Behavioral biases in number processing: The case of analysts' target prices*

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November 13, 2015

Abstract

Research in neuropsychology shows that the human brain processes differently small and large numbers. In this paper, we show that financial analysts process differently low prices and high prices, when they issue target prices one-year ahead. First, analysts are more optimistic on low price stocks than on high price stocks, even after controlling for risk factors. Second, the returns implied by target prices are significantly more dispersed for low price stocks. Third, we strengthen these results by showing that target prices become more optimistic and more dispersed after stock splits. Finally, we find that the link between risk-adjusted implied returns and stock prices survives after controlling for rounding, the 52-week high bias, the coverage of distressed firms and analysts' characteristics. Overall, our results suggest that a deeply-rooted behavioral bias in number processing explains a significant part of analysts' forecast errors.

Keywords: Financial analysts, target prices, behavioral biases, number perception

*This paper benefited from comments by Nicolas Eber, Maxime Merli, Pamela Moulton, Hélène Rainelli-Weiss, Marc Willinger as well as seminar participants at Paris-Dauphine University, EM Strasbourg Business School, and the 2015 Academy of Behavioral Finance and Economics. Patrick Roger gratefully acknowledges the financial support of the Chair in Behavioral Finance at EM Strasbourg Business School.

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1 Introduction

Sell-side analysts produce diverse information in their research reports: stock recommendations, earnings (or cash-flows) forecasts, target prices, and some justifications or explanations (Asquith, Mikhail, and Au, 2005; Bradshaw, Brown, and Huang, 2013). It is well-documented that earnings forecasts and target prices are biased (Ramnath, Rock, and Shane, 2008; Bradshaw, Huang, and Tan, 2014). Financial analysts are too optimistic: earnings forecasts are frequently higher than realized earnings, and target prices tend to be greater than current prices. For instance, Brav and Lehavy (2003) find an average implied return of 28% for the 1997-1999 period, while Bradshaw, Brown, and Huang (2013) report an implied return of 24% for the 2000-2009 period. These average implied returns greatly exceed realized market returns over the same periods.

Explanations for this optimism bias principally come from two streams of research. In the main stream of research, financial analysts are considered to be rational economic agents and their optimism reflects their incentive to produce inaccurate figures (Lim, 2001; Mehran and Stulz, 2007; Bradshaw, Huang, and Tan, 2014). In the other stream of research, financial analysts are characterized by some behavioral biases (bounded rationality). The use of some specific heuristics leads analysts to miscalculate (Cen, Hilary, and Wei, 2013; Clarkson, Nekrasov, Simon, and Tutticci, 2013).

In this paper, we investigate whether analysts exhibit a specific behavioral bias, which we call the low price bias, when issuing target prices. We argue that analysts process small numbers (in this case, low stock prices) differently than large numbers (*i.e.,* high stock prices).

Our argument for the existence of a low price bias is grounded in recent research in neuropsychology, where the mental representation of numbers has been extensively studied (Dehaene, 2011, for a review). The human brain processes numbers on a mental number line, that is, a spatial representation where small numbers are located on the left and large numbers on the right.[1] The mapping between a number and its spatial position on the line, however, is not linear.

When evaluating proximity relations between numbers, people exhibit two common

[1]This orientation from the left to the right is only valid in cultures where people write from the left to the right (Dehaene, 2011).

characteristics (Dehaene, Dehaene-Lambertz, and Cohen, 1998; Nieder, 2005). First, when people rank numbers, the reaction time and the error rate are a decreasing function of the difference between the two numbers. This first characteristic is called the distance effect. For instance, it is faster to recognize that 10 is greater than 1 than to perceive that 6 is greater than 5. The second characteristic is called the size effect. For a given difference between two numbers, people are slower in deciding, for instance, that 35 is greater than 34 than in deciding that 6 is greater than 5. The quantitative model of the distance and the size effects is known as Weber's law. In short, Weber's law means that numbers are measured on a logarithmic scale in the brain (Nieder, 2005, , for a detailed description). In particular, increasingly larger numbers are subjectively closer together. Weber's law also means that when people estimate numbers (analysts estimating target prices, for example), the dispersion of these estimates should be proportional to the average estimate. Dehaene, Izard, Spelke, and Pica (2008) and Hyde and Spelke (2009), however, show that deviations from the logarithmic scale are observed for small numbers, in particular as a result of formal education. People tend to use a linear scale for small numbers and a logarithmic scale for large numbers. In a simplified formulation, the mental representation of numbers, when applied to market participants, could be stated as follows: a price variation from \$3 to \$3.2 is a 20 cents increase, but a price variation from \$101 to \$110 is approximately a 10% increase (not a \$9 variation).

The literature on earnings forecasts provides evidence of the use of a linear scale for small numbers. Graham, Harvey, and Rajgopal (2005) find that market participants have a myopic focus on EPS (earnings per share) in absolute terms (*i.e.*, in cents per share, not in percentage of the stock price). Cheong and Thomas (2011) show that neither analysts' (unscaled) forecast errors, nor the dispersion of these forecast errors depend on the EPS magnitude. Moreover, Jung, Keeley, and Ronen (2013) develop a model that partly predicts analysts' earnings forecast revisions. They show that abnormal returns appear in portfolio strategies based on unscaled revisions but not in strategies based on scaled revisions. An important characteristic of EPS is that these figures are small numbers. These studies indicate that earnings per share are processed on a linear scale. On the contrary, stock prices may be small or large numbers.

The above arguments and results lead to the following hypothesis: If analysts use a linear scale for low price stocks and a logarithmic scale for high price stocks, they will provide more optimistic and more dispersed target prices for low price stocks than for high price stocks. To test this hypothesis, we use a sample of 814,117 target prices issued by 9,141 analysts (687 brokers) on 6,423 U.S. stocks over a fourteen year period (2000-2013). We first find that analysts are more optimistic on low price stocks than on high price stocks. Over the whole sample period, the average implied return (defined as the difference between the target price and the current stock price scaled by the current price) of target prices issued on stocks with a nominal stock price below \$10 is equal to 31.78%. The average implied return is only 17.00% for stocks with a nominal stock price above \$40. Because stock prices and market capitalization (firm size) are positively correlated (Baker, Greenwood, and Wurgler, 2009), we control that our results are not driven by a size effect. We double sort on nominal stock prices and market capitalization to disentangle the low price effect from a potential size effect. In the small capitalization quintile, the average implied return on low price stocks (<\$10) is 15% higher than the implied return on high price stocks (>\$40). In the large capitalization quintile, this difference is 8%.

We confirm that the low price bias is not a size effect by showing that analysts become more optimistic after splits. A stock split is the ideal natural experiment because a split generates a large price change while having no impact on fundamentals (He and Wang, 2012). We use propensity score matching to control for determinants of stock splits. Our differences-in-differences analysis indicates an increase in average implied returns following stock splits. We also find that target prices become significantly more dispersed.[2]

In our main analysis, we run a Fama-MacBeth regression (Fama and MacBeth, 1973) where expected returns are proxied by the average returns implied by target prices. In the first step of the analysis, the time series regressions use a five-factor model including the market, book-to-market, size, momentum and liquidity factors. In the second cross-sectional step, we include four nominal price dummies (\$0-\$10, \$10-\$20, \$20-\$30, \$30-\$40) as explanatory variables. Our results indicate a sharp difference in alphas between low price stocks and high price stocks. The use of Fama-MacBeth regressions allows us to eliminate the possibility that the low price bias is driven by the "usual suspects" (size, book-to-market, momentum and liquidity).

Finally, we perform a number of robustness tests to eliminate potential alternative explanations to the low price bias. In particular, we show that the rounding of target prices, the 52-week high bias, the selection bias induced by analysts ending coverage of distressed firms, or the selection bias induced by less experienced (or less skilled) analysts covering low price stocks, cannot explain the low price bias. We also look at stock recommendations to

[2] The implied return dispersion is defined as the standard deviation of implied returns calculated with analysts' target prices issued on a given stock over a given time-period.

confirm that our results come from the differential processing of small and large numbers and not from differences in unobservable economic factors. If the higher risk-adjusted returns on low price stocks are economically sound, analysts should issue more favorable recommendations on low price stocks. No differences should be observed, however, if the higher risk-adjusted returns result from a differential processing of small and large numbers. Our results indicate no preference for low price stocks. On the contrary, among large firms, the proportion of positive recommendations (Strong Buy or Buy) is larger for high price stocks. This finding is a strong signal that the higher implied returns found for low price stocks do result from a differential processing of small and large numbers.

Our paper contributes to the scarce literature on target prices (Bradshaw, 2002; Bonini, Zanetti, Bianchini, and Salvi, 2010; Bradshaw, Brown, and Huang, 2013; Bilinski, Lyssimachou, and Walker, 2013; Gleason, Johnson, and Li, 2013; Bradshaw, Huang, and Tan, 2014). This scarcity is surprising because target prices provide more relevant information to investors than earnings (or cash-flow) forecasts or even stock recommendations (Bradshaw, 2011). Furthermore, Brav and Lehavy (2003) show that market participants react to information contained in target prices, even though they are biased.

To date, the main explanation for analysts' optimism is their incentive to produce inaccurate figures. For instance, in two recent papers on target prices around the world, Bilinski, Lyssimachou, and Walker (2013) and Bradshaw, Huang, and Tan (2014) show that analysts' optimism is linked to the efficiency of country-level institutions (notably strong investor protection end effective legal enforcement). There are not many explanations based on behavioral biases (or bounded rationality) of analysts, however. Two exceptions are Cen, Hilary, and Wei (2013) who show that the well-documented anchorage bias can also explain analysts' optimism and, Clarkson, Nekrasov, Simon, and Tutticci (2013) who find that rounding and the 52-week price bias contribute to explaining the formation of target prices.

This paper also contributes to the literature on stock splits. We highlight that average implied returns and implied return dispersion significantly increase after stock splits. Finally, we contribute to the literature on the perception of numbers. We provide evidence of distortions in number processing for well-educated professionals who repeatedly use numbers on a daily basis. One would expect such professionals not to be prone to the low price bias, compared to people that are not familiar with number computation. Our findings, however, show that this low price bias is deeply rooted in the brain of financial analysts.

The paper is structured as follows. Section 2 gives an overview of the data and provides descriptive statistics on target prices and analysts. Section 3 contains the first results on the relationship between target prices' implied returns and the level of stock prices. In section 4, we look at analysts' target prices before and after stock splits. Section 5 shows that the low price bias remains strong after controlling for risk factors and conflicts of interest. Finally, section 6 provides a number of robustness tests, to control for other biases such as the rounding effect, the 52-week high bias and the self-selection bias, and to control for analysts' characteristics. A final subsection looks at stock recommendations to discard the possibility that our results are driven by unobservable economic factors. The last section concludes this paper.

2 Data and descriptive statistics

Our data are from the Center for Research in Security Prices (CRSP) and include all ordinary common shares (code 10 or 11) listed on NYSE, Amex and Nasdaq for the 2000-2014 period. Data on target prices come from the Institutional Brokers Estimate System (I/B/E/S) and span the years 2000 to 2013.[3] Ending in 2013 allows comparing one-year-ahead target prices issued by analysts with realized returns calculated with the CRSP database. We keep only target prices issued on stocks listed on NYSE, Amex or Nasdaq. To eliminate potential reporting errors, we remove forecasts for which the ratio of the target price to the stock price is in the bottom or top one percent of the distribution. Our final sample contains 814,117 target prices issued by 9,141 analysts (687 brokers) for 6,423 U.S. stocks. We also use stock recommendations from I/B/E/S. For the 2000-2013 period, we have a sample of 315,304 recommendations. These recommendations are standardized by I/B/E/S into five different ratings: Strong buy, Buy, Hold, Underperform and Sell. Finally, we have the Institutional Investor (I/I) All-American rankings for the years 2000 to 2010.

[**Table 1 here**]

[3] I/B/E/S started reporting target prices in 1999. It appears that, in the first few months, only a few brokers were disclosing their forecasts to I/B/E/S. We exclude the year 1999 to be sure that we do not have a sample bias.

Table 1 reports descriptive statistics on the distribution of target prices. Each line of the table corresponds to one year. Columns 2 to 6 provide, for each year, the number of target prices issued by analysts, the number of analysts who issued at least one target price, the average number of analysts per firm, the average number of firms covered by an analyst, and the average return implied by target prices. The central part of the table (columns 7 to 12) gives the number of firms covered by analysts in each nominal price category. For the sake of comparison, the right part of the table (columns 13 to 18) gives the number of firms (listed on NYSE, Amex and Nasdaq) in each price category at the beginning of the year. Our price categories are not the usual quintiles because we argue in this paper, that analysts process differently small and large prices. As a consequence, our categories use absolute (not statistical) intervals. The first category includes low price stocks (\$0 to \$10) and the remaining categories contain stocks with prices from \$10 to \$20, \$20 to \$30, \$30 to \$40 and, above \$40.

Table 1 shows that the number of target prices issued each year strongly increases over time. Between 2000 and 2013, the number of target prices increased by about 140%. Additionally, we observe two other changes. First, the average number of analysts per firm increased by about 70%, from 9.62 in 2000 to 16.03 in 2013. Second, the number of firms covered per analyst increased by about 40% over the period, starting at 10.49 and ending at 14.44. The global number of firms followed by analysts is almost unchanged (3,069 in 2000 and 2,654 in 2013, with a maximum of 3,125 in 2006). In the meantime, the aggregate number of firms (last column) on the NYSE, Amex and Nasdaq markets has declined significantly, from 6,531 in 2000 to 3,642 in 2013. These figures indicate that issuing target prices is an increasingly popular practice among financial analysts. Moreover, the average implied return, reported in column 6, shows that financial analysts have optimistic views on future prices.[4] The average yearly implied return over the sample period is 21.55%, the less (more) optimistic year being 2013 (2000) with 13.46% (37.89%). This figure can be compared to the actual yearly growth rate of the S&P500 index which was below 2% over the same time period.

The comparison of the number of firms covered by analysts (columns 7 to 11) in each price category, to the total number of firms (columns 13 to 17), shows two distinctive features. First, the coverage rate is positively linked to the stock price level. A greater number of analysts issued target prices for firms with high stock prices than firms with

[4]Bradshaw, Huang, and Tan (2014) show that analysts' optimistic behavior is not specific to the U.S. market.

low prices. In 2000, there were 2,840 stocks with a beginning-of-year nominal price in the \$0-\$10 range. Only about 20% of these stocks were covered by financial analysts. In contrast, this number reaches 80% for stocks whose nominal price was above \$40. The bias towards high price stocks implicitly shows the positive link between the stock price and the market capitalization of a firm. High price firms tend to be large firms[5] which are covered by more analysts than small firms (Bhushan, 1989). The difference in coverage between high and low price stocks decreases over time. In 2013, analysts published target prices for 56% of low price stocks and 89% of high price stocks.

The right side of Table 1 gives descriptive statistics on stock prices of firms listed on NYSE, Amex and Nasdaq. The percentage of stocks priced below \$10 varies from 30% in 2007 to 57% in 2009. A low percentage is more likely at the end of bullish periods and a high percentage is more likely following a financial crisis. These figures show that transitions from one price category to another are frequent, either because a natural market movement makes prices go up or down, or because firms split and move to another price category. The frequent changes of price categories for a given firm will reinforce our results based on absolute price categories (and not on quintiles). If we observe strong price-based regularities, after controlling for firm size, it will be difficult to attribute these regularities to variables other than the stock price.

3 Stock prices and implied returns

3.1 Preliminary results

We first examine the relation between nominal stock prices and returns implied by target prices. Our analysis focuses on two characteristics of target prices. First, each target price induces a yearly implied return defined as the ratio of the target price (at the issue date) divided by the current stock price, minus 1. In the following analysis, the implied return on a given stock i in a given month t (denoted $ER_{i,t}$) is the equally-weighted average of the implied returns deduced from all target prices issued on stock i during period t. $ER_{i,t}$ is defined as

$$ER_{i,t} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(\frac{TP_{j,i,t}}{S_{j,i,t}} - 1\right) \tag{1}$$

[5]The relationship between stock price and firm size, however, is far from perfect, as a result of the management of stock prices by firms through the choice of IPO prices, splits and stock dividends.

where $TP_{j,i,t}$ is the target price issued by analyst j on stock i in period t, $S_{j,i,t}$ is the stock price on the day analyst j publishes her forecast, and $J_{i,t}$ is the number of analysts issuing a target price on stock i in period t. The implied return $ER_{i,t}$ is then a measure of analysts' expectations about the future return on stock i.

The second variable of interest is the implied return dispersion across analysts (denoted $DISP_{i,t}$). It is defined as the standard deviation of returns implied by target prices on stock i in period t.

$$DISP_{i,t} = \sqrt{\frac{1}{(J_{i,t}-1)}\sum_{j=1}^{J_{i,t}}(R_{j,i,t} - ER_{i,t})^2} \tag{2}$$

where $R_{j,i,t} = \frac{TP_{j,i,t}}{S_{j,i,t}} - 1$ is the return implied by the target price issued on stock i in period t by analyst j.

$DISP_{i,t}$ measures the disagreement among analysts. In this paper, the results related to the dispersion of target prices are based on firm-period observations for which there are at least three target prices.

We define five price categories as stock price intervals. We choose absolute intervals ($0-$10, $10-$20, $20-$30, $30-$40, and greater than $40) instead of statistical intervals (quintiles), to be consistent with our hypothesis that small prices and large prices are processed differently in analysts' brains.

[**Figure 1 here**]

Figure 1 contains two panels based on the five price categories. Panel A shows the evolution over time of the average implied return in each category. For category k, the average is calculated as $\frac{1}{n_k}\sum_{i=1}^{n_k} ER_{i,t}$ where n_k is the number of firms in category $k = 1, ..., 5$. The two curves at the top of the figure correspond to low price stocks (stock prices lower than $10 for the top curve and stocks with prices between $10 and $20 for the second curve). Analysts are consistently more optimistic about the future returns of low price stocks compared to the ones of high price stocks. This pattern is persistent over time, to the exception of the third quarter of 2000 (the end of the dotcom bubble) and the second quarter of 2008 (the beginning of the market reversal following the subprime crisis). During these two quarters, the link between stock prices and implied returns tends to be weaker. Since strong price variations were observed during these quarters, it is likely that the price category of a large number of firms changed within these quarters. On average, the difference of implied returns between low price stocks (\$0-\$10) and high price stocks (>\$40) is approximately 15%.

Panel B of Figure 1 is built like panel A, but the average implied return is replaced by the implied return dispersion, within each price category, that is, $\frac{1}{n_k}\sum_{i=1}^{n_k} DISP_{i,t}$. The disagreement among analysts is a decreasing function of the stock price. Implied returns are more dispersed on low price stocks than on high price stocks. A possible reason for this larger dispersion of forecasts could be the lower number of forecasts for low price stocks, compared to high price stocks. The estimates of standard deviations $DISP_{i,t}$ are unbiased, however. As a consequence, there is no reason to observe a systematic overestimation of the implied return dispersion when the number of forecasts is low.

3.2 Size-based or price-based effects

The previous results reveal a relationship between nominal stock prices and target price implied returns. This relationship could be driven by a size effect, as a result of the positive link between share price and capitalization (Baker, Greenwood, and Wurgler, 2009). To disentangle the price and size effects, we use a double sort based on the price categories used in Figure 1 and on quintiles of capitalization defined with NYSE breakpoints. Figure 2 shows the results in three panels. Panel A gives, for each quintile of size, the implied return in the different price categories. For the four lowest quintiles of capitalization, the relationship between stock prices and implied returns is strictly decreasing. The difference in implied returns between high price stocks and low price stocks is 24.97% for small firms; it decreases steadily for the next three quintiles of size (respectively 15.94%, 9.15%, 7.39% and 3.17% for large-capitalization stocks). The difference is significant at all standard levels in each size quintile. Panel A also shows that, in size quintile $k = 1, 2, 3, 4$, the implied return on high price stocks is lower than the implied return on low price stocks of quintile $k + 1$. This result indicates that the low price bias is not masking a size effect. In particular, for the three high price categories there are no significant differences in implied returns between small firms and large firms.

[**Figure 2 here**]

Panel B of Figure 2 shows the implied return dispersion double-sorted on size quintiles and stock price categories. The graphs in panel B have the same shape as the ones in panel A. The differences in implied return dispersion between low price stocks (<\$10) and high price stocks (>\$40), however, are relatively stable across size quintiles, varying from 9.08% in the fourth size quintile to 14.49% in the first quintile. The differences in dispersion between the extreme price categories are highly significant. On the contrary, within price categories, the differences in dispersion between large caps and small caps are either positive (for low prices) or negative (for high prices). Our double sort analysis indicates again that the low price bias is distinct (and stronger) from a potential size effect.

In panel C, the variable under scrutiny is the accuracy of target prices. We use a standard measure of accuracy, the absolute forecast error (denoted AFE hereafter) which is defined as the difference between the target price and the realized price divided by the stock price at the time the target price was issued. Panel C shows that the AFE is a decreasing function of the share price across size quintiles. As a consequence, the price-based differences in target price optimism are not justified by the future one-year realized returns. For large firms, the difference in AFEs between low price stocks and high price stocks is 16.58%. This difference reaches 37.90% for small firms. Unsurprisingly, there is also a size effect for accuracy. In each price category, the difference between the AFE of small firms and the AFE of large firms is positive and significant. This difference may reflect the differential amount of information available on small and large firms (Lang and Lundholm, 1996). It may also reflect the fact that analysts covering large firms are not the same as analysts covering small firms. In a robustness test presented in section 6, we examine the link between analysts' characteristics and the low price bias.

4 Stock splits

In this section, we analyze stock splits. Such events represent a typical natural experiment, which allows us to disentangle price and size effects. A forward (reverse) split consists of increasing (decreasing) the number of shares while decreasing (increasing) the price per share. Hence, a split generates a price change, which can be large, while having no impact on fundamentals (He and Wang, 2012). If analysts are prone to the low price bias, we expect target prices to be more optimistic and more dispersed following forward stock splits.

Since the publication of the seminal paper of Fama, Fisher, Jensen, and Roll (1969), many papers analyze the motivation and the consequences of stock splits. In particular, some papers argue that splits signal positive inside information and, therefore, investors react favorably to the announcement of splits (Asquith, Healy, and Palepu, 1989; Ikenberry, Rankine, and Stice, 1996). For example, Ikenberry, Rankine, and Stice (1996) find a 3.8% abnormal return on the announcement date, and Lin, Singh, and Yu (2009) find more than 3%. Devos, Elliott, and Warr (2015) show that there is a price run up in the 10 days that precede the split announcement, and the stock price continues to increase a few days after the announcement. Hence, if analysts also consider that a stock split provides new information about future cash flows, then they should become more optimistic before the announcement, and maybe a few days after the announcement. The increase in analysts' optimism, however, should not come after the ex-split day, which occurs on average 52 days after the announcement (French and Foster, 2002), because the price increase due to the good news has already occurred.

More recently, Baker, Greenwood, and Wurgler (2009) proposed an alternative approach to the motivation of splits. They develop a catering theory of nominal share prices. The idea is as follows: Firms decide to split their stocks to reach a lower share price at times where investors are ready to pay a premium for low price stocks. If financial analysts are rational, they should perceive the overvaluation of stocks that splits and, therefore, issue post-split target prices with lower implied returns. On the contrary, finding an increase in implied returns after splits would reinforce our proposition of a low price bias.

Another cause of variation in average implied returns after splits, is the potential change in the set of analysts covering firms that split their stocks. To control for initiation and termination coverage effects, we duplicate our analysis on the subsample of analysts who issue target prices both before and after the splits

We present two tests hereafter. The first test shows that the average implied returns, the dispersion of implied returns, and the inaccuracy of target prices, increase after splits. The second test uses propensity score matching to control for a number of firm characteristics known to influence the propensity of firms to split.

4.1 Implied returns before and after stock splits

We distinguish two categories of splits.[6] The first category contains splits with ratios between 1.25 and 2 (type-1 splits) and the second category (type-2 splits) contains splits with ratios larger or equal to 2.

For each split, we calculate three statistics. First, we compute the average implied return of target prices issued in the quarter[7] preceding (following) the split, and the average across all stock splits of this implied return, for each of the two split types. Second, we calculate the dispersion of implied returns in the subsample of splits for which there are at least three target prices in the quarter preceding (following) the split. Finally, we calculate absolute forecast errors (*i.e.*, target price accuracy) before and after splits.

Our sample contains 1,401 stock splits, 532 type-1 splits and 869 type-2 splits. When computing implied returns dispersion, our sample is reduced to 982 splits, 347 of type-1 and 635 of type-2. The results appear in Table 2. In Panel A, all the target prices are taken into account. In panel B, to control for possible initiation or termination coverage effects due to splits, we consider only the subsample of analysts who issue target prices both before and after the split. We comment only on Panel A because the results are virtually unchanged in Panel B.

[**Table 2 here**]

The post-split implied returns are equal to 20.30% for type-1 splits and 22.81% for type-2 splits. The corresponding pre-split implied returns are 15.78% and 16.83%. For each type, the difference is highly significant, 4.53% for type-1 splits, 5.98% for type-2 splits. Because a stock-split has no impact on the market capitalization of the firm, differences in implied returns before and after stock splits cannot be driven by differences in market capitalization. The second column of Table 2 shows that the implied return dispersion also increases after splits, from 11.24% to 13.94% for type-1 splits and from 11.74% to 15.18% for type-2 splits. The last column of Table 2 illustrates the increase in inaccuracy following splits. The absolute forecast error increases from 33.37% to 35.67% for a split

[6] We consider neither reverse splits (splits with a ratio lower than 1), nor stock dividends (splits with a ratio between 1 and 1.25). The frequencies in each category are not sufficient to perform a relevant statistical analysis.

[7] We arbitrarily chose a three-month window but robustness checks with two-month and six-month windows provide similar results.

ratio between 1.25 and 2 and from 39.22% to 41.65% for a split ratio greater or equal to 2. The difference in absolute forecast errors is statistically significant at the 5% level for splits with a ratio between 1.25 and 2 and at the 1% level for splits with a ratio greater or equal to 2. The levels of significance are the same in Panel B where target prices (for a given firm) before and after splits are issued by the same set of analysts. These findings confirm that the increase in analysts' optimism is not caused by a size effect. Knowing that firms' fundamentals are unchanged after splits, we conclude that these results are a strong signal in favor of the existence of a low price bias. One could argue, however, that the behavior of the stock price of splitting firms could also come from the peculiarity of the sample of splitting firms. For example, our results could be driven by variables known to influence the decision to split a firm's stock or by a concentration of splits in some specific time periods.[8] The results in the next subsection show that it is not the case.

4.2 Propensity score matching

To control for firms' characteristics that distinguish firms that split their stock from firms that do not split, and to control for potential time-period effects, we use propensity score matching (Rosenbaum and Rubin, 1983). The purpose of propensity score matching is to select a sample of control firms that do not split, but share a number of significant characteristics with firms that split. We calculate propensity scores using probit regressions where independent variables (see Baker, Greenwood, and Wurgler, 2009) are the logarithm of the stock price at the end of the year $t-1$, the market capitalization at the end of year $t-1$, the last-year return, the last-year total volatility, the book-to-market ratio at the end of year $t-1$, and the average return implied by target prices issued in the last three month of year $t-1$.[9]

For each stock split in year t, we select (with replacement) a matching firm from the same year that belongs to the same industry[10] and has a propensity score closest to the score of the firm that splits its stock. All the technical details of the matching process are

[8]For instance, Minnick and Raman (2014) show that the number of splits has decreased over time due to the increasing institutional ownership of firms. For a more complete view on this literature, see He and Wang (2012).

[9]We also included in the probit regressions trading volume, bid-ask spread and industry average price. These variables are not significant and reduce the number of observations; therefore we decided not to keep these variables in the final model.

[10]We use Fama and French (1997) industry classification.

reported in the Appendix. To evaluate the quality of our matching, we follow the diagnostic approach of Lemmon and Roberts (2010). For each year from 2000 to 2013, we estimate propensity scores with probit regressions. The independent variables include the known determinants of stock splits used in Baker, Greenwood, and Wurgler (2009), together with pre-split analysts' implied returns. Table A1 in the Appendix reports the results of the probit regressions before and after matching. The after matching regression contains only firms that split and matching firms as well, ending in 1,456 observations. Before matching (first column of Table A1), all the determinants are significant. As expected, the last column of Table A1 indicates that none of the determinants remains significant after matching. In addition, Table A2 shows the balancing test after matching. It confirms that the average difference in characteristics between splitting firms and control firms is not significant. Overall, these results show that the two samples share similar pre-split characteristics and can be used for the differences-in-differences (DD) analysis.

[**Table 3 here**]

The results of the differences-in-differences analysis are reported in Table 3. For type-1 (type-2) splits, the DD of average implied returns is equal to 2.41% (3.66%). This difference is highly significant. Thus, the increase in implied returns following stock splits is not the result of an increased analysts' optimism during periods in which firms are prone to splitting. Our results also indicate that this increase in implied returns is not driven by splitting firms having different characteristics than non-splitting firms. Our findings are similar for the dispersion of implied returns (columns 4 to 6). For type-1 (type-2) splits, the DD of implied return dispersion is equal to 2.00% (1.89%). This difference is significant at the 5% level (1%). The last three columns of Table 3 report show that absolute forecast errors also increase following stock splits. Our differences-in-differences analysis confirm our previous findings. Following stock splits, target prices become more optimistic, more dispersed and less accurate.

5 Implied returns, stock prices and risk factors

The results in section 3 show the influence of the stock price level on both average implied returns and implied return dispersion. The higher implied returns on low price stocks, however, may result from a higher sensitivity to risk factors. To investigate this issue, we follow Brav, Lehavy, and Michaely (2005) who apply the two-step Fama-MacBeth methodology (Fama and MacBeth, 1973) to analysts' expectations (instead of realized future returns).

The first-step regressions are the standard time-series regressions based on the Fama and French (1993) three-factor model plus the Carhart (1997) momentum factor and the Pastor and Stambaugh (2003) liquidity factor. The model writes

$$\begin{aligned} R_{i,t} - R_{f,t} = \theta_i + \beta_{M,i}(R_{M,t} - R_{f,t}) + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t \\ + \beta_{MOM,i} MOM_t + \beta_{LIQ,i} LIQ_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $R_{M,t}$ is the month-t return on the value-weighted CRSP index, $R_{f,t}$ is the risk-free rate, proxied by the 1-month T-bill rate. The size (SMB) and value (HML) factors use independent sorting of stocks into two size groups and three book-to-market groups (independent 2x3 sorts). The size breakpoint is the NYSE median market capitalization, and the book-to-market breakpoints are the 30th and 70th percentiles for NYSE stocks. The intersections of the stocks sorting produce six value weighted portfolios. The size factor is obtained as the average of the three small stock portfolio returns minus the average of the three big stock portfolio returns. The value factor HML is obtained as the average of the two high book-to-market portfolio returns minus the average of the two low book-to-market portfolio returns. MOM is the momentum factor built with six value-weighted portfolios formed on size and prior returns (12 to 2 months before the current date). The monthly portfolios are the intersections of 2 portfolios formed on size and three portfolios formed on prior return. The monthly size breakpoint is the median NYSE market equity. The monthly prior return breakpoints are the 30th and 70th NYSE percentiles. MOM is the average return on the two high momentum portfolios minus the average return on the two low momentum portfolios. Finally, LIQ is the Pastor and Stambaugh (2003) aggregate liquidity factor. Factor returns and risk-free rates come from Kenneth French website.[11]

We estimate equation 3 for a given month t by using the preceding 60 monthly returns, from $t-61$ to $t-1$. When the available data do not cover 60 months, we require at least 24 monthly returns to perform the estimation.

[11] See http://mba.tuck.darmouth.edu/pages/faculty/ken.french

In the cross-sectional step of the Fama-Macbeth methodology, we regress the firms' average implied excess return ($ER_t - R_{f,t}$) on the factor loadings estimated in the first step, for every month t from January 2000 to December 2013. For month t, we first estimate the model (model 1)

$$\begin{aligned} ER_t - R_{f,t} = \alpha_t + \gamma_{M,t}\beta_{M,t} + \gamma_{SMB,t}\beta_{SMB,t} + \gamma_{HML,t}\beta_{HML,t} \\ + \gamma_{MOM,t}\beta_{MOM,t} + \gamma_{LIQ,t}\beta_{LIQ,t} + \epsilon_t \end{aligned} \tag{4}$$

where $\beta_{X,t}$ is the vector of β coefficients for factor X and month t with $X = M, SMB, HML, MOM, LIQ$. The γ coefficients are the slopes of the month-t cross-sectional regression. We then average the intercept and slopes over the 168 months (14 years times 12 months per year) of our time-period. We adjust standard errors using the Newey-West procedure.

The results are reported in the first column of Table 4. In line with studies using realized returns, the market and size factors have positive and significant premia at the 1% level. The t-statistic for the market (size) factor is equal to 8.54 (4.22). These coefficients are also comparable to those obtained by Brav, Lehavy, and Michaely (2005) on a different time-period and a different target price database. HML and MOM, though significant at the 5% level in the baseline case have t-statistics close to 2. Finally, the slope of the liquidity factor is significant and positive.

[**Table 4 here**]

The low price bias appears in the second column (model 2) of Table 4 where we report the regression results with price-based dummy variables ($PRICE\_CAT_{i,j,t}$). The four price-based dummy variables identify the first four price categories ($0-$10, $10-$20, $20-$30, $30-$40 numbered from 1 to 4) described in Section 2. $PRICE\_CAT_{i,j,t}$ is equal to 1 when the price of stock i is in price category j ($j = 1, ..., 4$) at the end of month $t-1$. Model 2 writes

$$\begin{aligned} ER_t - R_{f,t} = \alpha_t + \gamma_{M,t}\beta_{M,t} + \gamma_{SMB,t}\beta_{SMB,t} + \gamma_{HML,t}\beta_{HML,t} \\ + \gamma_{MOM,t}\beta_{MOM,t} + \gamma_{LIQ,t}\beta_{LIQ,t} + \sum_{j=1}^{4} \gamma_{price\_cat,j,t} PRICE\_CAT_{j,t} + \epsilon_t \end{aligned} \tag{5}$$

where $PRICE\_CAT_{j,t}$ is the vector of the $PRICE\_CAT_{i,j,t}$ for firms i for which a target price was issued within month t.

Model 2 provides a first proof of the existence of a low price bias on a risk-adjusted basis. The return premia on the price-based dummy variables are positive and significant for the first three price categories. More importantly, these premia are decreasing in the price level. The risk-adjusted return expected by analysts for stocks priced above $40 is 12.31% (the intercept of the regression). The average risk-adjusted return for stocks priced in the $30-$40 range is almost the same at 12.36%. It increases to 14.18% for stocks in the $20-$30 range, 18.12% for stocks in the $10-$20 range and 30.71% for stocks with a price below $10. These differences in risk-adjusted returns across price ranges are highly significant for low prices (<$30). In addition to being statistically significant, the magnitude of the difference in risk-adjusted returns between low price stocks and high price stocks is also economically significant. Finally, introducing price-based dummy variables increases the adjusted R^2 of the regression by almost 80%, from 10.12% in model 1 to 17.94% in model 2.

Finally, in model 3 of Table 4, we add control variables related to conflicts of interest. Conflicts of interest may arise when a firm has investment banking needs. Dechow, Hutton, and Sloan (1999), Hong and Kubik (2003), Lin and McNichols (1998), McNichols and O'Brien (1997) find that analysts face incentives to provide optimistic forecasts to secure profitable investment banking relationships.[12] Bradshaw, Richardson, and Sloan (2006) document a strong link between external financing and analysts' optimism. We, therefore, add external financing ($ExtFin$) in our controls.[13] In addition, as in Bradshaw, Huang, and Tan (2014), we consider the evidence in Teoh, Welch, and Wong (1998b,a) that firms manage accruals to increase earnings prior to financing activities such as Initial Public Offerings (IPO) or Seasonal Public Offerings (SEO). Our proxy for earnings management is the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model (Jones, 1991; Dechow, Sloan, and Sweeney, 1995).

Model 3 in Table 4 shows that controlling for conflicts of interest and earnings management using net external financing and discretionary accruals does not change the results. In fact, the low price bias is slightly reinforced. The main effect of the control variables is to decrease the market and size loadings. Overall, our findings clearly indicate that the

[12]Similarly, Philbrick (1993), Lim (2001), and Libby, Hunton, Tan, and Seybert (2008) show that analysts produce biased forecasts to obtain better access to management.

[13]Following Bradshaw, Richardson, and Sloan (2006), we define external financing as the change in equity plus the change in debt.

differences in analysts' optimism across price categories are not a by-product of differential sensitivities to risk factors or control variables.[14]

6 Robustness tests

The previous results highlight that financial analysts' optimism is strongly influenced by the level of stock prices. In this section, we show that this result is not questioned when competitive explanations are taken into account.

6.1 Rounding

The low price bias may be an artifact caused by analysts' psychological preference for rounded numbers. If an optimistic analyst rounds her "true" target price of $1.81 to the above nearest dime, that is, $1.90, the rounding process increases the implied return by approximately 5%. The same rounding on a target price of $31.81 (at $31.90) is almost negligible, representing 0.3% of the initial target price. Hence, rounding may be an alternative explanation for the low price bias. Thus, it is possible that the structure of regression coefficients in Table 4 results from target prices being systematically rounded in an optimistic way. We investigate this issue in this subsection.

The preference for rounded numbers (called "heaping") is documented in various fields like psychology, statistics, accounting, and finance. The analysts' tendency to use rounded numbers has been studied by Herrmann and Thomas (2005) and, more recently, by Dechow and You (2012) and Clarkson, Nekrasov, Simon, and Tutticci (2013). For example, Herrmann and Thomas (2005) find 55% of EPS forecasts ending by 0 or 5 in the penny location when the average percentage should be 20%. Clarkson, Nekrasov, Simon, and Tutticci (2013) show that rounding is significant in explaining the formation of target prices.

[**Figure 3 here**]

[14]In section 6, we develop a number of robustness checks to eliminate alternative explanations like the rounding of target prices, the 52-week high bias, and the self-selection bias.

Figure 3 provides a detailed illustration of the way analysts round their target prices across price categories. In addition, Figure 4 shows the distribution of target prices within price categories. We find that 92% of target prices are rounded to the dollar.[15] We note that the rounding magnitude varies across price categories. Not surprisingly, rounding to the nearest dollar is less frequent for low prices (70%). As mentioned above, however, the effect of rounding on implied returns is larger for low price stocks. We also find that rounding at the half-dollar, quarter, dime, and nickel is not negligible, especially for low price stocks. For example, over the 82,330 target prices in the low price category ($0-$10), 57,619 are rounded at the dollar, 14,357 at the half-dollar, 4,378 at the quarter, 3,863 at the dime, and 862 at the nearest nickel.

[**Figure 4 here**]

In this robustness test, we consider four scenarios describing how financial analysts may round target prices and we apply the relevant correction. The scenarios range from rounding at the dime level to rounding at the dollar level. For each scenario, we assume that: (1) all rounded target prices are higher than the "true" target price; and, (2) all the "true" target prices are the lowest possible target prices given the rounding magnitude.

In the first scenario, we consider that analysts round target prices at the nickel and at the dime level. We illustrate our approach with the following example. We consider a target price of $8.10. Our first assumption implies that the "true" target price is between $8.01 and $8.09.[16] Our second assumption leads us to consider a "true" target price equal to $8.01 (*i.e.*, the lowest possible target price when rounding occurs at the dime level). Therefore, we replace in our sample the observed target price of $8.10 with a target price of $8.01. Similarly, with rounding occurring at the nickel level, a target price of $8.35 will be replaced by a target price of $8.31.

Formally, the different scenarios are defined as follows. In the first scenario, we consider that analysts round at the dime level and at the nickel level. Our correction leads us to decrease by 4 cents any target price TP (expressed in cents) ending by 5 and to decrease by 9 cents any target price TP ending by 0. In the second scenario, we consider that

[15] Clarkson, Nekrasov, Simon, and Tutticci (2013) reports an average of 87% of target prices rounded to the dollar for the 1999-2007 period.

[16] Given the assumption that rounding occurs at most at the dime level, the "true" target price cannot be lower than $8.01. Indeed, otherwise the target price would have been rounded to $8.00.

analysts round at the quarter, the dime, and the nickel level. Therefore, we decrease by 21 cents any target price ending by 25, 50, 75 or 00, decrease by 9 cents any target price ending by 0 (but not the ones ending by 00 and 50), and decrease by 4 cents any target price ending by 5 (not the ones ending by 25 and 75). In the third scenario, we add a level of rounding and now consider that analysts also round at the half-dollar. Thus, in addition to correcting for rounding at the quarter, dime and nickel levels, we decrease by 49 cents target prices ending by 50 and 00. Finally, the fourth scenario considers rounding to the dollar. We apply a 99 cents correction to target prices ending by 00.

It is important here to stress that because our correction is in absolute terms (*i.e.*, in cents), the implied returns of target prices issued on low price stocks are more highly penalized compared to the ones issued on high price stocks. Additionally, in our first three scenarios, the number of target prices to which we apply a correction is much larger for low price categories. Figure 3 indicates that 28.71% of target prices in the \$0-\$10 category (10.70% in the \$10-\$20 category) are concerned by rounding of a magnitude up to the half-dollar (compared to only 2.08% of target prices in the above \$40 category). In the fourth scenario, the 99 cents correction impacts only 70% of target prices in the \$0-\$10 category (compared to more than 97% in the above \$40 category). It has a tremendous impact on the implied return of low target prices, however. This last scenario is highly unlikely to provide a realistic picture of the analysts' rounding process, especially for low target prices. Hence, if the low price bias is still observed when this last scenario is considered, we can be confident that the low price bias does not result from analysts rounding target prices.

[**Table 5 here**]

Table 5 provides the results of the second step of the Fama-MacBeth regressions for the four different rounding assumptions. This table shows that the low price bias is not explained by the rounding process, even in our worst case scenarios. Compared to the results of the benchmark model (column 3 of Table 4); we find that the regression coefficients decrease when the rounding process becomes more severe (*i.e.*, from the left to the right of the table). This result is predictable because the successive rounding corrections decrease implied returns. More importantly, the loading of the \$0-\$10 dummy variable decreases faster than the loadings of the other dummies. It falls at 4.14% for the most severe correction of target prices. This decrease is not surprising because, for low prices, correcting a target price by 99 cents can sharply decrease the implied return (at most a 99% decrease for a target price at \$1). Despite our rough rounding correction process, the low price bias remains strongly significant for all prices below \$20. The other important figures on Table 5 are the adjusted R^2 in the four analyses. The R^2 was equal to 20.69% in the benchmark case (Table 4). It decreases to 8.42% in the most severe rounding scenario. Thus, our results show that correcting for rounding mainly introduces noise, not information. We conclude that if optimistic rounding has a mechanical effect on implied returns, it does not explain the low price bias.

6.2 The 52-week high bias

The results obtained so far may be a statistical artifact if there is a strong link between the price level and the distance from the 52-week high, defined as the highest price reached by the stock over the last year. In fact, many financial newspapers, for example the *Wall Street Journal* or the *Financial Times*, attract the attention of investors on 52-week highs and lows by publishing every day the list of firms that reach these thresholds. A number of studies in different fields of research show that forecasts become less optimistic when stock prices are close to the 52-week high. For instance, in their study of mergers and acquisitions, Baker, Pan, and Wurgler (2012) show that shareholders of a target firm are more likely to accept an offer when the offer price is above the 52-week high. Highs and lows play the role of anchors, or psychological barriers. Grinblatt and Keloharju (2001) show that individual investors are more prone to sell stocks reaching a monthly high because these investors become less optimistic about the prospects of future returns. This strategy does not generate abnormal returns, however. George and Hwang (2004) obtain abnormal returns on long-short portfolios being long on stocks close to the 52-week high and short on stocks far from this threshold.

As a consequence, target prices being more optimistic on low price stocks may simply be the result of low price stocks being, on average, more distant from the 52-week high compared to high price stocks. In this subsection, we show that the distance from the 52-week high does not explain the low price bias. If analysts follow the same reasoning as individual investors and become less optimistic when stock prices are close to the 52-week high (Clarkson, Nekrasov, Simon, and Tutticci, 2013; Birru, 2014), they will be less optimistic (on average) on high price stocks (a 52-week high is more likely to be a high price than a low price).

To test the importance of this variable in the explanation of analysts' implied returns, we introduce the distance to the 52-week high as an independent variable in the second step of the Fama-MacBeth methodology. We first define the 52-week high variable (denoted 52WH) as the ratio of the current stock price and the highest price reached by the stock over the last year. We then define four dummy variables corresponding to the four first quintiles of 52WH. The results are reported in Table 6.

[**Table 6 here**]

The 52-week high dummies are positive, significant and their loadings are decreasing when we move from the lowest to the highest ratio. In other words, we find the expected result that analysts' optimism is stronger when prices are far from the 52-week high. Moreover, introducing these dummies improves the general quality of the regression; the adjusted R^2 improves, compared to the benchmark case. The low price bias and the 52-week high bias, however, are almost uncorrelated. The loading of the low price dummy (\$0-\$10) is still 15.45 % and the loadings of the second and third price dummies remain highly significant. Moreover, coefficients of price dummies are decreasing with respect to the share price, as in the baseline case (column 3 of Table 4). We can conclude that the 52-week high bias influences analysts' target prices but has no effect on the difference of optimism between low price stocks and high price stocks.

6.3 Distressed firms

Self-selection arises when analysts decide not to release unfavorable target prices, either because their employer could lose potential investment banking business or because issuing such target prices may reduce their access to the firm's management (McNichols and O'Brien, 1997; Chen and Matsumoto, 2006; Ke and Yu, 2006; Libby, Hunton, Tan, and Seybert, 2008; Mayew, 2008). While these concerns are particularly valid for the pre Reg-FD period, the change in regulation has not completely eliminated analysts' self-selection behavior (Mayew, 2008). Given the potential conflict of interests, analysts may decide not to release target prices for firms they think are on the edge of bankruptcy.[17] On the contrary, analysts may issue extremely optimistic forecasts when they expect a distressed

[17]Das, Levine, and Sivaramakrishnan (1998) argue that analysts value more access to management when earnings are difficult to forecast, which is likely when firms are in financial trouble.

firm to be able to quickly recover.[18] This self-selection bias has an impact on the observed distribution of forecasts (Baïk, 2006) which appears too optimistic. The bias may be particularly prominent among low price stocks because distressed firms are more likely to be in the subset of low price stocks. It follows that the low price bias could be the consequence of the self-selection bias.

To show that the low price bias is not caused by a self-selection bias, we replicate the regression analysis of Table 4 on various subsamples. We implement three complementary approaches to build the subsamples. The first approach to remove distressed firms is to keep only firm-month observations of firms that are still listed on the NYSE/Amex/Nasdaq markets two years after the issue of the target price. As a consequence, this analysis is reduced to the 2000-2012 period because our CRSP data ends in 2014. There are 221,741 firm-month implied returns over the 2000-2012 period. After removing distressed firms, the sample shrinks to 171,788 firm-month implied returns. We are aware that this approach is not perfect as many firms disappearing from the database are not distressed firms. The reduced sample may also be the result of mergers and acquisitions. This is the reason why we use alternative proxies for distress.

In our second approach, we remove penny stocks from the initial sample (*i.e.*, stocks with a price below \$5). Beyond the case of distressed firms, penny stocks are usually characterized by a lower liquidity and a higher uncertainty, compared to high price stocks (in particular because of the relationship between stock price and size). As a consequence, analysts may see penny stocks as firms on which to "gamble" by making highly optimistic forecasts. The selection of stocks priced above \$5 reduces the sample to 181,221 observations; approximately 8% of observations are removed.

The third approach uses the popular Altman Z-score (Altman, 1968) as a proxy to measure distress. Our aim here is to keep only firms with an excellent credit situation and to show that analysts also exhibit a low price bias on such firms. To achieve this goal, we keep in the sample only firms with a Z-score higher than 3 (*i.e.*, indicating a low probability of bankruptcy). This last approach is the most restrictive, as our sample is reduced to as little as 98,717 observations.

[**Table 7 here**]

[18] In fact, the probability distribution of returns of distressed firms is highly right skewed because the return cannot be less than −100%, but there is no theoretical limit on the upside.

The results, presented in Table 7, appear very similar to the ones presented in Table 4. For the sample of surviving firms (column 1), the coefficient of the \$0-\$10 price category is now 0.1857 instead of 0.1889. The coefficients of the other price dummy variables are slightly lower. A small variation in the other direction is observed in the intercept of the regression (0.1381 instead of 0.1350). Column 2 corresponds to the sample in which we removed penny stocks. The regression coefficient of the first price dummy variable (the \$5-\$10 price category) is reduced by approximately 4.4 percentage points when compared to the same coefficient (corresponding to the \$0-\$10 price category) in column 3 of Table 4. This coefficient remains highly significant, however. The coefficients of the other price dummy variables are virtually unchanged. The third column of Table 7 shows the results of the regression on the reduced sample of firms with an Altman Z-score greater than 3. For this sample as well, there is clear evidence of the low price bias. The regression coefficients are similar to the ones in Table 4 (column 3) with a small increase for price dummy variables coefficients. Overall, these three robustness tests confirm that the low price bias cannot be explained by the relationship between distressed firms and the level of stock prices.

6.4 Analysts' characteristics

Having established that financial analysts suffer from the low price bias, we now discuss whether this bias is reduced for experienced analysts, or for analysts with greater skills. The underlying idea for this robustness test is that more experienced analysts or analysts with greater skills may cover high price stocks.

6.4.1 Analysts' experience

The link between analysts' experience and performance has been extensively studied in the literature. Prior empirical work provides mixed evidence on whether experienced analysts are more accurate in forecasting earnings. While Mikhail, Walther, and Willis (1997) and Clement (1999) establish a positive link between experience and earnings forecast accuracy, Jacob, Lys, and Neale (1999) find no evidence of such positive association. Experience also influences the behavior of analysts. Mikhail, Walther, and Willis (2003) show that experienced analysts exhibit less underreaction to prior earnings information. Hong, Kubik, and Solomon (2000) document that experienced analysts deviate more from EPS consensus forecasts, are more likely to issue timely forecast, and tend to revise their forecasts less frequently. To the best of our knowledge, no previous work exists on the influence of experience on analysts behavioral biases. The impact of experience on behavioral biases, however, has been studied for other type of market participants. For instance, Feng and Seasholes (2005) show, using a sample of Chinese individual investors, that the magnitude of the disposition effect decreases with experience.

With regards to the existing evidence on the impact of experience on market participants' behavior, one could expect experience to alter the strength of the low price bias. On the one hand, learning by doing suggests that analysts would progressively become aware of the low price bias and thus issue less optimistic target prices on low price stocks. On the other hand, the low price bias is deeply-rooted in the human brain. Processing differently small numbers and large numbers is a widely observed phenomenon outside the field of finance among individuals of all ages (Dehaene, Izard, Spelke, and Pica, 2008; Hyde and Spelke, 2009). Therefore, it seems unlikely that extended practice leads to a complete disappearance of the low price bias.

To analyze whether experience impacts the low price bias, we divide our sample into three subsamples. The first subsample contains target prices issued by analysts with less than (or equal to) 5 years of experience.[19] The second subsample contains target prices issued by analysts with a level of experience ranging from 5 to 10 years. The third subsample corresponds to analysts with more than 10 years of experience.[20] We replicate our analysis on these three subsamples.

[**Table 8 here**]

The results are reported in Table 8. First, we find a strong low price bias in all three subsamples. Hence, this bias does not disappear with experience. We find, however, that this bias is slightly lower for experienced analysts compared to inexperienced analysts. The coefficient associated with the \$0-\$10 category is 0.1785 for inexperienced compared to 0.1555 for experienced analysts. This difference is significant at the 1% level. Similarly, the coefficient associated with the second price category (\$10-\$20) decreases from 0.0637 for

[19]Following Clement (1999), we define the experience variable as the number of years for which the analyst has been submitting forecasts to the I/B/E/S database.

[20]We use EPS forecasts, rather than target prices, to calculate analysts' experience because the data for target prices is left censored (there is no data available prior to 2000). Also, some analysts might have started issuing target prices after 2000 though they were already active prior to 2000.

inexperienced analysts to 0.0572 for experienced analysts. This difference is also significant at the 5% level. A comparison with the baseline case (last column of Table 4) also reveals that experienced analysts have a higher sensitivity to standard risk factors (market, size and liquidity).

6.4.2 Star analysts

Turning now to another important characteristic of financial analysts, we investigate whether star analysts exhibit the low price bias. Previous papers have examined the link between star status and forecasting performance. The literature provides mixed results on the superiority of star analysts. Emery and Li (2009) show that star and non-star analysts do not exhibit differential earnings forecast accuracy. Similarly, they do not find significant differences between the recommendations of star and non-star analysts. On the contrary, Fang and Yasuda (2014) show that recommendations by star analysts add more value compared to recommendations by nonstars analysts, and Kerl and Ohlert (2015) find that star analysts' earnings forecasts outperform their peers' forecasts.

We investigate whether star analysts are less subject to the low price bias by replicating our analysis on a sample of target prices issued by current or past star analysts. Our data on star analysts comes from *Institutional Investor* (I/I) rankings and covers the 2000-2010 period. Table 9 presents the results of our analysis. The number of observations is reduced to 60,794 (compared to a total of 185,906 firm-month observations over the 2000-2012 period for the whole sample of analysts). Although the low price bias remains present, its magnitude is reduced and only the coefficients associated with the first two price categories are significant. For firms with stock prices below $10, the low price bias is still strongly significant at 8.06%. It falls to 2.66% in the second price category (still significant at the 1% level). While the bias disappears in higher price categories, the two first price categories accounts, on average, for about 65% of firms in the CRSP database and 53% of firms covered by analysts. Therefore, even star analysts are prone to the low price bias.

[**Table 9 here**]

6.5 Risk-adjusted returns and recommendations

As a final robustness test of the low price bias, we look at stock recommendations to confirm that our results come from the differential processing of small and large numbers and not from differences in unobservable economic factors. If the higher risk-adjusted returns on low price stocks are economically sound, analysts should issue more favorable recommendations on low price stocks. No differences, however, should be observed if the higher risk-adjusted returns result from a differential processing of small and large numbers.

Figure 5 reports recommendations double-sorted on market capitalization and nominal prices.[21] There are five categories of recommendations: Strong Buy, Buy, Hold, Underperform, and Sell. Our results indicate that analysts do not issue more favorable recommendations for low price stocks. On the contrary, the proportion of Strong Buy and Buy recommendations is higher for high price stocks than for low price stocks. Symmetrically, the proportion of Hold, Underperform and Sell recommendations is higher for low price stocks than for high price stocks. The differences in proportion between the first price category ($0-$10) and the fifth price category (>$40) are all significant at the 1% level to the exception of the Strong Buy and Sell recommendations for small capitalization stocks. Figure 5, coupled with the results obtained in preceding sections, gives additional indications that analysts do not process small and large numbers in the same way, and therefore are biased in a systematic way.

[**Figure 5 here**]

7 Conclusion

In this paper, we provide strong empirical evidence of the existence of a low price bias. We show that financial analysts process differently low stock prices and high stock prices when they issue target prices one-year ahead. Specifically, analysts consistently issue more optimistic (and more dispersed) target prices on low price stocks than on high price stocks. This result is consistent with research in neuropsychology that shows deviations

[21]The double sort use terciles of capitalization using NYSE breakpoints. Results are unchanged when using quintiles of capitalization.

from Weber's law for small numbers. These deviations essentially come from the fact that the human brain processes small numbers on a linear scale and large numbers on a logarithmic scale. Financial analysts, though highly trained to use numbers on a daily basis, are subject to the same bias.

Our analysis also looks at target prices before and after stock splits. We find that analysts become more optimistic (and their target prices become more dispersed) after splits, a change that cannot be explained by changes in the sensitivity to risk factors. Overall, We show that the low price bias is not driven by the usual risk factors, namely market, size, book-to-market, momentum and liquidity. Moreover, the low price bias does not mask other explanations such as the tendency of analysts to use rounded numbers, the 52-week high bias, the following of distressed firms or the specific characteristics of analysts. Finally, to test whether the differences in risk-adjusted implied returns between low price stocks and high price stocks shape analysts' preferences, we investigate the relationship between stock prices and recommendations. We show that analysts do not recommend more strongly low price stocks compared to high price stocks.

All our findings point in the direction of a deeply rooted behavioral bias in number processing among financial analysts. Our results are remarkable for the study of the perception of numbers, because our sample is much larger than the samples usually used in neuropsychology.

This paper suggests directions of future research. If analysts are subject to a low price bias, then it is likely that other market participants are subject to the same bias (e.g. individual investors and professional investors). Some papers already analyze the special characteristics of low price stocks. For example, Birru and Wang (2014) show that investors overestimate the skewness of future returns of low price stocks. More generally, a number of papers show that individual investors have a preference for low price stocks (Gompers and Metrick, 2001; Dyl and Elliott, 2006; Kumar, 2009). It turns out that stock returns could be influenced by the stock price level. The literature on this topic is scarce, however. Finally, our results provide perspectives to neuroscientists for testing whether the perception of monetary amounts generates the same biases as the perception of other quantities.

8 Appendix A

We use propensity score matching (Rosenbaum and Rubin, 1983) to select the control sample. For each stock split in year t, we select (with replacement) a matching firm from the same year that does not split its stock in year t, belongs to the same industry[22] and has a propensity score closest to the firm that splits its stock. In our nearest-neighbor approach (Smith and Todd, 2005), we impose the constraint that the matching firm be within a given distance (*i.e.*, a caliper) of the splitting firm propensity score. This constraint is imposed to remove bad matches, that is, to guarantee that splitting firms and control firms share the same characteristics. Finally, to ensure the quality of the matching, we impose that splitting and control firms have a common support (Rosenbaum and Rubin, 1983). For each year from 2000 to 2013, we estimate propensity scores with the following probit regression. We include known determinants of stock splits (Baker, Greenwood, and Wurgler, 2009) and analysts' implied returns in our set of independent variables.

$$\begin{aligned}\Pr(Split_t = 1) = \alpha &+ \beta_1 \text{Log-price}_{t-1} + \beta_2 \text{Capitalization}_{t-1} + \beta_3 \text{Return}_{t-1} \\ &+ \beta_4 \text{Volatility}_{t-1} + \beta_5 \text{Book-to-market}_{t-1} + \beta_6 \text{Implied Return}_{t-1} + \epsilon_t \end{aligned} \tag{A1}$$

The dependent variable (Split_t) is equal to one if the firm splits its stocks in year t and 0 otherwise. Our independent variables are measured at the end of year $t-1$. We include the logarithm of the stock price (Log-price_{t-1}), the market capitalization ($\text{Capitalization}_{t-1}$), the one-year return ($\text{Return}_{t-1}$), the one-year total volatility (Volatility_{t-1}), the book-to-market ($\text{Book-to-Market}_{t-1}$) and the average return implied by target prices (Implied Return_{t-1}) issued in the last three month of year $t-1$.[23]

To evaluate the quality of our matching, we follow a diagnostic approach similar to the one of Lemmon and Roberts (2010). Table A1 reports the results of the probit regressions, before and after matching. Before matching, all the determinants significantly predict the probability of stock split.

[**Table A1 here**]

[22] We use Fama and French (1997) industry classification.

[23] We also included volume of trading, bid-ask spread and the industry average price in the probit regressions. Because they were not significant and because they reduced the number of observations, we decided not to keep these variables in the final model.

[**Table A2 here**]

If our matching is correct, the determinants should no longer explain stock splits after matching. The last column in Table A1 indicates that none of the determinants are significant. Table A2 shows the balancing test results after matching. We find that the difference in characteristics between splitting firms and control firms are not significant. Overall, these results suggest that our sample of splitting firms and our sample of control firms, share similar pre-split characteristics. Therefore, the differences in implied returns observed after stock splits can not be attributed to differences in firm characteristics.

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Figure 1
Nominal stock prices and target prices

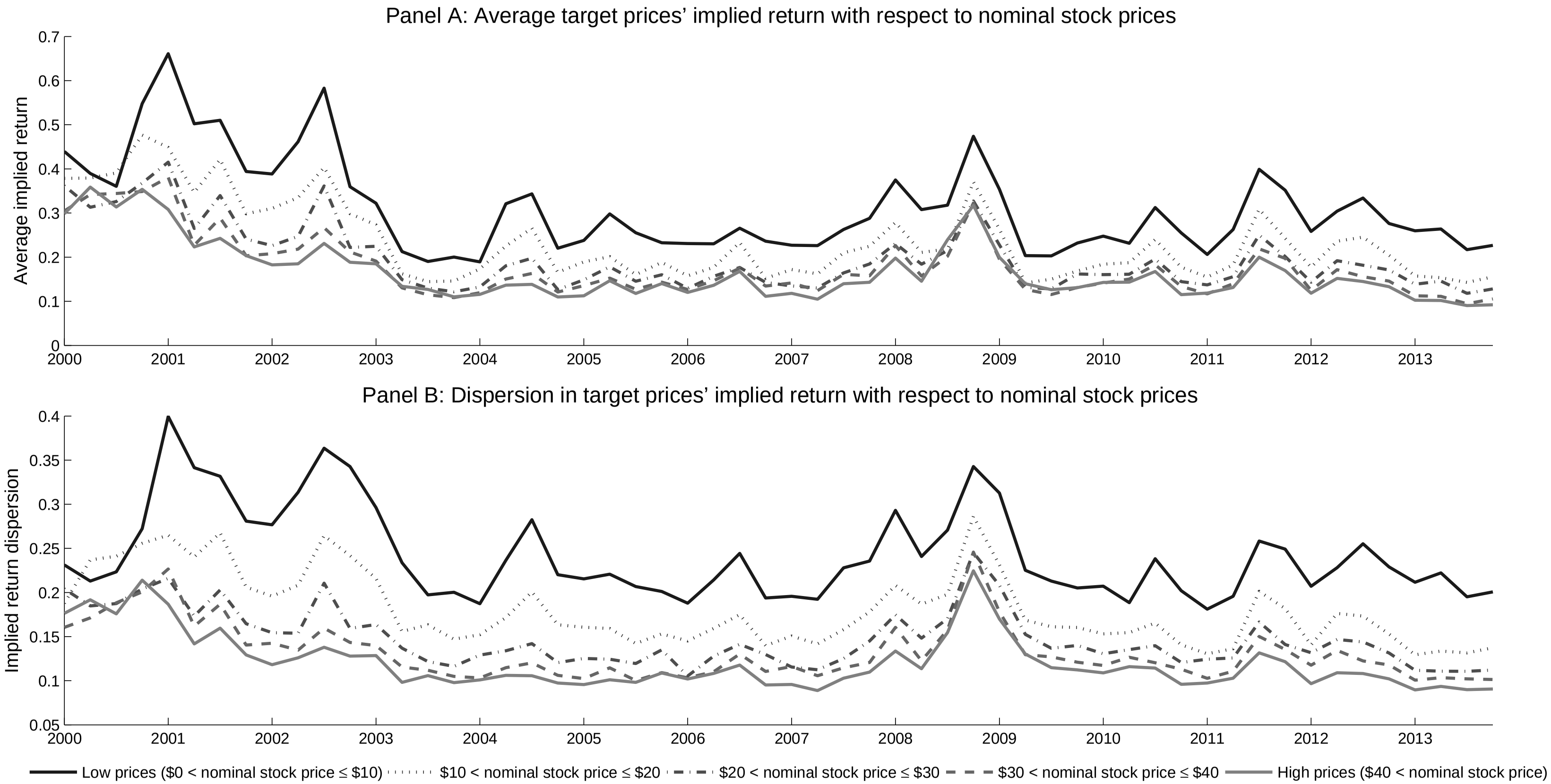
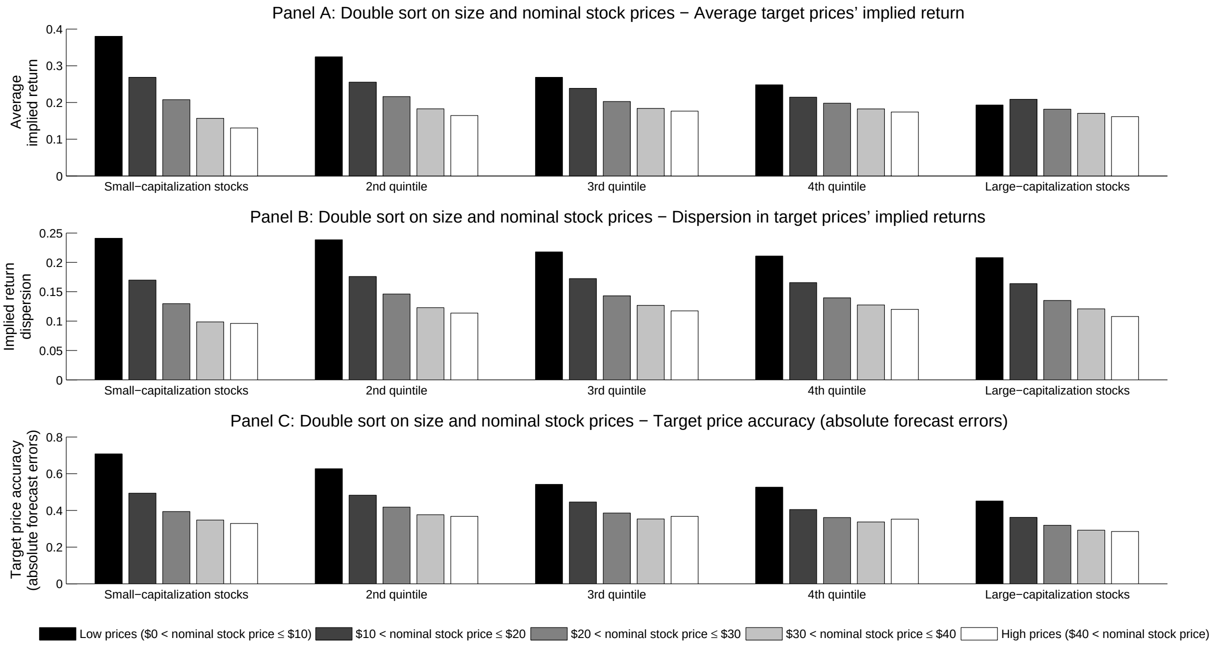


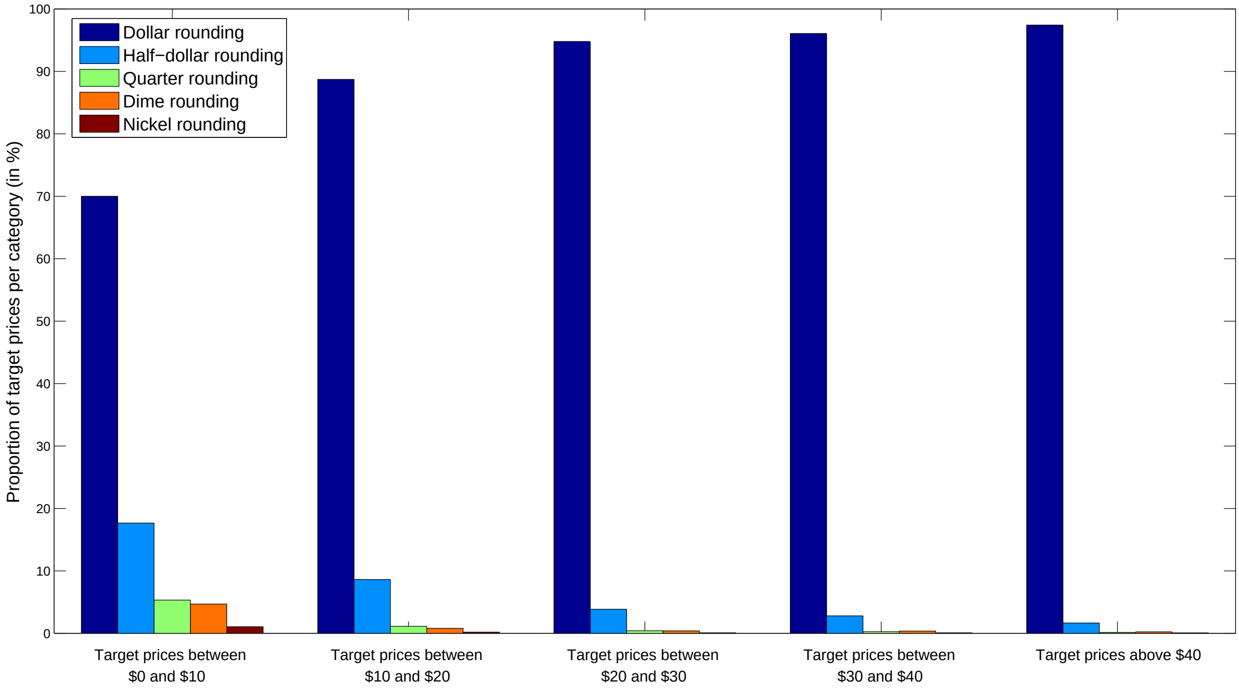
Figure 2

Double sort on market capitalization and nominal stock prices - Target prices



Panel A presents target prices' one-year ahead implied returns for stocks that are sorted on beginning-of-month size and beginning-of-month nominal stock price. The size quintiles are obtained by taking NYSE capitalization breakpoints for each year. The price categories are $0 to $10, $10 to $20, $20 to $30, $30 to $40, and above $40. Panel B presents the dispersion in target prices' implied returns (calculated, for a given quarter and a given stock, as the standard deviation of the implied returns associated with the different target prices) for stocks that are first sorted on beginning-of-month size and then on beginning-of-month nominal stock price. Panel C presents the target price accuracy (calculated as the absolute value of the deviation between the target price and the realized price divided by the concurrent price) for stocks that are first sorted on beginning-of-month size and then on beginning-of-month nominal stock price. The sample contains all stocks listed on NYSE-AMEX-NASDAQ for the 2000-2013 period. In order to be included in the sample, a firm-month observation must be associated with at least three different target prices.

Figure 3
Proportion of rounding per price category



This figure presents the proportion, per price category, of target prices that are rounded to, respectively, the dollar, the half-dollar, the quarter, the dime and the nickel.

Figure 4
Distribution of target prices

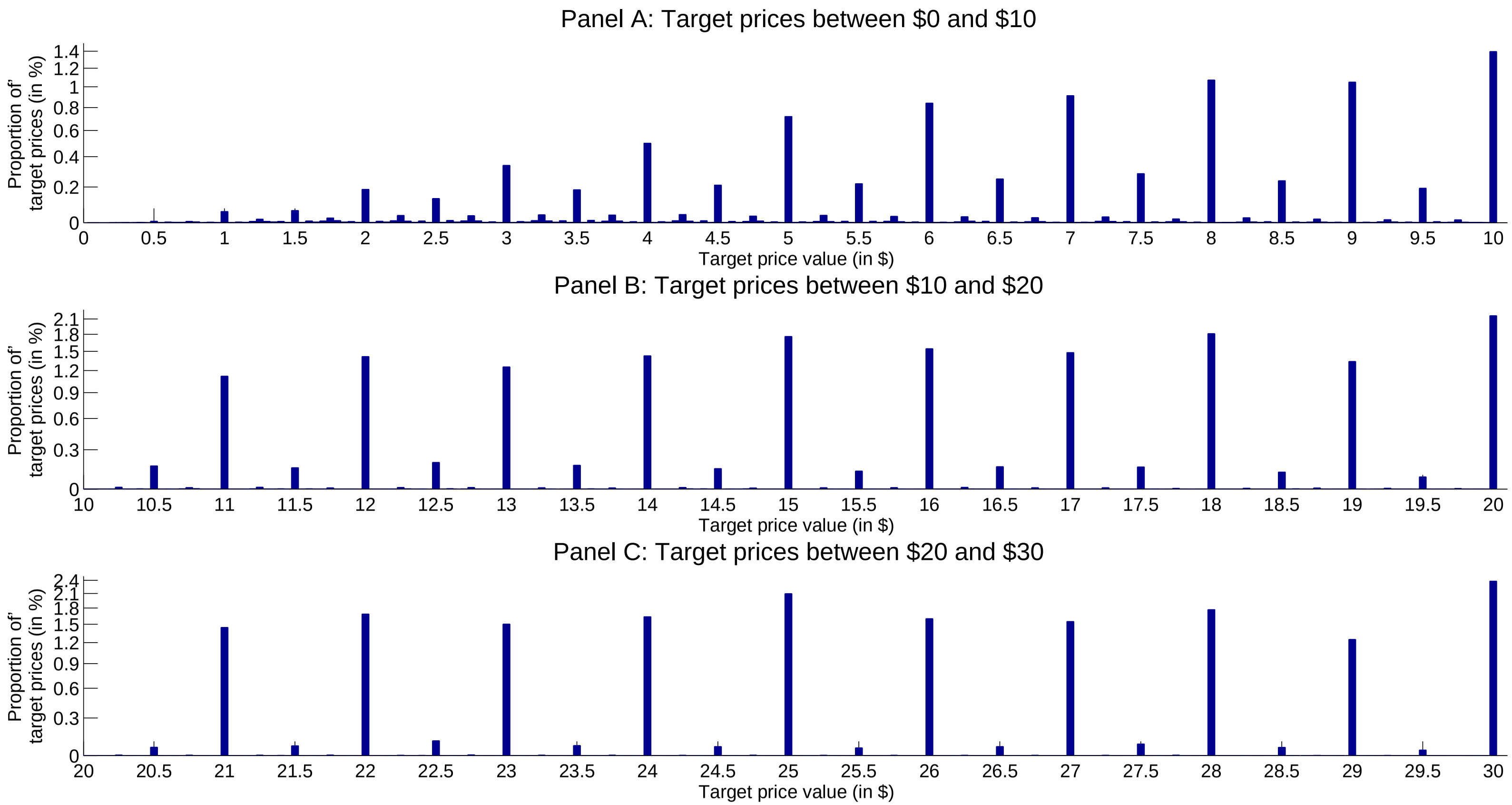
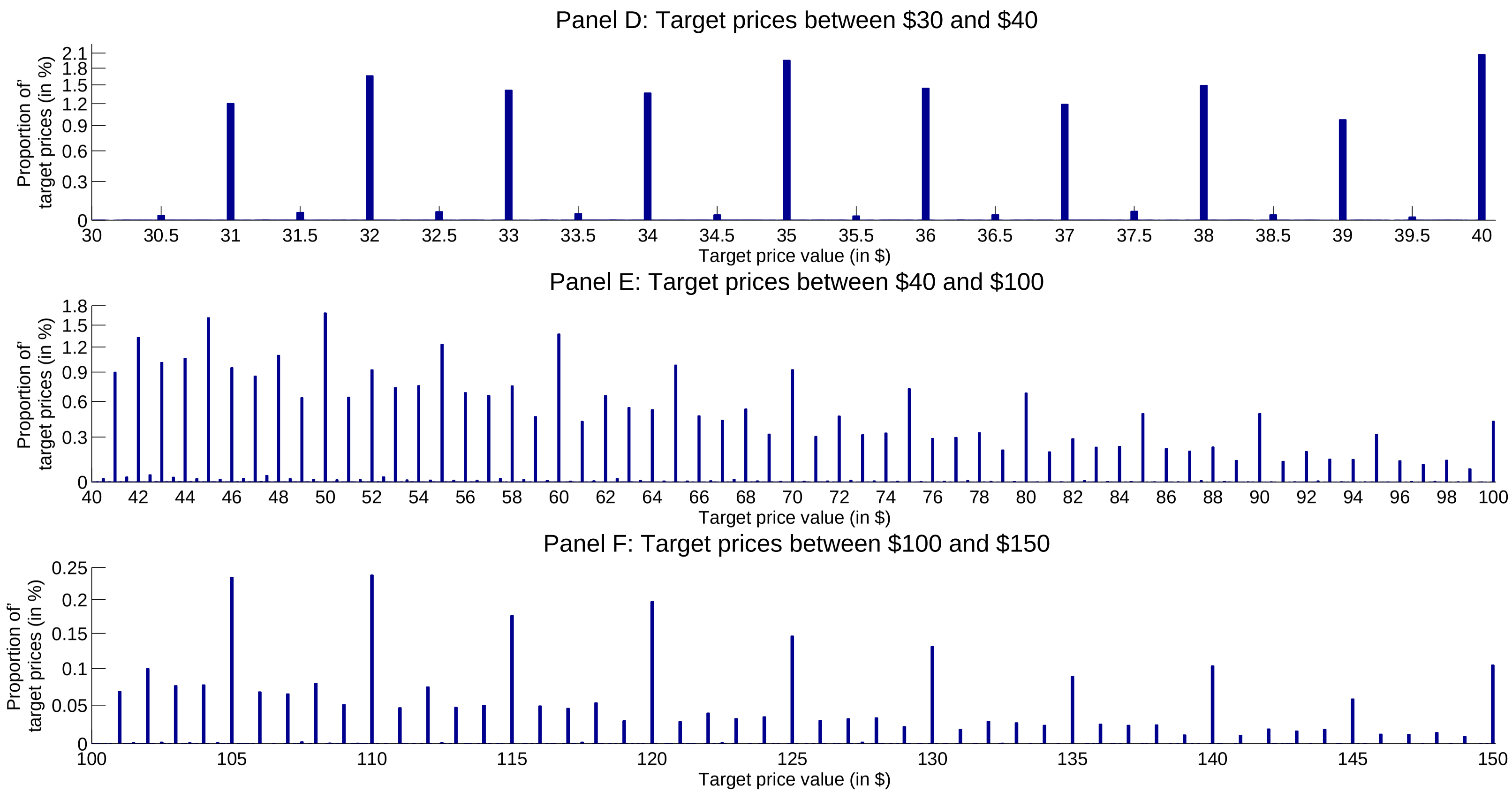


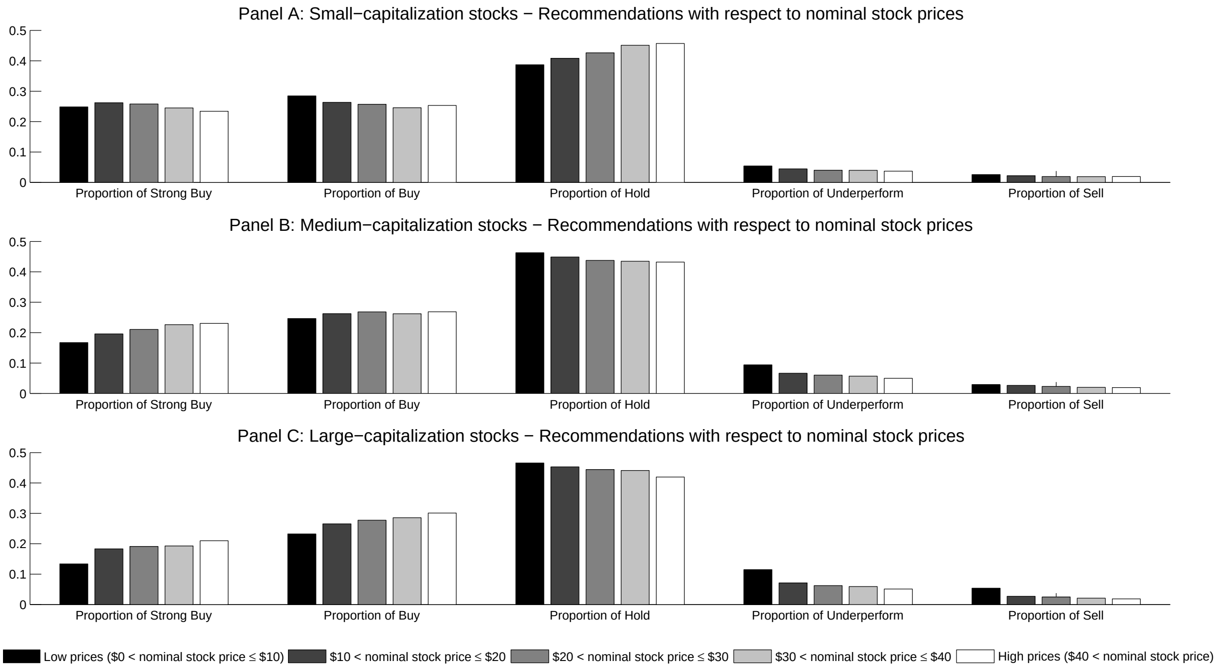
Figure 4 (Cont.)



The bar charts shown in this figure present the distribution of target prices. Panel A provides the target prices between \$0 and \$10. Panel B provides the target prices between \$10 and \$20. Panel C provides the target prices between \$20 and \$30. Panel D provides the target prices between \$30 and \$40. Panel E provides the target prices between \$40 and \$100. Panel F provides the target prices between \$100 and \$150. We use a logarithmic-like scale for the y-axis in order for low frequency values to be more visible.

Figure 5

Double sort on market capitalization and nominal prices - Recommendations



This figure presents the proportion of Strong buy, Buy, Hold, Underperform and Sell recommendations with respect to firms' size and nominal stock price. The size terciles are obtained by taking NYSE capitalization breakpoints for each year. The price categories are $0 to $10, $10 to $20, $20 to $30, $30 to $40, and above $40. Panel A shows the proportion of recommendations for small-capitalization stocks (first tercile). Panel B shows the proportion of recommendations for medium-capitalization stocks (second tercile). Panel C presents the proportion of recommendations for large-capitalization stocks (third tercile). The sample contains all stocks listed on NYSE-AMEX-NASDAQ for the 2000-2013 period. This sample amounts to a total of 315,304 recommendations. Each quarter, we measure for each stock the proportion of Strong buy, Buy, Hold, Underperform and Sell recommendations. We then compute, for each quarter, the average proportion per tercile of capitalization and category of nominal stock price. The results are then averaged over the whole sample period.

Table 1
Descriptive statistics

	Data on target prices (I/B/E/S)											Data on stock prices (CRSP)					
	Number of target prices	Number of analysts	No. of analysts per firm	No. of firms covered per analyst	Average implied return	Number of firms covered relative to nominal price						Number of firms relative to nominal price					
						\$0 to \$10	\$10 to \$20	\$20 to \$30	\$30 to \$40	> \$40	Total	\$0 to \$10	\$10 to \$20	\$20 to \$30	\$30 to \$40	> \$40	Total
2000	34,027	3,111	9.62	10.49	37.89%	624	822	588	335	700	3,069	2,840	1,572	820	447	852	6,531
2001	39,466	3,428	11.41	10.21	31.95%	819	786	520	349	484	2,958	3,293	1,280	681	421	574	6,249
2002	46,441	3,258	12.21	10.92	29.09%	696	849	612	372	388	2,917	2,566	1,314	808	433	446	5,567
2003	48,109	2,657	11.13	11.27	17.46%	1,035	819	548	311	238	2,951	2,598	1,175	722	371	284	5,150
2004	51,505	2,728	11.20	11.44	17.17%	712	781	635	412	482	3,022	1,714	1,144	859	536	567	4,820
2005	52,049	2,785	10.87	11.89	16.73%	688	721	655	417	619	3,100	1,569	1,078	859	519	731	4,756
2006	53,442	2,743	11.07	12.13	16.57%	741	746	624	412	602	3,125	1,523	1,117	842	506	700	4,688
2007	56,504	2,730	11.34	12.46	16.77%	695	695	586	461	634	3,071	1,431	1,072	764	580	775	4,622
2008	67,619	2,679	11.59	12.20	27.82%	799	779	506	340	593	3,017	1,707	1,103	634	400	699	4,543
2009	65,544	2,603	12.76	12.69	18.82%	1,254	710	409	216	235	2,824	2,455	868	463	244	268	4,298
2010	69,254	2,989	14.78	12.76	18.52%	988	663	448	281	399	2,779	1,896	840	531	320	450	4,037
2011	76,180	3,044	15.57	12.99	20.48%	790	666	428	306	554	2,744	1,561	853	517	346	625	3,902
2012	72,677	2,913	15.49	13.18	18.95%	883	616	383	275	523	2,680	1,615	794	444	309	591	3,753
2013	81,300	2,781	16.03	14.44	13.46%	782	592	382	293	605	2,654	1,403	788	445	328	678	3,642

The sample consists in a total of 814,117 target prices issued by 9,141 analysts (687 brokers) on 6,423 U.S. stocks listed on NYSE, Amex and Nasdaq for the 2000-2013 period. The first column indicates the number of target prices issued each year. The second column shows the number of active analysts. The third and four columns provide, respectively, the average number of analyst per firm and the average number of firms covered per analyst. The sixth column gives the average target price implied return. The six following columns report the number of firms covered relative to their nominal price range. The last six columns report the number of firms listed on NYSE, Amex and Nasdaq relative to their nominal price range.

Table 2
Target prices before and after stock splits

Panel A: Target prices and stock splits			
	Average implied return	Implied return dispersion	Target price accuracy
Split ratio between 1.25 and 2			
Before splits	0.1578	0.1124	0.3337
After splits	0.2030	0.1394	0.3567
Difference	0.0453***	0.0263***	0.0230**
Split ratio greater or equal to 2			
Before splits	0.1683	0.1174	0.3922
After splits	0.2281	0.1518	0.4166
Difference	0.0598***	0.0362***	0.0244***

Panel B: Target prices and stock splits - Controlling for coverage initiation and termination			
	Average implied return	Implied return dispersion	Target price accuracy
Split ratio between 1.25 and 2			
Before splits	0.1529	0.1099	0.3498
After splits	0.1967	0.1336	0.3583
Difference	0.0438***	0.0236***	0.0085**
Split ratio greater or equal to 2			
Before splits	0.1429	0.0986	0.3573
After splits	0.1948	0.1257	0.3690
Difference	0.0519***	0.0271***	0.0117***

This table presents statistics before and after splits, for two categories of splits: splits with a ratio between 1.25 and 2 and splits with a ratio greater or equal to 2. There are 532 splits with a split ratio between 1.25 and 2 (347 with at least three target prices) and 869 splits with a ratio larger or equal to 2 (635 with at least three target prices). The second column provides average implied returns. The third column reports the dispersion in implied returns. We compute the dispersion in implied returns only if there at least three target prices issued in the three-month period. The last column provides absolute forecast errors (target price accuracy).

Table 3

Target prices and stock splits - Differences-in-differences analysis

	Average implied return			**Implied return dispersion**			**Target price accuracy (absolute forecast errors)**		
	Splitting firms	Control firms	Difference	Splitting firms	Controls firms	Difference	Splitting firms	Control firms	Difference
Split ratio between 1.25 and 2									
Before splits	0.1455	0.1726	−0.0271	0.1090	0.1171	−0.0081	0.3066	0.3106	−0.0040
After splits	0.1846	0.1876	−0.0030	0.1337	0.1218	0.0119	0.3237	0.3011	0.0225
Difference	0.0391	0.0150	0.0241***	0.0247	0.0046	0.0200**	0.0171	−0.0095	0.0265**
Split ratio greater or equal to 2									
Before splits	0.1582	0.1971	−0.0388	0.1096	0.1238	−0.0142	0.3500	0.3633	−0.0133
After splits	0.2056	0.2078	−0.0023	0.1398	0.1352	0.0047	0.3686	0.3515	0.0172
Difference	0.0473	0.0108	0.0366***	0.0303	0.0114	0.0189***	0.0187	−0.0119	0.0305***

This table provides the results of the differences-in-differences analysis. Our first sample is composed of firms that split their stock during the 2000-2010 period. We select the sample of control firms by using propensity score matching. The determinants of the propensity scores are: log-price, market capitalization, past return, past volatility, book-to-market and past implied return. There are two categories of splits: splits with a ratio between 1.25 and 2 (352 observations) and splits with a ratio greater or equal to 2 (376 observations). Columns 1 to 3 provide average implied returns. Columns 4 to 6 show implied return dispersions. Columns 7 to 9 report absolute forecast errors (target price accuracy).

Table 4
Fama-MacBeth regressions based on target prices implied return

	Regression of target prices' implied returns on factor loadings		
	Model 1	Model 2	Model 3
Intercept	0.1415*** (0.0189)	0.1231*** (0.0152)	0.1350*** (0.0125)
γ_M	0.0538*** (0.0063)	0.0369*** (0.0069)	0.0275*** (0.0067)
γ_{SMB}	0.0447*** (0.0106)	0.0265*** (0.0092)	0.0198*** (0.0074)
γ_{HML}	-0.0209** (0.0100)	-0.0208** (0.0088)	-0.0142* (0.0081)
γ_{MOM}	-0.0095** (0.0043)	0.0083* (0.0048)	0.0065* (0.0035)
γ_{LIQ}	0.0250*** (0.0081)	0.0235*** (0.0083)	0.0171*** (0.0043)
Price categories			
Low price dummy ($0 to $10)		0.1840*** (0.0094)	0.1876*** (0.0103)
$10 to $20 dummy		0.0581*** (0.0076)	0.0665*** (0.0097)
$20 to $30 dummy		0.0187*** (0.0060)	0.0249*** (0.0066)
$30 to $40 dummy		0.0050 (0.0036)	0.0072 (0.0047)
Controls	NO	NO	YES
Average adjusted R^2	10.12%	17.94%	20.69%
Number of observations	239,746	239,746	196,470

This table presents the time-series averages of 168 slopes from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. The one-year expected return is equal to the difference between the target price implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table 5
Impact of rounding

	Regression of target prices' implied returns on factor loadings			
	Model 1 (Dime rounding correction)	Model 2 (Quarter rounding correction)	Model 3 (Half-dollar rounding correction)	Model 4 (Dollar rounding correction)
Intercept	0.1338***	0.1316***	0.1280***	0.1205***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)
γ_M	0.0269***	0.0263***	0.0252***	0.0234***
	(0.0067)	(0.0068)	(0.0068)	(0.0069)
γ_{SMB}	0.0194***	0.0190**	0.0181**	0.0169**
	(0.0074)	(0.0073)	(0.0073)	(0.0071)
γ_{HML}	-0.0139*	-0.0134*	-0.0129*	-0.0123*
	(0.008)	(0.0079)	(0.0077)	(0.0073)
γ_{MOM}	0.0071**	0.0078**	0.0089**	0.0105***
	(0.0035)	(0.0034)	(0.0035)	(0.0036)
γ_{LIQ}	0.0167***	0.0163***	0.0158***	0.0154***
	(0.0041)	(0.0039)	(0.0038)	(0.0039)
Price categories				
Low price dummy ($0 to $10)	0.1708***	0.1435***	0.1032***	0.0414***
	(0.0104)	(0.0105)	(0.0106)	(0.0098)
$10 to $20 dummy	0.0626***	0.0558***	0.0447***	0.0241**
	(0.0096)	(0.0096)	(0.0095)	(0.0094)
$20 to $30 dummy	0.0232***	0.0202***	0.0153**	0.0058
	(0.0065)	(0.0065)	(0.0065)	(0.0064)
$30 to $40 dummy	0.0064	0.0050	0.0027	-0.0020
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Controls	YES	YES	YES	YES
Average adjusted R^2	19.02%	16.37%	12.75%	8.42%
Number of observations	196,470	196,470	196,470	196,470

This table presents the time-series averages of 168 slopes from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. Models 1 to 4 correspond to four approaches to correct target prices for rounding. The severity of the correction increases from model 1 to model 4. In model 1: (1) If the target price's last digit is a 5, we subtract 4 cents; (2) If the target price's last digit is a 0, we subtract 9 cents. In model 2: (1) If the target price's last digit is a 5, we subtract 4 cents; (2) If the target price's last digit is a 0, we subtract 9 cents; (3) If the target price's two last digits are 00, 25, 50 or 75, we subtract 24 cents. In model 3: (1) If the target price's last digit is a 5, we subtract 4 cents; (2) If the target price's last digit is a 0, we subtract 9 cents; (3) If the target price's two last digits are 25 or 75, we subtract 24 cents; (4) If the target price's two last digits are 00 or 50, we subtract 49 cents. In model 4: (1) If the target price's last digit is a 5, we subtract 4 cents; (2) If the target price's last digit is a 0, we subtract 9 cents; (3) If the target price's two last digits are 25 or 75, we subtract 24 cents; (4) If the target price's two last digits are 50, we subtract 49 cents; and, (5) If the target price's two last digits are 00, we subtract 99 cents. The one-year expected return is equal to the difference between the target price's implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table 6
Impact of 52-week high

Regression of target prices' implied returns on factor loadings		
	Estimates	Standard errors
Intercept	0.1153***	0.0104
γ_M	0.0175***	0.0051
γ_{SMB}	0.0170**	0.0075
γ_{HML}	−0.0095**	0.0047
γ_{MOM}	0.0061*	0.0033
γ_{LIQ}	0.0133***	0.0031
Price categories		
Low price dummy ($0 to $10)	0.1545***	0.0060
$10 to $20 dummy	0.0445***	0.0067
$20 to $30 dummy	0.0119**	0.0050
$30 to $40 dummy	0.0004	0.0034
52-week high ratio quintiles		
1st quintile dummy	0.0963***	0.0137
2st quintile dummy	0.0699***	0.0093
3rd quintile dummy	0.0415***	0.0055
4th quintile dummy	0.0194***	0.0025
Controls	YES	
Average adjusted R^2	22.35%	
Number of observations	196,740	

This table presents the time-series averages of 168 slopes from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. The 52-week high ratio is defined as the ratio of the closing price at the end of month $t-1$ to the highest stock price in the 12-month period ending in month $t-1$. 52-week high ratio quintiles are computed on a monthly basis. The one-year expected return is equal to the difference between the target price implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table 7
Distressed firms

	Regression of target prices' implied returns on factor loadings		
	Sample 1 – Surviving stocks	Sample 2 – No penny stocks	Sample 3 – Altman stocks
Intercept	0.1381***	0.1288***	0.1393***
	(0.012)	(0.0128)	(0.0124)
γ_{M}	0.0286***	0.0327***	0.0241***
	(0.0073)	(0.0065)	(0.0066)
γ_{SMB}	0.0213***	0.0211***	0.0169**
	(0.0078)	(0.0072)	(0.0073)
γ_{HML}	-0.0139*	-0.0111	-0.0086
	(0.0084)	(0.0087)	(0.0081)
γ_{MOM}	0.0080**	0.0072**	0.0093**
	(0.0038)	(0.0033)	(0.0037)
γ_{LIQ}	0.0159***	0.0176***	0.0183***
	(0.0044)	(0.0041)	(0.0038)
Price categories			
Low price dummy ($0 to $10)	0.1857***	0.1438***	0.1875***
	(0.0100)	(0.0130)	(0.0112)
$10 to $20 dummy	0.0657***	0.0658***	0.0720***
	(0.0104)	(0.0096)	(0.0124)
$20 to $30 dummy	0.0244***	0.0245***	0.0261***
	(0.0071)	(0.0066)	(0.0072)
$30 to $40 dummy	0.0071	0.0070	0.0108**
	(0.0050)	(0.0047)	(0.0048)
Controls	YES	YES	YES
Average adjusted R^2	20.19%	16.69%	19.59%
Number of observations	171,788	181,221	98,717

This table presents the time-series averages of 168 slopes (156 for sample 1) from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. Sample 1 contains only firm-month observations of firms that are still listed on the NYSE/Amex/Nasdaq markets two years after the issue of the target price (the sample period is 2000-2012). Sample 2 corresponds to non-penny stocks, that is, the sample contains only firm-month observations with an associated nominal stock price above $5. Sample 3 contains only firms with excellent credit characteristics, that is, firms with an Altman-Z score higher than 3. The one-year expected return is equal to the difference between the target price implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table 8
Experience and the low price bias

	Regression of target prices' implied returns on factor loadings		
	Sample 1 – Low experience ($\leq$ 5 years)	Sample 2 – Experience between 5 to 10 years	Sample 3 – High experience (> 10 years)
Intercept	0.1338***	0.1342***	0.1326***
	(0.0114)	(0.0135)	(0.0154)
γ_M	0.0263***	0.0311***	0.0353***
	(0.0076)	(0.0067)	(0.0052)
γ_{SMB}	0.0191**	0.0187***	0.0237***
	(0.0078)	(0.0066)	(0.0051)
γ_{HML}	-0.0122	-0.0121	-0.0129
	(0.0079)	(0.0085)	(0.0101)
γ_{MOM}	0.0086**	0.0061	0.0059*
	(0.0041)	(0.0037)	(0.0032)
γ_{LIQ}	0.0152***	0.0200***	0.0209***
	(0.0047)	(0.0037)	(0.0045)
Price categories			
Low price dummy ($0 to $10)	0.1785***	0.1634***	0.1555***
	(0.0115)	(0.0117)	(0.0119)
$10 to $20 dummy	0.0637***	0.0582***	0.0572***
	(0.0101)	(0.0128)	(0.0069)
$20 to $30 dummy	0.0279***	0.0223***	0.0204***
	(0.0073)	(0.0078)	(0.004)
$30 to $40 dummy	0.0084*	0.0056	0.0081***
	(0.0045)	(0.0061)	(0.0029)
Controls	YES	YES	YES
Average adjusted R^2	18.38%	16.56%	15.75%
Number of observations	121,700	107,514	94,967

This table presents the time-series averages of 168 slopes from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. The first column (sample 1) provides results from a sample of target prices issued by analysts with up to 5 years of experience. Sample 2 corresponds to analysts with a level of experience between 5 and 10 years. The third column (sample 3) corresponds to analysts with more than 10 years of experience. The one-year expected return is equal to the difference between the target price implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table 9
Star analysts and the low price bias

Regression of target prices' implied returns on factor loadings		
	Estimates	Standard errors
Intercept	0.1288***	0.0144
γ_M	0.0359***	0.0083
γ_{SMB}	0.0208***	0.0073
γ_{HML}	−0.0143	0.0120
γ_{MOM}	0.0056	0.0051
γ_{LIQ}	0.0165***	0.0020
Price categories		
Low price dummy ($0 to $10)	0.0806***	0.0176
$10 to $20 dummy	0.0266**	0.0122
$20 to $30 dummy	0.0047	0.0058
$30 to $40 dummy	0.0027	0.0053
Controls	YES	
Average adjusted R^2	10.48%	
Number of observations	60,794	

This table presents the time-series averages of 132 slopes from month-by-month regressions of one-year expected returns on a set of estimated factor loadings. The sample contains only target prices issued by analysts who are or had been included in the *Institutional Investor* ranking during the 2000-2010 period. The one-year expected return is equal to the difference between the target price implied return and the one-month treasury bill rate. We estimate factor loadings for month t by using data from month $t-61$ to $t-1$. Control variables are external financing ($ExtFin$) and the absolute value of discretionary accruals ($AbsDCA$) from the Modified Jones Model. Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table A1
Probit regression of stock split on the determinants

	Before matching	**After matching**
Intercept	−4.4187***	−1.7486
	(0.203)	(1.4952)
Log-price$_{t-1}$	0.8515***	0.4584
	(0.0636)	(0.3961)
Capitalization$_{t-1}$	−0.0167***	−0.0929
	(0.0047)	(0.0798)
Return$_{t-1}$	0.8919***	0.6656
	(0.0839)	(0.5069)
Volatility$_{t-1}$	−1.1892**	−4.1282
	(0.4130)	(3.3926)
Book-to-Market$_{t-1}$	−0.2692***	3.7237
	(0.0368)	(3.0744)
Implied Return$_{t-1}$	0.4459**	3.4091
	(0.1988)	(2.7062)
Number of observations	29,619	1,456
Pseudo R^2	7.67%	

This table reports the average coefficients of our probit regressions (for each year between 2000 to 2013). Standard errors (reported in parentheses) are adjusted using the Newey-West procedure.

Table A2
Mean values of the determinants and propensity scores for splitting firms and control firms

	Splitting firms	**Control firms**	**Difference**
Propensity score	0.1170	0.1171	−0.0002
Log price	3.6670	3.6586	0.0084
Capitalization	6.5422	5.9001	0.6421
Return	0.4061	0.4110	−0.0050
Volatility	0.4110	0.4143	−0.0034
Book-to-market	0.4433	0.4663	−0.0230
Implied Return	0.1816	0.1904	−0.0088

This table compares the mean values of the determinants and propensity scores for splitting firms and control firms. Significance is computed using a two-tailed test.