6%
1997	4.6%	6.6%	13.1%	19.0%	5.4%	10.3%	16.8%	20.9%	3.3%
1998	4.8%	6.0%	13.9%	18.6%	5.2%	10.2%	17.0%	20.8%	3.4%
1999	4.5%	5.7%	13.0%	18.4%	4.7%	9.4%	17.3%	23.4%	3.5%
2000	4.7%	5.5%	11.9%	17.1%	4.0%	9.6%	17.0%	27.0%	3.3%
2001	4.9%	5.1%	12.1%	16.6%	3.6%	11.5%	17.9%	25.1%	3.4%
2002	4.4%	5.1%	12.2%	17.6%	3.9%	11.2%	19.1%	23.2%	3.3%
2003	4.6%	5.3%	12.2%	17.5%	4.0%	11.1%	21.2%	20.6%	3.5%
2004	5.4%	5.5%	12.0%	17.4%	3.7%	11.3%	20.6%	20.9%	3.3%
in terms of mktcap									
1996	5.5%	5.1%	11.9%	15.8%	12.1%	12.8%	13.9%	20.9%	2.0%
1997	4.4%	5.6%	12.3%	15.1%	11.6%	11.9%	14.7%	22.1%	2.3%
1998	3.4%	4.1%	12.3%	15.6%	10.2%	12.7%	15.9%	23.3%	2.6%
1999	2.9%	2.9%	10.7%	14.3%	7.6%	12.3%	15.7%	31.6%	2.0%
2000	4.4%	2.1%	8.9%	11.1%	5.1%	11.3%	15.4%	39.7%	1.9%
2001	5.6%	2.5%	10.0%	11.9%	6.4%	14.0%	20.1%	26.6%	2.8%
2002	5.7%	3.0%	9.2%	13.8%	8.2%	13.7%	21.7%	21.9%	2.7%
2003	6.8%	3.3%	9.8%	14.0%	7.0%	13.4%	22.4%	20.7%	2.6%
2004	8.1%	3.6%	9.6%	14.2%	6.9%	11.9%	22.6%	20.3%	2.9%
S&P 500 in terms of mktcap									
2000	6.56%	2.29%	10.54%	10.26%	8.09%	14.33%	17.31%	26.83%	3.78%
2001	6.34%	2.61%	11.28%	13.14%	8.24%	14.35%	17.81%	23.11%	3.12%
2002	6.00%	2.83%	11.53%	13.44%	9.47%	14.93%	20.45%	18.48%	2.85%
2003	5.80%	3.04%	10.90%	11.30%	10.98%	13.31%	20.64%	21.19%	2.84%
2004	5.60%	6.40%	11.40%	17.40%	7.20%	11.00%	16.40%	18.00%	6.60%

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

Table 2: Returns on within-sector TPER-sorted portfolios of S&P 500 stocks

At the end of each month from Jan 1999 to Nov 2004 and within each sector, we rank S&P 500 stocks in our sample into 9 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 excess returns (in excess of the equally weighted S&P 500 index return). Finally, we equally-weigh the excess returns of all stocks in the same portfolio. Panel A reports the average excess returns and risk-adjusted alphas (using the Fama-French three-factor model). Panel B reports the four-factor alphas and the results after excluding January. All returns and alphas are monthly.

Panel A: Excess returns and three-factor alphas of TPER-sorted portfolios

	First mth excess return	Three-factor model				Future excess return				
		alpha	MKT	SMB	HML	month 2	month 3	month 4	month 5	month 6
1	**0.90%**	**0.93%**	0.387	-0.090	0.018	0.50%	-0.04%	-0.08%	-0.05%	0.40%
	2.32	*2.61*	*4.62*	*-1.11*	*0.18*	*1.40*	*-0.12*	*-0.29*	*-0.14*	*1.05*
2	0.23%	0.26%	0.227	-0.051	-0.021	-0.14%	-0.08%	0.13%	-0.01%	-0.11%
	0.87	*1.07*	*3.94*	*-0.90*	*-0.30*	*-0.52*	*-0.38*	*0.62*	*-0.06*	*-0.46*
3	-0.08%	0.02%	-0.006	-0.092	-0.040	-0.48%	-0.30%	-0.14%	-0.14%	0.04%
	-0.35	*0.09*	*-0.10*	*-1.59*	*-0.56*	*-2.79*	*-1.39*	*-0.82*	*-0.78*	*0.23*
4	0.27%	0.38%	-0.057	-0.053	-0.097	-0.01%	0.17%	-0.19%	-0.02%	-0.23%
	1.52	*2.05*	*-1.29*	*-1.23*	*-1.84*	*-0.07*	*0.85*	*-1.08*	*-0.13*	*-1.16*
5	0.09%	0.26%	-0.157	-0.105	-0.093	-0.28%	-0.04%	-0.21%	0.11%	0.41%
	0.41	*1.17*	*-3.02*	*-2.07*	*-1.50*	*-1.56*	*-0.21*	*-1.00*	*0.55*	*2.11*
6	-0.11%	-0.01%	-0.195	-0.049	-0.072	-0.16%	0.09%	0.09%	0.05%	-0.45%
	-0.54	*-0.03*	*-4.11*	*-1.06*	*-1.27*	*-0.83*	*0.38*	*0.46*	*0.23*	*-1.87*
7	-0.20%	0.07%	-0.220	-0.125	-0.210	0.01%	-0.12%	-0.09%	-0.06%	0.23%
	-0.89	*0.34*	*-4.57*	*-2.68*	*-3.65*	*0.08*	*-0.57*	*-0.43*	*-0.28*	*1.22*
8	-0.23%	0.02%	-0.189	-0.095	-0.218	-0.24%	0.11%	0.09%	-0.16%	-0.06%
	-0.92	*0.08*	*-3.27*	*-1.70*	*-3.17*	*-0.95*	*0.52*	*0.45*	*-0.73*	*-0.29*
9	**-0.87%**	**-1.03%**	-0.085	0.131	0.077	-0.13%	-0.34%	-0.28%	-0.02%	0.28%
	-4.09	*-4.80*	*-1.69*	*2.68*	*1.27*	*-0.60*	*-1.42*	*-1.49*	*-0.08*	*1.30*
1-9	**1.77%**	**1.96%**	0.472	-0.221	-0.059	**0.63%**	**0.30%**	**0.20%**	**-0.03%**	**0.12%**
	3.55	*4.34*	*4.45*	*-2.15*	*-0.46*	*1.37*	*0.58*	*0.55*	*-0.07*	*0.27*

Panel B: Four-factor alphas and Ex-Jan returns of TPER-sorted portfolios

	Four-factor-model results using all calendar months					Excess returns and three-factor model results excluding January				
	alpha	MKT	SMB	HML	UMD	excess return	alpha	MKT	SMB	HML
1	1.02%	0.283	-0.027	-0.016	-0.157	0.77%	0.74%	0.413	-0.103	0.075
	3.05	*3.31*	*-0.34*	*-0.17*	*-3.13*	*1.98*	*2.13*	*5.22*	*-1.35*	*0.78*
2	0.33%	0.159	-0.009	-0.043	-0.104	0.19%	0.24%	0.222	-0.074	-0.026
	1.40	*2.68*	*-0.16*	*-0.65*	*-2.98*	*0.76*	*1.04*	*4.12*	*-1.43*	*-0.39*
3	0.04%	-0.026	-0.080	-0.047	-0.031	0.02%	0.12%	-0.002	-0.084	-0.051
	0.17	*-0.40*	*-1.33*	*-0.65*	*-0.81*	*0.08*	*0.44*	*-0.04*	*-1.41*	*-0.68*
4	0.34%	-0.014	-0.079	-0.083	0.065	0.29%	0.41%	-0.053	-0.041	-0.100
	1.89	*-0.30*	*-1.84*	*-1.63*	*2.40*	*1.62*	*2.14*	*-1.21*	*-0.96*	*-1.89*
5	0.20%	-0.094	-0.143	-0.073	0.096	0.16%	0.31%	-0.157	-0.085	-0.091
	0.95	*-1.76*	*-2.90*	*-1.23*	*3.05*	*0.72*	*1.39*	*-3.03*	*-1.69*	*-1.44*
6	-0.05%	-0.149	-0.077	-0.057	0.069	-0.13%	-0.03%	-0.193	-0.039	-0.061
	-0.25	*-2.99*	*-1.66*	*-1.04*	*2.37*	*-0.57*	*-0.14*	*-3.93*	*-0.82*	*-1.02*
7	0.00%	-0.142	-0.172	-0.185	0.118	-0.22%	0.07%	-0.229	-0.117	-0.221
	-0.01	*-3.05*	*-4.02*	*-3.58*	*4.33*	*-0.95*	*0.35*	*-4.83*	*-2.55*	*-3.84*
8	-0.05%	-0.114	-0.140	-0.195	0.112	-0.30%	-0.03%	-0.187	-0.092	-0.231
	-0.22	*-1.95*	*-2.59*	*-3.00*	*3.28*	*-1.19*	*-0.10*	*-3.24*	*-1.66*	*-3.29*
9	-1.09%	-0.016	0.089	0.099	0.105	-0.78%	-0.92%	-0.102	0.149	0.067
	-5.50	*-0.31*	*1.90*	*1.77*	*3.55*	*-3.50*	*-4.27*	*-2.06*	*3.13*	*1.12*
1-9	**2.12%**	**0.298**	-0.116	-0.115	-0.262	**1.55%**	**1.66%**	0.515	-0.252	0.008
	5.27	*2.92*	*-1.22*	*-1.01*	*-4.38*	*5.35*	*6.82*	*9.24*	*-4.69*	*0.11*

Table 3: Returns on TPER-sorted portfolios of S&P 500 stocks without sector control

At the end of each month from Jan 1999 to Nov 2004, we rank all S&P 500 stocks in our sample into 9 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 excess returns (in excess of the equally weighted S&P 500 index return). Finally, we equally-weigh the excess returns of all stocks in the same portfolio. We report the average excess returns and risk-adjusted alphas (using Fama-French three-factor model). All returns and alphas are monthly.

	First month excess return	Three-factor model				TPER
		alpha	MKT	SMB	HML	
1	0.18%	0.52%	0.639	-0.160	-0.382	71.4%
	0.26	*0.92*	*4.82*	*-1.25*	*-2.41*	
2	0.03%	0.24%	0.181	-0.174	-0.122	36.1%
	0.09	*0.83*	*2.67*	*-2.64*	*-1.50*	
3	0.54%	0.61%	0.045	-0.068	-0.026	27.6%
	2.27	*2.40*	*0.75*	*-1.17*	*-0.36*	
4	-0.06%	0.07%	-0.025	-0.111	-0.041	22.3%
	-0.31	*0.33*	*-0.55*	*-2.47*	*-0.74*	
5	0.32%	0.36%	-0.165	-0.025	-0.004	17.9%
	1.23	*1.37*	*-2.72*	*-0.43*	*-0.05*	
6	0.24%	0.39%	-0.266	-0.086	-0.085	13.8%
	0.90	*1.64*	*-4.73*	*-1.58*	*-1.26*	
7	-0.19%	-0.13%	-0.299	-0.006	-0.049	9.7%
	-0.71	*-0.53*	*-5.38*	*-0.10*	*-0.74*	
8	-0.41%	-0.32%	-0.272	-0.036	-0.047	4.7%
	-1.31	*-1.08*	*-3.87*	*-0.53*	*-0.56*	
9	-0.61%	-0.76%	-0.182	0.141	0.067	-10.0%
	-2.11	*-2.68*	*-2.74*	*2.19*	*0.85*	
1-9	0.79%	1.27%	0.822	-0.301	-0.450	81.4%
	0.86	*1.65*	*4.52*	*-1.71*	*-2.07*	

Table 4: Characteristics of TPER-sorted portfolios using S&P 500 stocks

We report various characteristics of TPER-sorted portfolios using S&P 500 stocks. 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 defined as 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; Pimpact measures the percentage change in price caused by trading 1 million worth of the stock within half an hour; Pspread is the percentage bid-ask spread; Amihud is a liquidity measure (multiplied by 10^7); Price is the closing price at the end of the month of portfolio formation; RET1M is the return during the month of portfolio formation.

Panel A: 12 characteristics studied in Jegadeesh et.al. (2004)

	Momentum and trading volume					Valuation Multipliers		Growth Indicators		Firm Size	Fundamental Indicators	
	RETP	RET2P	FREV (bp)	SUE	TURN	EP	BP	LTG	SG	size	CAPEX	TA
mean												
1	-3.39%	4.00%	-12.30	0.39	0.74	0.013	0.45	15.27	1.156	16.30	3.87%	-2.31%
2	0.80%	4.33%	7.68	0.57	0.70	0.036	0.40	15.21	1.151	16.37	4.24%	-2.05%
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%
4	4.65%	5.29%	15.19	0.61	0.68	0.040	0.38	14.28	1.130	16.37	4.12%	-1.90%
5	5.68%	4.94%	12.17	0.60	0.67	0.037	0.38	14.63	1.119	16.38	4.04%	-1.59%
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%
7	6.61%	5.26%	7.29	0.65	0.66	0.040	0.38	13.37	1.111	16.30	3.93%	-1.86%
8	7.59%	5.22%	5.46	0.66	0.66	0.033	0.39	13.50	1.107	16.24	3.94%	-2.25%
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%
median												
1	-6.57%	-0.3%	18.98	0.24	0.77	0.039	0.38	13.63	1.087	16.30	2.77%	-2.03%
2	-1.87%	1.6%	21.39	0.29	0.72	0.043	0.34	13.54	1.080	16.29	3.10%	-1.82%
3	-0.18%	1.6%	24.00	0.35	0.70	0.044	0.34	13.19	1.077	16.37	3.00%	-1.97%
4	1.46%	1.8%	22.26	0.34	0.69	0.045	0.33	12.56	1.074	16.29	3.02%	-1.81%
5	3.74%	2.4%	19.83	0.34	0.67	0.046	0.33	12.65	1.066	16.28	3.13%	-1.53%
6	4.54%	1.9%	21.38	0.33	0.67	0.046	0.34	12.48	1.073	16.21	3.09%	-1.94%
7	5.31%	2.6%	15.28	0.32	0.67	0.046	0.32	12.08	1.068	16.15	2.97%	-1.86%
8	5.15%	2.2%	15.52	0.33	0.67	0.045	0.33	11.94	1.063	16.13	3.02%	-2.03%
9	4.23%	0.2%	9.14	0.29	0.72	0.046	0.36	11.24	1.060	16.04	3.05%	-1.73%

Panel B: Other characteristics

	Liquidity			Others		
	Pimpact (in bp)	Pspread (in bp)	Amihud	Price	RET1M	TPER
mean						
1	18.3	48.3	8.02	31.8	-5.31%	67.9%
2	14.4	42.0	6.34	37.2	-3.22%	36.4%
3	12.9	39.1	5.52	39.5	-1.13%	28.4%
4	12.4	38.4	5.33	42.8	-0.03%	23.0%
5	12.2	36.5	5.29	44.9	1.62%	18.8%
6	12.0	35.6	5.04	45.2	2.79%	14.8%
7	12.6	34.9	5.34	46.8	3.97%	10.7%
8	12.8	35.5	5.50	46.5	5.22%	5.1%
9	14.6	37.0	6.18	45.1	6.04%	-9.0%
median						
1	10.4	44.0	4.12	28.2	-4.52%	53.0%
2	8.6	38.1	3.59	34.2	-3.36%	34.1%
3	8.2	35.3	3.22	36.8	-1.22%	27.1%
4	7.7	34.7	3.20	40.2	-0.01%	22.4%
5	7.7	32.7	3.09	41.8	1.07%	18.4%
6	7.6	32.0	3.13	42.2	2.30%	14.4%
7	7.8	31.2	3.18	43.0	3.34%	10.3%
8	8.4	31.9	3.37	42.6	4.27%	5.3%
9	9.0	32.5	3.68	40.3	4.77%	-5.1%

Table 5: Cross sectional regressions with S&P 500 stock sample

Each month from Feb 1999 to May 2004, we run a cross-sectional regression of return on the 12 characteristics studied in Jegadeesh et.al (2004) and TPER. All variables are cross-sectionally demeaned so the intercept term is zero. In addition, the 13 LHS variables are also standardized so the regression slope coefficient can be interpreted as the impact on return of a one standard deviation change in the variable. The slope coefficients are then averaged cross time and are reported. The robust t value is computed using Newey-West autocorrelation adjusted standard error with 12 lags. We also tried first demeaning all variables within sector and report the result in Panel B. There are, on average 250 S&P 500 stocks in each cross-section with the complete 13 characteristics.

	LTG	FREV	EP	BP	CAPEX	SG	SUE	TA	RETP	RET2P	TURN	SIZE	TPER	average R2
Panel A: No Sector Demean:														
coeff	-0.0005	0.0000	-0.0007	-0.0014	0.0005	0.0004	0.0014	-0.0013	0.0011	0.0001	0.0028	-0.0025	0.0029	22.69%
robust t	*-0.31*	*-0.01*	*-0.42*	*-0.76*	*0.52*	*0.44*	*1.80*	*-1.27*	*0.51*	*0.04*	*1.98*	*-0.97*	*2.02*	
Panel B: Sector Demeaned First:														
coeff	-0.0003	-0.0001	-0.0001	-0.0008	0.0006	0.0007	0.0012	-0.0015	0.0006	0.0010	0.0018	-0.0025	0.0029	17.18%
robust t	*-0.29*	*-0.04*	*-0.07*	*-0.50*	*0.63*	*0.94*	*1.76*	*-1.72*	*0.30*	*0.76*	*1.76*	*-1.56*	*2.41*	

Table 6: Profits to alternative sector-neutral long-short strategies in the S&P sample

At the end of each month from Jan 1999 to Nov 2004, we construct various sector-neutral long-short strategies using S&P 500 stocks in our sample. For each strategy, we report the equally-weighted first-month excess return (in excess of the equally weighted S&P 500 index return) separately in the long and short portfolio, the profit to the overall long-short strategy (long minus short) and its associated Fama-French three-factor alpha. All returns and alphas are monthly.

TPER: Within each sector, we sort stocks into 9 portfolios according to the current month TPERs, then long stocks with the highest TPER and short stocks with the lowest TPER.

Ret: Within each sector, we sort stocks into 9 portfolios according to the current month returns, then long past losers and short past winners.

DTP: Within each sector, we sort stocks into 9 portfolios according to the current month DTP (change in target price, defined as $\Delta TP_t / TP_{t-1}$), then long stocks with the highest DTP and short stocks with the lowest DTP.

DTP×Ret: Within each sector, we conduct a 3 by 3 independent sort based on DTP and Ret, then long past losers with high DTP and short past winners with low DTP.

Rec: We focus on a sub-sample of stocks where there was at least one stock recommendation announcement during the first 25 calendar days of the portfolio month. Within each sector, we sort stocks into 9 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 focus on a sub-sample of stocks where there was at least one stock recommendation announcement during the first 25 calendar days of the portfolio month, and there were also stock recommendation announcements during the 3rd or 2nd month preceding the current month, so we can compute the most recent revision in recommendations (ΔRec) during the past three month before portfolio formation. Within each sector, we sort stocks into 9 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 3 by 3 independent sort based on ΔRec and Ret, then long past losers with high ΔRec and short past winners with low ΔRec.

	TPER	Ret	DTP	DTP×Ret	Rec	ΔRec	ΔRec×Ret
Long	0.90%	0.68%	0.01%	0.73%	-0.27%	0.24%	0.15%
	2.32	*1.76*	*0.04*	*1.96*	*-0.86*	*1.11*	*0.59*
Short	-0.87%	-0.54%	0.05%	-0.83%	0.39%	-0.25%	-0.27%
	-4.09	*-1.82*	*0.21*	*-2.67*	*1.20*	*-1.00*	*-0.89*
Profit	1.77%	1.22%	-0.04%	1.56%	-0.66%	0.49%	0.42%
	3.55	*2.24*	*-0.13*	*3.00*	*-1.55*	*1.37*	*0.94*
alpha	1.96%	0.90%	0.07%	1.42%	-0.52%	0.33%	0.25%
	4.34	*1.62*	*0.20*	*2.59*	*-1.13*	*0.87*	*0.31*

Table 7: Change in Target Price for within-sector TPER-sorted portfolios for S&P 500 stocks

We examine the most recent target price change in the past three months for each stock in the within-sector TPER-sorted portfolios. If the current target price exceeds 1.05 × last target price, we classify the change as an upgrade; if the current target price is smaller than 0.95 × 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 3rd and 2nd month preceding the current month, we classify it as missing. We then report the percentage of upgrade, downgrade, reiteration and missing for each portfolio.

	% of missing	% of upgrade	% of downgrade	% of reiteration
1	2.03%	55.35%	21.96%	20.7%
2	1.34%	46.18%	22.35%	30.1%
3	1.10%	39.46%	26.55%	32.9%
4	1.25%	38.90%	25.57%	34.3%
5	1.32%	36.90%	25.36%	36.4%
6	0.96%	34.13%	28.21%	36.7%
7	1.56%	30.93%	32.00%	35.5%
8	1.56%	25.52%	39.93%	33.0%
9	1.87%	19.74%	56.73%	21.7%

Table 8: Effect of earning announcement on the S&P 500 sample

From Jan 99 to Dec 04, we focus on stocks in 9 within-sector TPER-sorted portfolios of S&P 500 where there was no earning announcement during the month of portfolio formation. We then compute the excess returns and the associated three-factor alphas for both full sample and the sub-sample with no earning announcement. All returns and alphas are monthly.

Port	% of obs without earn_anno	Sub-sample without earn_anno	
		excess return	Three-factor alpha
High TPER	61.8%	1.03%	1.13%
		1.93	*2.07*
2	59.0%	0.58%	0.56%
		1.45	*1.47*
3	57.8%	0.27%	0.62%
		0.60	*1.34*
4	57.1%	0.30%	0.57%
		0.65	*1.16*
5	55.7%	0.01%	0.13%
		0.02	*0.32*
6	56.0%	0.29%	0.24%
		0.55	*0.43*
7	57.0%	0.06%	0.06%
		0.16	*0.15*
8	56.3%	-0.43%	-0.13%
		-1.08	*-0.32*
Low TPER	59.2%	-1.03%	-1.04%
		-3.01	*-2.87*
1-9		2.07%	2.17%
		3.15	*3.25*

Table 9: Liquidity related characteristics of TPER-sorted portfolios in the S&P 500 sample

Panel A reports the turnover during the month before (t-1), during (t) and after (t+1) the portfolio formation for our nine within-sector TPER-sorted portfolios using S&P 500 stock sample from Jan 99 to Dec 04. The turnover is defined as total monthly trading volume divided by the number of share outstanding. Panel B reports two average order imbalance measures during both portfolio formation month (t) and during the month after (t+1): OIB1is the buyer-initiated shares purchased less than the seller-initiated shares sold (daily). OIB2 is OIB1 scaled by the total number of shares traded. Panel C reports the average percentage change in bid-ask spread (Pspread) , price impact measure (Pimpact), Amihud 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 computing 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: turnover before, during and after portfolio formation

Portfolio	turnover (t-1)	turnover (t)	turnover (t+1)	change from t-1 to t	t-value of the change
1	18.73%	19.76%	19.53%	1.02%	2.69
2	16.30%	16.79%	16.47%	0.50%	1.61
3	15.29%	15.60%	15.51%	0.30%	1.07
4	14.52%	14.87%	14.68%	0.35%	1.20
5	14.29%	14.59%	14.37%	0.30%	1.00
6	14.14%	14.27%	14.09%	0.13%	0.50
7	13.92%	14.03%	13.81%	0.11%	0.37
8	14.95%	15.21%	14.70%	0.27%	0.78
9	15.75%	16.13%	15.85%	0.38%	1.10

Panel B: Order imbalance measures during and after portfolio formation

port	OIB1 during formation month (1)	OIB1 one month later (2)	(2)-(1)	t-value	OIB2 at formation (3)	OIB2 one month later (4)	(4)-(3)	t-value
1	88830.5	156595.1	67764.6	5.19	0.0393	0.0549	0.0155	6.23
2	117721.3	134149.1	16427.8	1.71	0.0453	0.0548	0.0096	4.01
3	137495.0	146562.8	9067.8	0.61	0.0497	0.0559	0.0062	2.74
4	139808.3	139294.6	-513.7	-0.05	0.0571	0.0603	0.0032	1.46
5	153430.8	147019.8	-6411.0	-0.70	0.0634	0.0623	-0.0011	-0.55
6	161499.7	147136.1	-14363.6	-1.70	0.0680	0.0643	-0.0037	-1.81
7	173850.1	157260.6	-16589.5	-1.79	0.0725	0.0642	-0.0083	-4.00
8	174748.0	148157.9	-26590.1	-2.76	0.0742	0.0643	-0.0099	-4.46
9	193638.6	160568.1	-33070.5	-3.11	0.0769	0.0639	-0.0130	-5.75

Panel C: Changes in liquidity related characteristics when stock moves into the extreme portfolios (1 or 9)

	When stock enters portfolio 1				When stock enters portfolio 9			
	pspread	pimpact	Amihud	Dispersion	pspread	pimpact	Amihud	Dispersion
Percentage change	6.5%	11.4%	9.9%	61.9%	7.0%	9.7%	7.5%	72.3%
t-value	3.42	3.36	3.71	6.41	3.96	3.31	3.50	8.31

Table 10: Correlation between alpha and liquidity characteristics

We compute the correlations among price impact measure (Pimpact), bid-ask-spread (Pspread), the Amihud liquidity measure and the three-factor-alpha of next-month excess returns on two TPER-sorted portfolios using S&P 500 stocks from Jan 99 to Nov 04. Portfolio 1 is where we long the highest TPER stocks and short the S&P 500 equally-weighted index and portfolio 9 is where we long the S&P 500 equally-weighted index and short the lowest TPER stocks. The standard correlation coefficients are reported in the lower triangle and the spearman rank correlation coefficients are reported in the upper triangle.

	Portfolio 1					Portfolio 9			
	alpha	pimpact	pspread	Amihud		alpha	pimpact	pspread	Amihud
alpha		0.267	0.344	0.262	alpha		0.241	0.296	0.250
pimpact	0.227		0.734	0.880	pimpact	0.226		0.544	0.817
pspread	0.351	0.667		0.838	pspread	0.365	0.522		0.636
Amihud	0.241	0.849	0.793		Amihud	0.285	0.842	0.614	

Table 11: Returns on within-sector TPER-sorted portfolios for the full sample

At the end of each month from Dec 1996 to Dec 2004 and within each sector, we rank stocks into 9 groups according to the current month TPERs and label them from 0 to 9 (0 with the highest TPER and 9 with the lowest TPER). For each stock, we compute its future excess returns (in excess of the equally-weighed return of all stocks in the same sector). Finally, we equally-weigh the excess returns of all stocks within the same portfolio. We report the average excess returns and risk-adjusted alphas (using the Fama-French three-factor model). All returns and alphas are monthly.

Port	excess return	Fama-French three-factor model				TPER	
		alpha	MKT	SMB	HML	mean	median
1	0.61%	0.44%	0.262	0.149	-0.042	56.4%	54.5%
	2.32	*2.17*	*5.46*	*3.04*	*-0.67*		
2	0.31%	0.16%	0.213	0.058	0.053	42.0%	40.5%
	1.57	*0.89*	*4.98*	*1.33*	*0.95*		
3	0.50%	0.43%	0.093	0.023	0.034	33.4%	32.4%
	4.08	*3.52*	*3.28*	*0.78*	*0.92*		
4	0.12%	0.09%	0.040	-0.044	0.058	27.1%	26.2%
	1.12	*0.82*	*1.54*	*-1.66*	*1.71*		
5	0.07%	0.09%	-0.023	-0.055	0.018	21.8%	21.3%
	0.68	*0.93*	*-1.03*	*-2.40*	*0.63*		
6	-0.02%	0.06%	-0.095	-0.062	-0.003	17.0%	16.6%
	-0.12	*0.44*	*-3.21*	*-2.06*	*-0.08*		
7	-0.34%	-0.23%	-0.183	-0.075	0.002	12.1%	11.8%
	-2.03	*-1.64*	*-5.61*	*-2.24*	*0.05*		
8	-0.52%	-0.39%	-0.191	-0.029	-0.047	6.2%	6.1%
	-3.04	*-2.54*	*-5.29*	*-0.78*	*-1.01*		
9	-0.69%	-0.65%	-0.103	0.034	-0.010	-7.4%	-5.3%
	-3.70	*-3.39*	*-2.29*	*0.74*	*-0.17*		
1-9	1.30%	1.09%	0.366	0.115	-0.032		
	3.29	*3.11*	*4.42*	*1.36*	*-0.30*		

Table 12: Future returns on within-sector TPER-sorted portfolios for the full sample

At the end of each month from Dec 1996 to Dec 2004 and within each sector, 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). For each stock, we compute its future excess returns (in excess of the equally-weighed return of all stocks in the same sector). Finally, we equally-weigh the excess returns of all stocks within the same portfolio. We report the average excess returns from the 2nd to the 6th month after portfolio formation. All returns and alphas are monthly.

	Future excess return				
Port	month 2	month 3	month 4	month 5	month 6
1	-0.13%	-0.18%	-0.26%	-0.15%	-0.25%
	-0.52	*-0.76*	*-1.17*	*-0.56*	*-0.92*
2	0.05%	0.03%	-0.02%	-0.03%	-0.01%
	0.26	*0.20*	*-0.10*	*-0.19*	*-0.09*
3	-0.07%	0.09%	0.02%	0.09%	0.02%
	-0.55	*0.71*	*0.17*	*0.65*	*0.15*
4	0.12%	-0.12%	0.17%	-0.15%	-0.16%
	1.08	*-1.13*	*1.49*	*-1.07*	*-1.41*
5	0.11%	0.05%	0.03%	0.09%	-0.14%
	0.96	*0.40*	*0.30*	*0.87*	*-1.26*
6	0.08%	-0.07%	-0.15%	0.24%	-0.02%
	0.69	*-0.64*	*-1.34*	*1.89*	*-0.15*
7	0.10%	0.10%	0.09%	0.01%	0.19%
	0.73	*0.63*	*0.65*	*0.07*	*1.34*
8	0.03%	0.09%	0.10%	-0.10%	0.13%
	0.16	*0.58*	*0.61*	*-0.74*	*0.88*
9	-0.30%	0.03%	-0.01%	-0.05%	0.26%
	-1.65	*0.19*	*-0.06*	*-0.30*	*1.52*
1-9	0.18%	-0.21%	-0.25%	-0.10%	-0.51%
	0.49	*-0.61*	*-0.74*	*-0.26*	*-1.40*

Table 13: Returns on TPER-sorted portfolios of the full sample without sector control

At the end of each month from Dec 1996 to Dec 2004, we rank all stocks in our sample into 9 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 its future excess returns (in excess of the equally-weighed return of all stocks in the same sector). Finally, we equally-weigh the excess returns of all stocks within the same portfolio. We report the average excess returns and risk-adjusted alphas (using Fama-French three-factor model). All returns and alphas are monthly.

	First month excess return	Three-factor model			
		alpha	MKT	SMB	HML
1	-0.11%	-0.10%	0.479	0.154	-0.600
	-0.17	*-0.22*	*4.41*	*1.39*	*-4.23*
2	0.09%	-0.01%	0.293	0.021	-0.122
	0.29	*-0.03*	*5.25*	*0.36*	*-1.67*
3	0.36%	0.25%	0.140	0.039	0.045
	2.31	*1.70*	*4.04*	*1.09*	*1.00*
4	0.21%	0.14%	0.031	-0.059	0.142
	1.71	*1.40*	*1.26*	*-2.40*	*4.49*
5	0.22%	0.20%	-0.038	-0.105	0.144
	1.31	*1.54*	*-1.23*	*-3.37*	*3.60*
6	0.19%	0.24%	-0.157	-0.091	0.138
	0.96	*1.63*	*-4.62*	*-2.61*	*3.11*
7	-0.12%	-0.07%	-0.222	-0.086	0.169
	-0.49	*-0.38*	*-5.52*	*-2.09*	*3.22*
8	-0.35%	-0.23%	-0.294	-0.036	0.068
	-1.35	*-1.10*	*-6.11*	*-0.73*	*1.08*
9	-0.48%	-0.43%	-0.233	0.161	0.014
	-1.53	*-1.42*	*-3.31*	*2.24*	*0.15*
1-9	0.37%	0.32%	0.712	-0.007	-0.613
	0.41	*0.45*	*4.17*	*-0.04*	*-2.75*

Table 14: Profits to alternative sector-neutral long-short strategies in the full sample

At the end of each month from Dec 1996 to Dec 2004, we construct various sector-neutral long-short strategies using stocks in the full sample. For each strategy, we report the equally-weighted first-month excess return (in excess of the equally weighted S&P 500 index return) separately in the long and short portfolio, the profit to the overall long-short strategy (long minus short) and its associated Fama-French three-factor alpha. All returns and alphas are monthly.

TPER: Within each sector, we sort stocks into 9 portfolios according to the current month TPERs, then long stocks with the highest TPER and short stocks with the lowest TPER.

Ret: Within each sector, we sort stocks into 9 portfolios according to the current month returns, then long past losers and short past winners.

DTP: Within each sector, we sort stocks into 9 portfolios according to the current month DTP (change in target price, defined as $\Delta TP_t / TP_{t-1}$), then long stocks with the highest DTP and short stocks with the lowest DTP.

DTP×Ret: Within each sector, we conduct a 3 by 3 independent sort based on DTP and Ret, then long past losers with high DTP and short past winners with low DTP.

Rec: We focus on a sub-sample of stocks where there was at least one stock recommendation announcement during the first 25 calendar days of the portfolio month. Within each sector, we sort stocks into 9 portfolios according to the current month average level of analyst stock recommendation (Rec), go long stocks with the highest recommendations and short stocks with the lowest recommendations.

ΔRec: We focus on a sub-sample of stocks where there was at least one stock recommendation announcement during the first 25 calendar days of the portfolio month, and there were also stock recommendation announcements during the 3rd or 2nd month preceding the current month, so we can compute the most recent revision in recommendations (ΔRec) during the past three month before portfolio formation. Within each sector, we sort stocks into 9 portfolios according to ΔRec, then go long stocks with the highest ΔRec and short stocks with the lowest ΔRec.

ΔRec ×Ret: Within each sector, we conduct a 3 by 3 independent sort based on ΔRec and Ret, then long past losers with high ΔRec and short past winners with low ΔRec.

	TPER	Ret	DTP	DTP×Ret	Rec	ΔRec	ΔRec×Ret
Long	0.61%	0.56%	0.32%	0.40%	0.56%	0.14%	0.22%
	2.32	*2.04*	*1.28*	*1.82*	*1.44*	*0.88*	*1.00*
Short	-0.69%	-0.33%	-0.10%	-0.86%	-0.52%	-0.11%	-0.18%
	-3.70	*-1.13*	*-0.45*	*-4.01*	*-2.12*	*-0.64*	*-0.86*
Profit	1.30%	0.89%	0.42%	1.25%	1.07%	0.25%	0.40%
	3.29	*1.79*	*1.04*	*3.42*	*2.77*	*1.23*	*1.08*
Alpha	1.09%	0.86%	0.43%	1.29%	0.90%	0.27%	0.33%
	3.11	*1.74*	*1.06*	*3.50*	*2.36*	*1.24*	*0.88*

Table 15: Change in Target Price for within-sector TPER-sorted portfolios for the full sample

We examine the most recent target price change in the past three months for each stock in the within-sector TPER-sorted portfolios. If the current target price exceeds 1.05 × last target price, we classify the change as an upgrade; if the current target price is smaller than 0.95 × 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 3rd and 2nd month preceding the current month, we classify it as missing. We then report the percentage of upgrade, downgrade, reiteration and missing for each portfolio.

	% of missing	% of upgrade	% of downgrade	% of reiteration
1	16.29%	40.00%	23.27%	20.44%
2	14.33%	39.87%	22.81%	22.98%
3	13.00%	38.91%	23.01%	25.08%
4	12.42%	37.59%	23.50%	26.49%
5	11.30%	36.25%	24.09%	28.36%
6	11.45%	35.30%	25.01%	28.24%
7	11.13%	33.08%	27.25%	28.54%
8	11.49%	29.73%	32.13%	26.65%
9	14.12%	21.65%	46.51%	17.72%

Table 16: Effect of earning announcement on the full sample

From Dec 96 to Dec 04, we focus on stocks in 9 within-sector TPER-sorted portfolios of the full sample where there was no earning announcement during the month of portfolio formation. We then compute the excess returns and the associated three-factor alphas for both full sample and the sub-sample with no earning announcement. All returns and alphas are monthly.

Port	% of obs without earn_anno	Sub-sample without earn_anno	
		excess return	Three-factor alpha
1	55.9%	0.71%	0.51%
		2.11	*1.84*
2	56.1%	0.22%	0.09%
		0.83	*0.37*
3	55.7%	0.58%	0.49%
		3.04	*2.70*
4	55.3%	0.31%	0.32%
		1.49	*1.54*
5	54.8%	0.04%	0.10%
		0.29	*0.63*
6	55.0%	-0.04%	0.03%
		-0.21	*0.16*
7	54.7%	-0.38%	-0.23%
		-1.57	*-0.95*
8	54.9%	-0.58%	-0.48%
		-3.19	*-2.65*
9	57.7%	-0.49%	-0.44%
		-2.28	*-1.95*
1-9	56.8%	1.20%	0.95%
		2.62	*2.25*

Table 17: Characteristics of TPER-sorted portfolios of the full sample

We report various characteristics of TPER-sorted portfolios of the full sample. 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 defined as 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; Pimpact measures the percentage change in price caused by trading 1 million worth of the stock within half an hour; Pspread is the percentage bid-ask spread; Amihud is a liquidity measure (multiplied by 10^7); Price is the closing price at the end of the month of portfolio formation; RET1M is the return during the month of portfolio formation.

Panel A: 12 characteristics studied in Jegadeesh et.al. (2004)

	Momentum and trading volume					Valuation Multipliers		Growth Indicators		Firm Size	Fundamental Indicators	
	RETP	RET2P	FREV (bp)	SUE	TURN	EP	BP	LTG	SG	size	CAPEX	TA
mean												
1	3.81%	10.70%	674.8	0.44	0.66	0.004	0.48	20.96	1.531	13.62	6.21%	-0.05%
2	5.66%	10.54%	353.2	0.47	0.66	0.021	0.46	19.96	1.417	13.89	6.00%	-0.27%
3	7.26%	9.34%	64.6	0.57	0.65	0.025	0.45	19.13	1.348	14.06	5.84%	-0.74%
4	8.21%	9.38%	179.2	0.59	0.64	-0.041	0.43	18.35	1.332	14.18	5.66%	-0.74%
5	9.51%	9.71%	198.0	0.59	0.64	0.035	0.40	18.06	1.307	14.29	5.55%	-0.53%
6	11.07%	9.21%	69.3	0.68	0.63	0.029	0.43	17.60	1.248	14.37	5.47%	-0.68%
7	11.87%	8.89%	203.8	0.64	0.63	0.035	0.44	17.11	1.257	14.36	5.06%	-1.00%
8	13.23%	9.46%	194.3	0.61	0.63	0.026	0.44	17.34	1.234	14.32	5.25%	-1.17%
9	14.48%	9.50%	172.2	0.45	0.64	0.018	0.47	17.32	1.316	14.07	5.28%	-1.36%
median												
1	-3.96%	1.4%	27.5	0.28	0.71	0.040	0.42	17.67	1.185	13.70	3.76%	-0.74%
2	-1.20%	2.1%	25.5	0.28	0.70	0.044	0.41	16.62	1.158	13.96	3.66%	-0.77%
3	1.06%	2.6%	25.8	0.34	0.69	0.045	0.40	16.09	1.148	14.13	3.62%	-1.07%
4	2.77%	3.1%	23.0	0.34	0.68	0.046	0.40	15.39	1.137	14.23	3.56%	-1.01%
5	3.95%	3.3%	22.3	0.36	0.67	0.046	0.39	15.12	1.127	14.37	3.61%	-0.69%
6	5.39%	3.6%	20.8	0.41	0.66	0.046	0.38	14.89	1.124	14.43	3.57%	-0.81%
7	6.36%	3.5%	20.6	0.36	0.65	0.047	0.39	14.40	1.119	14.42	3.39%	-1.05%
8	7.23%	3.5%	17.5	0.34	0.66	0.047	0.38	14.65	1.118	14.37	3.48%	-1.16%
9	6.75%	2.9%	14.3	0.25	0.68	0.042	0.41	14.68	1.118	14.11	3.44%	-1.27%

Panel B: Other characteristics

	Liquidity			Others		
	Pimpact (in bp)	Pspread (in bp)	Amihud	Price	RET1M	TPER
	mean					
1	339.1	105.5	1,006.87	22.2	-3.25%	56.4%
2	244.8	92.3	695.49	25.9	-1.33%	42.0%
3	198.6	83.2	588.53	28.7	0.11%	33.4%
4	171.6	77.5	482.09	31.2	1.60%	27.1%
5	151.4	71.5	392.49	33.5	2.94%	21.8%
6	137.4	68.2	352.62	35.5	4.53%	17.0%
7	141.0	66.6	371.75	36.8	6.10%	12.1%
8	131.1	66.0	317.69	38.0	8.41%	6.2%
9	166.9	72.5	514.05	36.6	11.04%	-7.4%
	median					
1	69.8	83.2	94.57	18.2	-3.81%	54.5%
2	51.2	70.8	61.72	21.6	-2.06%	40.5%
3	39.8	63.9	47.87	24.4	-0.85%	32.4%
4	33.9	58.4	36.05	26.8	0.43%	26.2%
5	29.5	53.9	29.63	28.8	1.62%	21.3%
6	26.9	51.8	26.13	30.7	3.07%	16.6%
7	25.5	50.3	24.49	31.7	4.32%	11.8%
8	26.3	49.9	25.48	32.2	6.34%	6.1%
9	33.0	55.1	35.27	30.8	7.70%	-5.3%

Table 18: Cross sectional regressions with the full sample

Each month from Jan 1997 to May 2004, we run a cross-sectional regression of return on the 12 characteristics studied in Jegadeesh et.al (2004) and TPER. All variables are cross-sectionally demeaned so the intercept term is zero. In addition, the 13 LHS variables are also standardized so the regression slope coefficient can be interpreted as the impact on return of a one standard deviation change in the variable. The slope coefficients are then averaged cross time and are reported. The robust t value is computed using Newey-West autocorrelation adjusted standard error with 12 lags. We also tried first demeaning all variables within sector and report the result in Panel B. There are, on average 650 stocks in each cross-section with the complete 13 characteristics.

	LTG	FREV	EP	BP	CAPEX	SG	SUE	TA	RETP	RET2P	TURN	SIZE	TPER	average R2
Panel A: No Sector Demean:														
coeff	-0.0003	-0.0005	-0.0009	-0.0010	-0.0010	-0.0008	0.0008	-0.0019	0.0055	0.0008	0.0009	-0.0041	0.0047	12.79%
robust t	*-0.11*	*-0.70*	*-0.64*	*-0.78*	*-1.37*	*-0.91*	*1.04*	*-3.00*	*2.45*	*0.46*	*0.52*	*-1.88*	*3.65*	
Panel B: Sector Demeaned First:														
coeff	-0.0010	-0.0007	-0.0006	-0.0013	-0.0009	-0.0009	0.0010	-0.0021	0.0047	0.0011	0.0004	-0.0039	0.0051	9.33%
robust t	*-0.68*	*-0.92*	*-0.54*	*-1.21*	*-1.36*	*-1.01*	*1.54*	*-3.54*	*2.47*	*0.89*	*0.27*	*-1.85*	*5.56*	

Table 19: Liquidity related characteristics of TPER-sorted portfolios in the full sample

Panel A reports the turnover during the month before (t-1), during (t) and after (t+1) the portfolio formation for our nine within-sector TPER-sorted portfolios using the full sample from Jan 97 to Dec 04. The turnover is defined as total monthly trading volume divided by the number of share outstanding. Panel B reports two average order imbalance measures during both portfolio formation month (t) and during the month after (t+1): OIB1is the buyer-initiated shares purchased less than the seller-initiated shares sold (daily). OIB2 is OIB1 scaled by the total number of shares traded. Panel C reports the average percentage change in bid-ask spread (Pspread), price impact measure (Pimpact), the Amihud liquidity measure (Amihud) 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 computing 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: turnover before, during and after portfolio formation

Portfolio	turnover (t-1)	turnover (t)	turnover (t+1)	change from t-1 to t	t-value of the change
1	18.51%	20.10%	18.66%	1.59%	5.43
2	17.67%	18.83%	17.90%	1.16%	4.42
3	17.45%	18.34%	17.81%	0.89%	2.61
4	16.44%	17.38%	16.82%	0.94%	3.56
5	16.21%	16.59%	16.22%	0.37%	1.28
6	15.88%	16.60%	16.05%	0.72%	2.58
7	15.22%	16.17%	15.75%	0.95%	4.27
8	15.71%	17.29%	16.52%	1.58%	5.93
9	17.58%	19.47%	18.23%	1.89%	5.43

Panel B: Order imbalance measures during and after portfolio formation

port	OIB1 during formation month (1)	OIB1 one month later (2)	(2)-(1)	t-value	OIB2 at formation (3)	OIB2 one month later (4)	(4)-(3)	t-value
1	28480.1	43393.3	14913.3	5.68	0.0136	0.0249	0.0113	5.42
2	39052.8	44968.8	5916.0	1.97	0.0228	0.0296	0.0068	3.43
3	44754.4	49953.3	5199.0	1.79	0.0255	0.0311	0.0055	3.74
4	50960.2	52138.5	1178.4	0.32	0.0331	0.0363	0.0032	2.07
5	56344.5	54394.7	-1949.8	-0.69	0.0386	0.0391	0.0006	0.35
6	64093.8	61074.4	-3019.4	-1.14	0.0446	0.0396	-0.0050	-3.50
7	68286.3	60154.8	-8131.4	-2.85	0.0502	0.0410	-0.0093	-6.64
8	71512.5	59287.6	-12225.0	-3.85	0.0527	0.0382	-0.0145	-9.90
9	67081.7	55917.4	-11164.3	-3.88	0.0493	0.0367	-0.0126	-7.95

Panel C: Changes in liquidity related characteristics when stock moves into the extreme portfolios (1 or 9)

	When stock enters portfolio 1				When stock enters portfolio 9			
	pspread	Pimpact*	Amihud	Dispersion	pspread	Pimpact*	Amihud	Dispersion
Percentage change	7.0%	76.9%	72.1%	66.8%	6.9%	28.7%	21.2%	165.2%
t-value	6.61	3.18	4.89	4.21	7.09	5.53	3.49	2.35

*To ensure Pimpact is estimated with reasonable accuracy, we exclude stocks that are not frequently traded (if we do not observe a price for the stock during more than 25% of the trading hour). This filter removes about 32% of stocks in portfolio1 and 23% of stocks in portfolio 9 when computing percentage change in Pimpact.

Table 20: Performance of sector-neutral long-short strategies across exchanges

We report the performance of our sector-neutral long-short strategies in NYSE and NASDAQ respectively. The sampling period is from Jan 1997 to Dec 2004. All returns and alphas are monthly.

	NYSE					NASDAQ				
	excess return	alpha	MKT	SMB	HML	excess return	alpha	MKT	SMB	HML
1	0.70%	0.38%	0.262	-0.188	0.511	0.67%	0.65%	0.305	0.462	-0.585
	2.16	*1.68*	*4.92*	*-3.46*	*7.34*	*1.09*	*1.73*	*3.48*	*5.17*	*-5.12*
2	0.21%	0.02%	0.130	-0.280	0.448	0.31%	0.32%	0.247	0.343	-0.516
	0.64	*0.10*	*2.86*	*-6.02*	*7.55*	*0.62*	*1.10*	*3.58*	*4.88*	*-5.74*
3	0.35%	0.20%	0.014	-0.227	0.454	0.83%	0.91%	0.143	0.401	-0.592
	1.19	*1.49*	*0.44*	*-7.00*	*10.96*	*1.62*	*3.18*	*2.12*	*5.85*	*-6.75*
4	0.12%	0.04%	-0.044	-0.288	0.411	0.40%	0.42%	0.196	0.293	-0.445
	0.38	*0.30*	*-1.28*	*-8.26*	*9.20*	*0.91*	*1.52*	*3.05*	*4.47*	*-5.31*
5	-0.03%	-0.08%	-0.099	-0.265	0.383	0.40%	0.52%	0.065	0.253	-0.488
	-0.11	*-0.56*	*-2.95*	*-7.74*	*8.74*	*1.06*	*2.27*	*1.20*	*4.57*	*-6.88*
6	-0.39%	-0.42%	-0.132	-0.273	0.401	0.39%	0.60%	0.027	0.257	-0.623
	-1.18	*-3.25*	*-4.30*	*-8.75*	*10.03*	*0.89*	*2.17*	*0.41*	*3.88*	*-7.36*
7	-0.41%	-0.34%	-0.226	-0.273	0.297	-0.05%	0.22%	-0.132	0.174	-0.533
	-1.26	*-2.50*	*-7.00*	*-8.28*	*7.04*	*-0.15*	*0.89*	*-2.30*	*2.98*	*-7.14*
8	-0.54%	-0.52%	-0.170	-0.266	0.335	-0.25%	-0.05%	-0.093	0.329	-0.548
	-1.68	*-3.67*	*-5.10*	*-7.80*	*7.67*	*-0.58*	*-0.16*	*-1.35*	*4.67*	*-6.08*
9	-0.58%	-0.67%	-0.096	-0.171	0.385	-0.78%	-0.62%	-0.009	0.260	-0.501
	-1.96	*-3.94*	*-2.41*	*-4.20*	*7.41*	*-1.84*	*-1.98*	*-0.12*	*3.48*	*-5.23*
1-9	1.28%	1.05%	0.358	-0.017	0.126	1.45%	1.26%	0.314	0.202	-0.084
	4.07	*3.63*	*5.28*	*-0.25*	*1.42*	*2.61*	*2.36*	*2.49*	*1.57*	*-0.51*

Table 21: Performance of sector-neutral long-short strategies across value and growth stocks

Each month, we sort stocks in our sample into three groups according to their book-to-market ratios, we then report the performance of our sector-neutral long-short strategies in the group with the highest book-to-market ratio (value stocks) and the group with the lowest book-to-market ratio (growth stocks). The sampling period is from Jan 1997 to Dec 2004. All returns and alphas are monthly.

	Value					Growth				
	excess return	alpha	MKT	SMB	HML	excess return	alpha	MKT	SMB	HML
1	1.09%	0.69%	0.193	0.131	0.580	0.37%	0.55%	0.361	0.248	-0.801
	3.26	*2.49*	*3.02*	*2.01*	*6.92*	*0.53*	*1.34*	*3.81*	*2.57*	*-6.46*
2	0.66%	0.34%	0.089	0.014	0.528	0.27%	0.45%	0.301	0.170	-0.624
	1.96	*1.28*	*1.45*	*0.22*	*6.60*	*0.48*	*1.24*	*3.60*	*1.99*	*-5.71*
3	0.41%	0.09%	0.062	-0.058	0.603	0.29%	0.52%	0.237	0.010	-0.591
	1.13	*0.36*	*1.12*	*-1.03*	*8.32*	*0.56*	*1.38*	*2.68*	*0.11*	*-5.13*
4	0.58%	0.20%	-0.037	0.089	0.665	-0.25%	0.03%	0.122	0.017	-0.596
	1.52	*0.82*	*-0.65*	*1.54*	*8.94*	*-0.48*	*0.06*	*1.20*	*0.17*	*-4.51*
5	0.09%	-0.12%	-0.098	-0.085	0.497	-0.37%	0.02%	0.005	-0.081	-0.683
	0.26	*-0.47*	*-1.71*	*-1.46*	*6.65*	*-0.91*	*0.08*	*0.07*	*-1.16*	*-7.69*
6	-0.12%	-0.33%	-0.088	-0.074	0.490	-0.04%	0.30%	-0.089	-0.110	-0.519
	-0.35	*-1.56*	*-1.80*	*-1.49*	*7.70*	*-0.12*	*1.04*	*-1.31*	*-1.58*	*-5.87*
7	-0.43%	-0.61%	-0.157	-0.016	0.429	-0.39%	0.08%	-0.153	-0.160	-0.673
	-1.12	*-2.04*	*-2.26*	*-0.23*	*4.74*	*-1.14*	*0.31*	*-2.56*	*-2.62*	*-8.61*
8	-0.29%	-0.48%	-0.143	-0.053	0.479	-0.57%	-0.14%	-0.267	0.046	-0.654
	-0.84	*-2.38*	*-3.04*	*-1.09*	*7.78*	*-1.49*	*-0.50*	*-4.00*	*0.68*	*-7.49*
9	-0.60%	-0.83%	-0.089	0.042	0.511	-1.02%	-0.65%	-0.137	-0.002	-0.673
	-1.62	*-3.08*	*-1.42*	*0.66*	*6.23*	*-2.04*	*-1.48*	*-1.34*	*-0.02*	*-5.05*
1-9	1.68%	1.51%	0.282	0.088	0.069	1.40%	1.19%	0.497	0.250	-0.128
	4.27	*3.96*	*3.17*	*0.97*	*0.59*	*1.92*	*1.80*	*3.22*	*1.59*	*-0.63*

Table 22: Performance of sector-neutral long-short strategies across small and large stocks

Each month, we sort stocks in our sample into three groups according to their market capitalizations, we then report the performance of our sector-neutral long-short strategies in the group with the smallest stocks and the group with the largest stocks. The sampling period is from Jan 1997 to Dec 2004. All returns and alphas are monthly.

	Small					Large				
	excess return	alpha	MKT	SMB	HML	excess return	alpha	MKT	SMB	HML
1	0.64%	0.63%	0.169	0.053	-0.183	0.25%	0.15%	0.274	-0.019	-0.066
	2.11	*2.30*	*2.62*	*0.81*	*-2.17*	*0.82*	*0.55*	*4.25*	*-0.29*	*-0.79*
2	0.60%	0.57%	0.049	0.083	-0.039	0.25%	0.17%	0.156	0.018	-0.014
	2.95	*2.76*	*1.01*	*1.68*	*-0.62*	*1.14*	*0.81*	*3.19*	*0.36*	*-0.23*
3	0.38%	0.40%	0.089	-0.126	-0.024	0.16%	0.10%	0.090	-0.026	0.051
	1.74	*1.79*	*1.72*	*-2.39*	*-0.36*	*1.05*	*0.63*	*2.52*	*-0.73*	*1.10*
4	0.25%	0.15%	0.031	0.112	0.103	0.20%	0.25%	0.008	-0.111	-0.025
	1.52	*0.86*	*0.77*	*2.75*	*1.99*	*1.39*	*1.73*	*0.23*	*-3.24*	*-0.57*
5	0.34%	0.27%	0.056	0.003	0.087	0.13%	0.12%	-0.022	0.039	0.017
	1.71	*1.29*	*1.14*	*0.07*	*1.34*	*0.97*	*0.84*	*-0.69*	*1.20*	*0.40*
6	-0.06%	-0.07%	-0.001	-0.004	0.023	-0.03%	0.03%	-0.104	-0.086	0.051
	-0.31	*-0.34*	*-0.02*	*-0.08*	*0.37*	*-0.19*	*0.17*	*-3.00*	*-2.41*	*1.13*
7	-0.33%	-0.27%	-0.145	-0.013	0.034	-0.24%	-0.09%	-0.190	-0.009	-0.090
	-1.56	*-1.31*	*-3.02*	*-0.27*	*0.54*	*-1.37*	*-0.58*	*-5.05*	*-0.24*	*-1.83*
8	-0.69%	-0.57%	-0.188	-0.033	-0.021	-0.25%	-0.21%	-0.138	0.083	-0.008
	-3.10	*-2.69*	*-3.76*	*-0.64*	*-0.32*	*-1.51*	*-1.32*	*-3.79*	*2.24*	*-0.17*
9	-1.14%	-1.10%	-0.053	-0.058	0.020	-0.52%	-0.57%	-0.060	0.126	0.072
	-4.21	*-3.91*	*-0.80*	*-0.86*	*0.23*	*-2.08*	*-2.23*	*-0.99*	*2.06*	*0.92*
1-9	1.78%	1.73%	0.223	0.111	-0.203	0.76%	0.72%	0.333	-0.145	-0.138
	3.87	*3.97*	*2.17*	*1.06*	*-1.51*	*1.62*	*1.60*	*3.14*	*-1.34*	*-1.00*

Table 23: Performance of sector-neutral long-short strategies across size and book-to-market sorted groups

Each month, we conduct a size and book-to-market 3 by 2 double sort and sort all stocks in our full sample into six groups, we then report the performance of our sector-neutral long-short strategies in each. The sampling period is from Jan 1997 to Dec 2004. All returns and alphas are monthly.

Group	Size	B/M	excess return	alpha	MKT	SMB	HML
Small value	272,647	0.84	2.42%	2.34%	0.118	0.137	-0.013
			4.91	*4.61*	*1.01*	*1.14*	*-0.08*
Small Growth	322,905	0.30	1.11%	1.10%	0.392	-0.056	-0.213
			1.32	*1.31*	*2.02*	*-0.28*	*-0.84*
Medium value	1,263,608	0.68	1.03%	0.87%	0.360	-0.117	0.156
			2.02	*1.72*	*3.08*	*-0.98*	*1.02*
Medium growth	1,285,998	0.24	0.62%	0.38%	0.644	0.045	-0.011
			0.82	*0.54*	*3.93*	*0.27*	*-0.05*
Large value	10,844,724	0.55	0.96%	1.00%	0.249	-0.216	-0.101
			2.09	*2.23*	*2.38*	*-2.02*	*-0.74*
Large growth	25,703,362	0.18	0.69%	0.69%	0.343	-0.033	-0.222
			0.90	*0.91*	*1.97*	*-0.18*	*-0.97*

Table 24: Performance of sector-neutral long-short strategies across sectors

We report the performance of our sector-neutral long-short strategies within each of our nine sectors. The sampling period is from Jan 1997 to Dec 2004. All returns and alphas are monthly.

GICS	Sector	excess return	alpha	MKT	SMB	HML
10	Energy	1.87%	1.30%	0.740	0.151	0.296
		2.42	*1.76*	*4.26*	*0.85*	*1.31*
15	Materials	1.53%	1.40%	0.229	0.234	-0.143
		2.50	*2.32*	*1.61*	*1.61*	*-0.77*
20	Industrials	1.82%	1.55%	0.479	0.028	0.038
		3.47	*3.14*	*4.12*	*0.24*	*0.25*
25	Consumer Discretionary	2.36%	2.33%	0.100	0.071	-0.096
		5.85	*5.64*	*1.03*	*0.71*	*-0.76*
30	Consumer Staples	1.21%	0.94%	0.353	0.267	-0.007
		1.59	*1.23*	*1.95*	*1.45*	*-0.03*
35	Health Care	-0.29%	-0.31%	0.383	0.049	-0.368
		-0.30	*-0.32*	*1.71*	*0.22*	*-1.26*
40	Financials	1.13%	0.86%	0.309	-0.023	0.239
		3.12	*2.42*	*3.70*	*-0.27*	*2.20*
45 & 50	Technology	1.11%	0.93%	0.474	0.252	-0.300
		1.29	*1.15*	*2.49*	*1.29*	*-1.21*
55	Utilities	0.86%	0.54%	0.334	0.142	0.213
		1.29	*0.78*	*2.05*	*0.85*	*1.00*