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Behavioral bias in number processing: Evidence from analysts' expectations☆

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ABSTRACT

Research in neuropsychology shows that individuals process small and large numbers differently. Small numbers are processed on a linear scale, while large numbers are processed on a logarithmic scale. In this paper, we show that financial analysts process small prices and large prices differently. When they are optimistic (pessimistic), analysts issue more optimistic (pessimistic) target prices for small price stocks than for large price stocks. Our results are robust when controlling for the usual risk factors such as size, book-to-market, momentum, profitability and investments. They are also robust when we control for firm and analyst characteristics, or for other biases such as the 52-week high bias, the preference for lottery-type stocks and positive skewness, and the analyst tendency to round numbers. Finally, we show that analysts become more optimistic after stock splits. Overall, our results suggest that a deeply-rooted behavioral bias in number processing drives analysts' return expectations.

1. Introduction

Sell-side analysts produce diverse information in their research reports: stock recommendations, earnings (or cash-flow) forecasts, target prices, and some justifications or explanations (Asquith et al., 2005; Bradshaw et al., 2013). It is well-documented that earnings forecasts and target prices are biased (Bradshaw et al., 2014; Ramnath et al., 2008). Financial

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analysts are 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 return implied by target prices of 28% for the 1997–1999 period, while Bradshaw et al. (2013) report an implied return of 24% for the 2000–2009 period. These 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 first stream of research, financial analysts are viewed as rational economic agents and their optimism reflects their incentives to produce inaccurate figures (Bradshaw et al., 2014; Lim, 2001; Mehran and Stulz, 2007). In the second stream of research, financial analysts are characterized by some behavioral biases. The use of specific heuristics leads analysts to miscalculate (Cen et al., 2013; Clarkson et al., 2013).

In this paper, we contribute to the latter stream of research by showing that analysts process small numbers (*i.e.*, small stock prices) differently from large numbers (*i.e.*, large stock prices). They exhibit a specific behavioral bias, which we call the small price bias, when issuing target prices. This bias leads analysts to produce bolder forecasts for small price stocks than for large price stocks. Since analysts tend to issue optimistic target prices (*i.e.*, target prices with positive implied returns), they are, on average, more optimistic on small price stocks than on large price stocks. However, for the minority of pessimistic target prices (about 13%), analysts are more pessimistic on small price stocks than on large price stocks. Working with analysts' target prices allows us to directly test the small price bias on individuals' expectations.[1]

Our argument for the existence of a small 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 of numbers. 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 characteristics (Dehaene et al., 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 effect and the size effect is known as Weber's law. In short, Weber's law states that numbers are measured on a logarithmic scale in the brain (Nieder, 2005): increasingly larger numbers are subjectively closer together.

Dehaene et al. (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. Hyde and Spelke (2009) argue that "Despite many years of experience with symbolic systems that apply equally to all numbers, adults spontaneously process small and large numbers differently. They appear to treat small number arrays as individual objects to be tracked through space and time, and large-number arrays as cardinal values to be compared and manipulated" (p. 1039).

People tend to use a linear scale for small numbers and a logarithmic scale for large numbers.[2] This linear scale for small numbers implies that people are able to correctly evaluate absolute distances between small numbers. The use of a logarithmic scale for large numbers, however, leads to a compressed mental number line. People underrepresent absolute distances between large numbers. A corollary can be derived for relative distances. Relative distances between large numbers are correctly assessed (as a result of the use of a logarithmic scale) while relative distances between small numbers are exaggerated. Since the norm in finance is to work with relative distances (*i.e.*, stock returns), we expect market participants to incorrectly process small prices. The linear scale corresponds to a slope equal to ± 1 on the mental number line and the logarithmic scale to a slope lower than 1 in absolute value. We thus expect the use of a linear scale to lead to bolder forecasts for small price stocks.[3]

These arguments allow us to formulate the following hypothesis: if analysts use a linear scale for small price stocks and a logarithmic scale for large price stocks, optimistic (pessimistic) target prices will be more optimistic (pessimistic) for small price stocks than for large price stocks.

To test this hypothesis, we use a sample of 814,117 target prices issued by 9141 analysts on 6423 U.S. stocks, over a fourteen year period (2000–2013). We find that analysts issue bolder forecasts on small price stocks than on large price stocks. We use target price implied returns as an *ex-ante* measure of optimism (pessimism). We also measure optimism (pessimism) *ex-post* by using signed forecast errors. Implied returns are computed by comparing target prices to current stock prices while signed forecast errors are obtained by comparing target prices to future (realized) prices. Over the whole sample period, the average implied return[4] of optimistic (pessimistic) target prices issued on stocks with a nominal stock price below \$10, is about 39% (−10%). The corresponding figure for stocks with prices above \$40 is approximately 19% (−8%).

Since stock prices and market capitalization (firm size) are positively correlated (Baker et al., 2009), we ensure that our results are not driven by a size effect. To disentangle the small price bias from a potential size effect, we double sort

[1] Target prices provide more relevant information to investors than earnings (or cash-flow) forecasts or even stock recommendations (Bradshaw, 2011). In addition, Brav and Lehavy (2003) show that market participants react to information contained in target prices.

[2] Even if formal education is supposed to induce the use of a linear scale, Dehaene et al. (2008) and Viarouge et al. (2010) conclude that "a logarithmic representation may remain dormant in all of us for large numbers".

[3] The derivative of $f(x) = ln(x)$ is $1/x$ which is lower than 1 for $x > 1$.

[4] Implied return is defined as the difference between the target price and the current stock price scaled by the current price.

the implied returns on nominal stock prices and market capitalization. In the small capitalization quintile, the difference in implied returns between small price stocks (<\$10) and large price stocks (> \$40) is 30.87% for optimistic forecasts and −3.55% for pessimistic ones. In the large capitalization quintile, this difference is 8.30% for optimistic forecasts and −2.76% for pessimistic ones. Our results, therefore, indicate that the small price bias does not hide a size effect. In addition, we show that these price-based differences in target price optimism are not justified by the future one-year realized returns. For small firms and optimistic (pessimistic) forecasts, the difference in signed forecast errors[5] between small price stocks and large price stocks is 26.88% (−18.09%). This corresponding figure is 5.20% (−6.44%) for large firms.

Our main analysis takes place within a Fama–MacBeth regression framework (Fama and MacBeth, 1973) in which expected returns are proxied by the returns implied by target prices. Each month, we regress implied returns on the usual factors, namely size, book-to-market, and momentum, and on four nominal price dummies (\$0–\$10, \$10–\$20, \$20–\$30, \$30–\$40). In our model, we also control for the sign of implied returns by including a dummy variable and interaction variables between this dummy and the price dummies. We average the regression coefficients over the 168 months of the period under scrutiny. Our results show that the coefficients of the price-based dummies and interaction variables are not only highly significant, but they also decrease in absolute value in the price level. Our findings support the differential treatment of small and large numbers by financial analysts. Our results are robust to the introduction of analyst and industry fixed effects. Moreover, they remain significant when controlling for a number of firm characteristics, for the 52-week high bias, and for the tendency of analysts to round numbers. Finally, we take into account the findings of Birru and Wang (2016) that investors' preference for small price stocks comes from an overestimation of skewness. Our results remain significant when we control for lottery-like features of stocks by introducing the LIDX index[6] defined in Kumar et al. (2016), and the skewness of returns.

We investigate stock recommendations to confirm that our results are driven by the differential processing of small and large numbers and not by differences in unobservable economic factors. If higher risk-adjusted returns on small price stocks are economically sound, analysts should issue more favorable recommendations on small 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 small price stocks. On the contrary, among large firms, the proportion of favorable recommendations is larger for large price stocks.

Finally, we confirm that the small price bias is not explained by unobserved firm-level factors by showing that analysts become more optimistic after stock splits. A stock split is an interesting event for our study because a split generates a large price change while having no impact on fundamentals (He and Wang, 2012). After controlling for endogeneity with the implementation of propensity score matching, our difference-in-differences analysis indicates an increase in average implied returns and in signed forecast errors following stock splits.

This paper contributes to the literature on the perception of numbers. We provide evidence of distortions in number processing for well-educated professionals who use numbers on a daily basis. One would expect such professionals not to be prone to the small price bias, compared to people who are not familiar with number computation. Our findings, however, show that this small price bias is prevalent among financial analysts. The use of a linear scale when processing small numbers is also supported by studies on earnings forecasts. Graham et al. (2005) find that market participants have a myopic focus on earnings per share (EPS) 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 EPS magnitude. Moreover, Jung et al. (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.

Our paper also contributes to the literature on analysts' optimism. To date, the main explanation for analysts' optimism is their incentives to produce inaccurate figures. For instance, in two recent papers on target prices around the world, Bilinski et al. (2013) and Bradshaw et al. (2014) show that analysts' optimism is linked to the efficiency of country-level institutions (notably strong investor protection end effective legal enforcement). However, there are few explanations based on the behavioral biases of analysts. Two exceptions are Cen et al. (2013) who show that the well-documented anchorage bias can also explain analysts' optimism, and Clarkson et al. (2013) who find that rounding and the 52-week price bias contribute to explaining the formation of target prices.

Our article focuses on financial analysts, but the small price bias is likely to affect other market participants as well. The difference in processing small numbers and large numbers may explain results from previous studies on nominal prices. For example, it provides an interesting explanation as to why small price stocks comove together more than they comove with large price stocks (Green and Hwang, 2009). Moreover, our approach provides an answer to a conjecture of Green and Hwang (2009) who state that "certain investors may perceive low-priced stocks as being closer to zero and farther from infinity, thus having more upside potential" (p. 38). We argue that reality is more complex (at least for analysts), because, when pessimistic, analysts issue more pessimistic target prices on small price stocks than on large price stocks. Following Kumar (2009) and Barberis and Huang (2008), who show the preference of investors for positive skewness, Birru and Wang (2016) explain the overvaluation of small price stocks by an overestimation of the skewness of returns. Our paper

[5] Signed forecast errors are defined as the difference between implied returns and realized returns.
[6] This index is a combination of idiosyncratic volatility, idiosyncratic skewness and price level.

provides another explanation, related to number processing, for the observed differences in implied returns derived from analysts' target prices.

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 returns implied by target prices and the magnitude of stock prices. Section 4 is dedicated to the analysis of the small price bias while controlling for risk factors, and firm and analyst characteristics. Section 5 contains additional evidence of the small price bias based on the analysis of stock recommendations and stock splits. The last section concludes the paper.

2. Data and descriptive statistics

Our data are from the Center for Research in Security Prices (CRSP) database 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.[7] Ending in 2013 allows to compare one-year-ahead target prices issued by analysts with realized returns calculated with the CRSP database. 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.

Table 1 reports descriptive statistics on our data. 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 proportion of optimistic target prices, and the average implied return. 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, as we argue in this paper, analysts process small and large prices differently. As a consequence, our categories use absolute (not statistical) intervals. The first category includes small price stocks ($0 to $10) and the remaining categories contain stocks with prices from $10–$20, $20–$30, $30–$40 and, above $40.[8]

Table 1 shows that the number of target prices issued each year gradually increases over time. Between 2000 and 2013, the number of target prices increased by about 140%. In addition, the average number of analysts per firm increased by about 70%, from 9.62 in 2000 to 16.03 in 2013. The global number of firms covered by analysts is almost unchanged (3069 in 2000 and 2654 in 2013, with a maximum of 3125 in 2006). In the meantime, the aggregate number of firms (last column) listed on the NYSE, Amex and Nasdaq markets, declined significantly, from 6531 in 2000 to 3642 in 2013. These figures indicate that issuing target prices is an increasingly popular practice among financial analysts. Moreover, the proportion of optimistic target prices and the average implied return, reported in columns 5 and 6, show that financial analysts have optimistic views on future prices.[9] The average yearly implied return over the sample period is 21.55%, the least (most) 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.

Comparing 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 magnitude. A greater number of analysts issued target prices for firms with large stock prices than for firms with small prices. In 2000, there were 2840 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.[10] The difference in coverage between large and small price stocks decreases over time. In 2013, analysts published target prices for 56% of small price stocks and 89% of large price stocks.

Second, 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 in 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.

[7] I/B/E/S started reporting target prices in 1999, but only a few brokers disclosed target prices in the first months. Therefore, we exclude the year 1999.

[8] These price categories are chosen arbitrarily, but our results hold with different categories.

[9] Bradshaw et al. (2014) find that analysts' optimistic behavior is not specific to the U.S. market.

[10] The bias towards large price stocks implicitly shows the positive link between the stock price and the market capitalization of a firm. Large price firms tend to be large firms, which are covered by more analysts than small firms (Bhushan, 1989).

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	Proportion of optimistic target prices	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	3111	9.62	96.04%	37.89%	624	822	588	335	700	3069	2840	1572	820	447	852	6531
2001	39,466	3428	11.41	93.64%	31.95%	819	786	520	349	484	2958	3293	1280	681	421	574	6249
2002	46,441	3258	12.21	92.40%	29.09%	696	849	612	372	388	2917	2566	1314	808	433	446	5567
2003	48,109	2657	11.13	84.40%	17.46%	1035	819	548	311	238	2951	2598	1175	722	371	284	5150
2004	51,505	2728	11.20	85.55%	17.17%	712	781	635	412	482	3022	1714	1144	859	536	567	4820
2005	52,049	2785	10.87	86.46%	16.73%	688	721	655	417	619	3100	1569	1078	859	519	731	4756
2006	53,442	2743	11.07	85.69%	16.57%	741	746	624	412	602	3125	1523	1117	842	506	700	4688
2007	56,504	2730	11.34	86.83%	16.77%	695	695	586	461	634	3071	1431	1072	764	580	775	4622
2008	67,619	2679	11.59	88.44%	27.82%	799	779	506	340	593	3017	1707	1103	634	400	699	4543
2009	65,544	2603	12.76	82.22%	18.82%	1254	710	409	216	235	2824	2455	868	463	244	268	4298
2010	69,254	2989	14.78	87.62%	18.52%	988	663	448	281	399	2779	1896	840	531	320	450	4037
2011	76,180	3044	15.57	89.11%	20.48%	790	666	428	306	554	2744	1561	853	517	346	625	3902
2012	72,677	2913	15.49	87.53%	18.95%	883	616	383	275	523	2680	1615	794	444	309	591	3753
2013	81,300	2781	16.03	83.43%	13.46%	782	592	382	293	605	2654	1403	788	445	328	678	3642

The sample consists in a total of 814,117 target prices issued by 9141 analysts (687 brokers) on 6423 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 and third column shows, respectively, the number of active analysts and the average number of analysts per firm. Column 4 provides the proportion of optimistic target prices (*i.e.*, the number of target prices with positive implied return divided by the total number of target prices). The fifth 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.

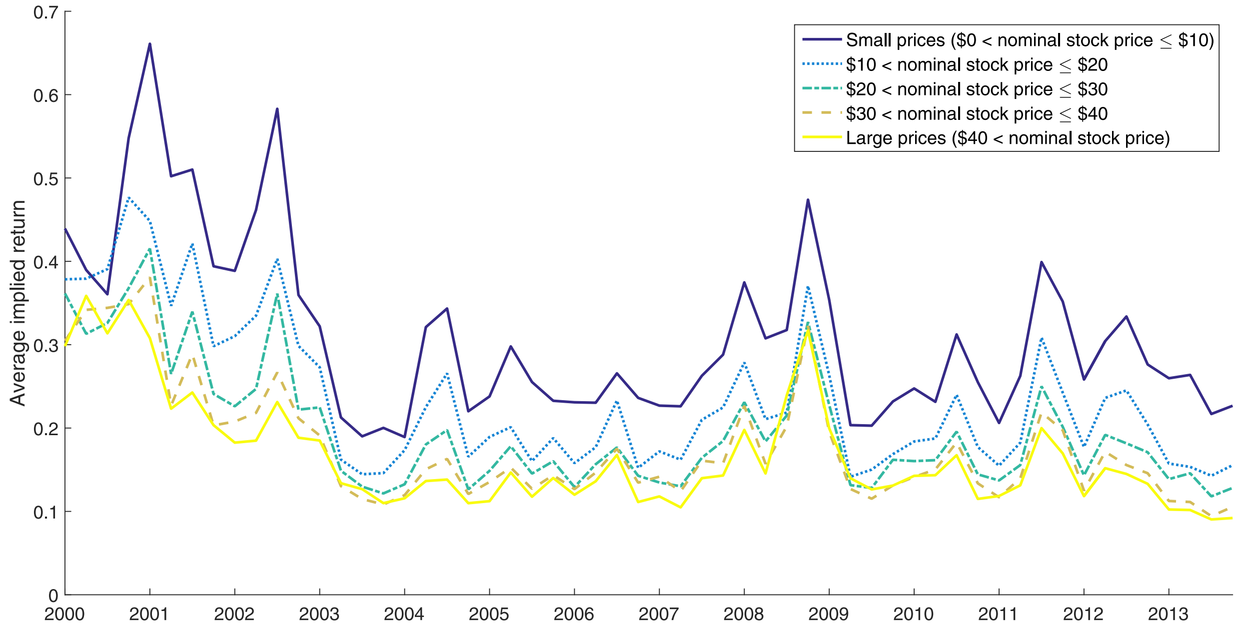

Fig. 1. Average target price implied returns with respect to nominal stock prices This figure presents average target price implied returns, calculated on a quarterly basis, for five price categories. The price categories are: $0 to $10, $10 to $20, $20 to $30, $30 to $40, and above $40. The sample contains all stocks listed on NYSE-AMEX-NASDAQ for the 2000–2013 period.

3. Stock prices and implied returns

3.1. Preliminary results

We start by examining the relationship between nominal stock prices and returns implied by target prices. The yearly return implied by a target price is defined as the ratio of the target price (at the issue date) divided by the current stock price, minus 1. We have

$$IR_{i,j,t} = \frac{TP_{i,j,t}}{S_{i,j,t}} - 1 \tag{1}$$

where $TP_{i,j,t}$ is the target price issued by analyst i on stock j in period t, $S_{i,j,t}$ is the stock price on the day analyst i publishes her target price.

In the following analysis, we consider the average implied return (denoted $\overline{IR}_{j,t}$) on a given stock j in a given month t. The average implied return is defined as the equally-weighted average of the implied returns deduced from all target prices issued on stock j during period t. We note

$$\overline{IR}_{j,t} = \frac{1}{I_{j,t}} \sum_{i=1}^{I_{j,t}} IR_{i,j,t} \tag{2}$$

where $I_{j,t}$ is the number of analysts who issue a target price on stock j in period t. The average implied return $\overline{IR}_{j,t}$ is a measure of analysts' expectations about the future return on stock j.

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 by financial analysts.

Fig. 1 shows the evolution over time of the average implied return in each category. In this preliminary analysis, we do not distinguish between optimistic and pessimistic target prices. For category k, the average is calculated as $\frac{1}{n_k}\sum_{j=1}^{n_k} \overline{IR}_{j,t}$ where n_k is the number of firms in category $k = 1, \ldots, 5$. The two curves at the top of the figure correspond to small 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 small price stocks compared to those of large price stocks. This pattern persists over time, with 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

Table 2
Target prices – Double sort on market capitalization and nominal stock prices.

	Small capitalization	2nd quintile	3rd quintile	4th quintile	Large capitalization
Panel A: Optimistic target prices – Implied returns					
Small price stocks (≤$10)	0.4927	0.3822	0.3236	0.3075	0.2639
$10 to $20 category	0.3005	0.2963	0.2701	0.2487	0.2435
$20 to $30 category	0.2193	0.2400	0.2314	0.2212	0.2100
$30 to $40 category	0.1929	0.2090	0.2093	0.2031	0.1949
Large price stocks (> $40)	0.1840	0.2017	0.1997	0.1959	0.1809
Panel B: Pessimistic target prices – Implied returns					
Small price stocks (≤$10)	−0.0971	−0.0983	−0.0945	−0.0904	−0.0945
$10 to $20 category	−0.0847	−0.0863	−0.0875	−0.0852	−0.0851
$20 to $30 category	−0.0721	−0.0829	−0.0787	−0.0772	−0.0797
$30 to $40 category	−0.0697	−0.0707	−0.0743	−0.0711	−0.0704
Large price stocks (> $40)	−0.0616	−0.0754	−0.0694	−0.0716	−0.0669
Panel C: Optimistic target prices – Signed forecast errors					
Small price stocks (≤$10)	0.3291	0.2608	0.2038	0.1812	0.1804
$10 to $20 category	0.1900	0.1975	0.1672	0.1384	0.1447
$20 to $30 category	0.1002	0.1414	0.1411	0.1242	0.1370
$30 to $40 category	0.0658	0.1135	0.1296	0.1061	0.1303
Large price stocks (> $40)	0.0602	0.0983	0.1300	0.1177	0.1283
Panel D: Pessimistic target prices – Signed forecast errors					
Small price stocks (≤$10)	−0.2860	−0.2253	−0.1723	−0.1980	−0.1849
$10 to $20 category	−0.1520	−0.1714	−0.1740	−0.1628	−0.1724
$20 to $30 category	−0.1637	−0.1613	−0.1567	−0.1575	−0.1340
$30 to $40 category	−0.1048	−0.1779	−0.1310	−0.1505	−0.1214
Large price stocks (> $40)	−0.1051	−0.1263	−0.1426	−0.1377	−0.1205

Panels A and B present target price implied returns for stocks that are sorted on beginning-of-month size and beginning-of-month nominal stock price. Panel C and D present signed forecast errors (defined as the difference between implied returns and realized returns) for stocks that are first sorted on beginning-of-month size and then on beginning-of-month nominal stock price. Panels A and C (respectively, B and D) include only optimistic (pessimistic) target prices, *i.e.*, target prices with a positive (negative) implied return. Size quintiles are obtained by taking NYSE capitalization breakpoints for each year. The price categories are: $0–$10, $10–$20, $20–$30, $30–$40, and above $40. The sample contains all stocks listed on NYSE-AMEX-NASDAQ for the 2000–2013 period.

these quarters, it is likely that a large number of firms changed price categories within these quarters. On average, the difference of implied returns between small price stocks ($0–$10) and large price stocks (> $40) is approximately 15%.

3.2. Size-based and price-based effects

The previous results reveal a relationship between nominal stock prices and implied returns. This relationship could be driven by a size effect, as a result of the positive link between share price and market capitalization (Baker et al., 2009). To disentangle the price and size effects, we use a double sort based on the price categories used in the previous section and on quintiles of capitalization, defined with NYSE breakpoints. We also distinguish between optimistic (*i.e.*, positive implied return) and pessimistic (*i.e.*, negative implied return) target prices. Panel A of Table 2 provides, for each quintile of size, the average implied return associated with optimistic target prices in the different price categories. For all size quintiles, the relationship between stock price and implied return is strictly decreasing. The difference in implied returns between small price stocks and large price stocks is 30.87% for small firms. This difference decreases steadily for the next three quintiles of size (respectively 18.05%, 12.39%, 11.15%) and ends at 8.30% for large-capitalization stocks. Concerning pessimistic target prices (Panel B), small price stocks exhibit lower implied returns than large price stocks. The differences in implied returns between small price stocks and large price stocks range from −3.55% to −1.87%. Table 2 also shows that, in size quintiles $k = 1, 2, 3, 4$, the implied return on large price stocks is lower (in absolute value) than the implied return on small price stocks of quintile $k + 1$. This result indicates that the small price bias does not hide a size effect. In particular, for the three largest price categories, there are no significant differences in implied returns between small firms and large firms.

In panels C and D, the variable under scrutiny is the signed forecast error. Signed forecast error is defined as the difference between the implied return and the realized return. Panel C shows that, for optimistic target prices, the signed forecast errors are a decreasing function of the stock 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 signed forecast errors between small price stocks and large price stocks is 5.20%. This difference reaches 26.89% for small firms. Panel D indicates that analysts are too pessimistic (*i.e.*, forecast errors are negative) when issuing target prices with negative implied returns. In addition, we find that signed errors are more negative for small price stocks than for large price stocks. We conclude that the differences in implied returns between small price stocks and large price stocks are not justified by the future one-year realized returns.

4. Implied returns, stock prices and risk factors

4.1. The model

The results in Section 3 document the relationship between the stock price magnitude and implied returns. The higher absolute value of implied returns on small price stocks, however, may result from a higher sensitivity to risk factors. To investigate this issue, we follow Brav et al. (2005) and Barber et al. (2013). We estimate the return premium using monthly cross-sectional regressions (within a Fama–MacBeth framework), regressing analysts' implied returns (instead of realized future returns) on firm size, book-to-market, momentum, our price-based dummy variables and a set of control variables.[11]

For each month t of the sample period, we estimate the following regression

$$\begin{aligned} IR_{i,j,t} = {} & \alpha_t + \beta_{1,t} SIZE_{j,t} + \beta_{2,t} BTM_{j,t} + \beta_{3,t} MOM_{j,t} + NegativeIR_{i,j,t} \\ & + \sum_{k=1}^{4} \gamma_{k,t} PRICE\_CAT^k_{j,t} + NegativeIR_{i,j,t} \times \sum_{k=1}^{4} \theta_{k,t} PRICE\_CAT^k_{j,t} \\ & + \zeta_{i,t} AFE_{i,t} + \eta_{j,t} IFE_{j,t} + \delta_t Firm\text{-}Controls_{j,t} + \epsilon_{i,j,t} \end{aligned} \quad (3)$$

where $IR_{i,\,j,\,t}$ is the return implied by the target price issued by analyst i on stock j during month t, $SIZE_{j,\,t}$ is the logarithm of the market capitalization of firm j at the end of month $t-1$, $BTM_{j,\,t}$ is the logarithm of the book-to-market ratio for firm j as of the end of the fiscal year preceding month t, $MOM_{j,\,t}$ is the buy-and-hold return on firm j for the 11-month period ending one month prior to month t, $NegativeIR_{i,j,t}$ is a dummy variable which takes the value 1 if the implied return is negative and 0 otherwise, $AFE_{i,\,t}$ are analyst fixed effects and $IFE_{j,\,t}$ are industry fixed effects.[12] The four price-based dummy variables ($PRICE\_CAT^k_{j,t}$) identify the first four price categories ($0-$10, $10-$20, $20-$30, $30-$40 numbered from 1 to 4) described in Section 2. $PRICE\_CAT^k_{j,t}$ is equal to 1 when the price of stock j is in price category k ($k = 1, \ldots, 4$) at the end of month $t-1$ and 0 otherwise. We include the interactions between $NegativeIR_{i,j,t}$ and the different price-based dummy variables to disentangle the effect of the price magnitude on pessimistic and optimistic target prices. Finally, $Firm\text{-}Controls_{j,t}$ is a set of variables that control for firm characteristics (a detailed discussion of the control variables follows in subsection 4.2). The regression 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 sample period. We adjust standard errors using the Newey–West procedure.

4.2. Control variables

4.2.1. Operating profitability and investments

Following Novy-Marx (2013) and Titman et al. (2004), Fama and French (2015) complete their three-factor model (Fama and French, 1993) by adding two more factors, namely operating profitability and investments. They show that the five-factor model is a strong improvement of their initial three-factor model. As a consequence, we also introduce the two variables, operating profitability and investments as controls in our multivariate analysis. We calculate the value of these variables as in Fama and French (2015). Operating profitability is measured with accounting data for the fiscal year ending in year $t-1$. It is equal to revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investments is the change in total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, divided by $t-2$ total assets.

4.2.2. Dividend yield

Financial analysts forecast future prices, not future returns. Because dividends mechanically reduce future prices, we expect the dividend yield to influence analysts' target prices. Dividend-paying firms are likely to have lower implied returns. We, therefore, include the dividend yield in our control variables. Dividend yields do not change much from one year to the next. We thus use the dividend yield that prevailed during the year preceding the target price issue date, as our control variable.[13]

4.2.3. Conflicts of interest

Analysts' target prices can also be impacted by conflicts of interest. Conflicts of interest may arise when a firm has investment banking needs. Dechow et al. (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.[14] Bradshaw et al. (2006) document a strong link between external financing and analysts' optimism. We, therefore,

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[11] A panel regression with clustered standard errors yields similar results.

[12] We define industries using the Fama–French 48-industry classification (Fama and French, 1997).

[13] We do not use dividend forecasts because using this variable implies losing a large number of observations. The results of this partial analysis (not reported here) are qualitatively unchanged.

[14] Similarly, Francis and Philbrick (1993) and Lim (2001) show that analysts produce biased forecasts to obtain better access to management.

include external financing in our controls. Following Bradshaw et al. (2006), we define external financing as the change in equity plus the change in debt.

In addition, as in Bradshaw et al. (2014), we consider the evidence in Teoh et al. (1998a,b) that firms manage accruals to increase earnings prior to financing activities such as Initial Public Offerings (IPO) and Seasonal Public Offerings (SEO). Our proxy for earnings management is the absolute value of discretionary accruals from the Modified Jones Model (Dechow et al., 1995; Jones, 1991).

4.2.4. 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 (Chen and Matsumoto, 2006; Ke and Yu, 2006; Mayew, 2008; McNichols and O'Brien, 1997). 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 conflicts of interest, analysts may decide not to release target prices for firms they think are on the edge of bankruptcy.[15] On the contrary, analysts may issue extremely optimistic forecasts when they expect a distressed firm to be able to recover quickly.[16] This self-selection bias has an impact on the observed distribution of forecasts (Baïk, 2006) which appears overly optimistic. The bias may be particularly prominent among small price stocks because distressed firms are more likely to be in the subset of small price stocks.

To ensure that the small price bias is not driven by a potential self-selection bias, we control for distressed firms by including a dummy variable, which takes the value 1 if a firm has negative earnings in the previous year and 0 otherwise.

4.2.5. 52-week high

In their study of mergers and acquisitions, Baker et al. (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. Many financial newspapers (*e.g.*, the *Wall Street Journal* or the *Financial Times*) attract investors' attention to 52-week highs and lows by publishing the list of firms that reach these thresholds, daily. 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. 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. 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. The 52-week high then plays either an anchor or psychological barrier role.

We include the 52 week-high in our control variables to confirm that the observed differences in implied return between small price stocks and large price stocks are the result of the small price bias and not the result of a potential anchoring to the 52 week-high. Indeed, our findings may simply be the result of small price stocks being, on average, more distant from the 52-week high compared to large price stocks. If analysts exhibit the same behavior as individual investors and become less optimistic when stock prices are close to the 52-week high (Birru, 2014; Clarkson et al., 2013), they will be less optimistic (on average) about large price stocks (a 52-week high is more likely to be a large price than a small price).

To test the importance of anchoring in explaining analysts' implied returns, we introduce the distance to the 52-week high, as an independent variable in the regression specification. We define the distance to the 52-week high, as the ratio of the current stock price and the largest price reached by the stock over the last year, as in Birru (2014).

4.2.6. Lottery-type stocks

Kumar (2009) defines lottery-type stocks as stocks sharing three characteristics: high idiosyncratic volatility, high idiosyncratic skewness, and low price. To summarize these three variables, Kumar et al. (2016) build an index denoted LIDX as follows. The set of stocks under scrutiny is ranked in vigintiles using each of the three above variables. A given stock is then characterized by three ranks between 1 and 20. A score is defined for each stock by adding the three ranks. Finally, the LIDX index is the standardized value of the score defined by $LIDX = (Score - 3)/(60 - 3)$ which lies between 0 and 1. To be consistent, the ranking on price is reversed (the 20th vigintile is the one with the lowest prices) in such a way that stocks that are the most lottery-like get a $LIDX$ value close to 1.

There is also an abundant literature showing that investors like positive skewness (Barberis and Huang, 2008; Ebert and Wiesen, 2011; Mitton and Vorkink, 2007), and not only idiosyncratic skewness. Moreover, as we deal with analysts' forecasts, it is likely that analysts do not think in terms of portfolios when they issue target prices. We also introduce past skewness (estimated over 6 months of daily returns) as a control variable in our model.

4.3. Results

The results of our tests are reported in Table 3. The first column shows the coefficients of the baseline model (Model 1), in which neither fixed effects nor control variables are included. The return premia on the price-based dummy variables

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

[16] 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.

Table 3
Fama-MacBeth regression analysis of target price implied returns.

	Regression of target prices' implied returns on firm characteristics							
	Model 1		Model 2		Model 2 (Reduced sample)		Model 3	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Intercept	0.4199***	0.0271						
Negative IR	−0.2638***	0.0134	−0.2215***	0.0104	−0.2265***	0.0104	−0.2220***	0.0097
Small price dummy ($0 to $10)	0.1956***	0.0134	0.1560***	0.0109	0.1569***	0.0101	0.0981***	0.0053
$10 to $20 dummy	0.0736***	0.0092	0.0637***	0.0065	0.0685***	0.0065	0.0355***	0.0039
$20 to $30 dummy	0.0314***	0.0046	0.0301***	0.0035	0.0344***	0.0043	0.0175***	0.0031
$30 to $40 dummy	0.0114***	0.0032	0.0141***	0.0025	0.0171***	0.0029	0.0089***	0.0023
Small price dummy ($0 to $10) × Negative IR	−0.2429***	0.0129	−0.1963***	0.0082	−0.1963***	0.0079	−0.2008***	0.0086
$10 to $20 dummy × Negative IR	−0.1016***	0.0085	−0.0813***	0.0048	−0.0952***	0.0053	−0.0959***	0.0050
$20 to $30 dummy × Negative IR	−0.0481***	0.0035	−0.0379***	0.0023	−0.0513***	0.0046	−0.0512***	0.0044
$30 to $40 dummy × Negative IR	−0.0179***	0.0030	−0.0131***	0.0029	−0.0190***	0.0039	−0.0192***	0.0039
Size	−0.0110***	0.0008	−0.0063***	0.0012	−0.0073***	0.0015	0.0010***	0.0012
Log book-to-market	−0.0216***	0.0037	−0.0078***	0.0018	−0.0084***	0.0021	−0.0048***	0.0017
Momentum	−0.0110***	0.0061	−0.0170***	0.0047	−0.0162***	0.0045	0.0163***	0.0027
Operating profitability							−0.0027***	0.0012
Investment							0.0038***	0.0012
Dividend Yield							−0.6962***	0.1143
External financing							0.0455***	0.0068
Earnings management							0.0011***	0.0020
Negative earnings dummy							0.0262***	0.0000
52 week high ratio							−0.2435***	0.0200
LIDX							0.0513***	0.0100
Skewness							−0.0040***	0.0000
Industry fixed effects	NO		YES		YES		YES	
Analyst fixed effects	NO		YES		YES		YES	
Average adjusted R^2	32.81%		70.59%		73.90%		75.05%	
Number of observations	761,271		761,271		490,733		490,733	

This table presents the time-series averages of 168 slopes from monthly regressions of

$$IR_{i,j,t} = \alpha_t + \beta_{1,t}SIZE_{j,t} + \beta_{2,t}BTM_{j,t} + \beta_{3,t}MOM_{j,t} + NegativeIR_{i,j,t} + \sum_{k=1}^{4}\gamma_{k,t}PRICE\_CAT^{k}_{j,t} + NegativeIR_{i,j,t} \times \sum_{k=1}^{4}\gamma_{k,t}PRICE\_CAT^{k}_{j,t} + \zeta_{i,t}AFE_{i,t} + \eta_{j,t}IFE_{j,t} + \delta_t Firm\text{-}Controls_{j,t} + \epsilon_{i,j,t}$$

where $IR_{i,j,t}$ is the return implied by the target price issued by analyst i on stock j during month t, $SIZE_{j,t}$ is the logarithm of the market capitalization of firm j at the end of month $t-1$, $BTM_{j,t}$ is the logarithm of the book-to-market ratio for firm j as of the end of the fiscal year preceding month t, $MOM_{j,t}$ is the buy-and-hold return on firm j for the 11-month period ending one month prior to month t, $NegativeIR_{i,j,t}$ is a dummy variable which takes the value 1 if the implied return is negative and 0 otherwise, $AFE_{i,t}$ are analyst fixed effects and $IFE_{j,t}$ are industry fixed effects. We define industries using the Fama-French 48-industry classification (Fama and French, 1997). The four price-based dummy variables ($PRICE\_CAT^{k}_{j,t}$) identify the first four price categories ($0-$10, $10-$20, $20-$30, $30-$40 numbered from 1 to 4) described in Section 2. $PRICE\_CAT^{k}_{j,t}$ is equal to 1 when the price of stock j is in price category k ($k = 1, \ldots, 4$) at the end of month $t-1$ and 0 otherwise. We include the interactions between $NegativeIR_{i,j,t}$ and the different price-based dummy variables. Finally, $Firm\text{-}Controls_{j,t}$ is a set of variables that control for firm characteristics. These controls are: (1) operating profitability, (2) investment, (3) dividend yield, (4) external financing, (5) the absolute value of discretionary accruals from the Modified Jones Model, (6) a negative earnings dummy, (7) the 52-week high ratio, (8) the LIDX of Kumar et al. (2016), and (9) past skewness of returns . The regression 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 sample period. Standard errors are adjusted using the Newey-West procedure. In Model 2 (Reduced sample), we use the same sample as in Model 3.

are positive (negative) and highly significant and, more importantly, decrease (increase) in the price level. For stocks priced below $10, the risk-adjusted return implied by optimistic target prices is 19.56 percentage points higher than for stocks priced above $40. This difference in risk-adjusted implied return is 7.36% for stocks priced in the $10-$20 range, 3.14% for stocks priced in the $20-$30 range and 1.14% for stocks priced in the $30-$40 range. The coefficients of the interaction variables between *NegativeIR* and the price based dummy variables are negative, significant and increase in the price level. The average adjusted R-squared of the regression is approximately 33% (Table A1, in the appendix, shows that the adjusted R-squared is only about 6% without the price dummy variables). These differences in risk-adjusted returns across price ranges show that analysts strongly, but maybe unconsciously, differentiate forecasts on small price stocks and forecasts on large price stocks, in a way that favors the two-mental scales hypothesis. To confirm this result and take into account alternative explanations, we introduce fixed effects and control variables in Models 2 and 3.

In Model 2, we add analyst and industry fixed effects. Analyst fixed effects allow us to control for the fact that analysts covering small price stocks may not be the same as analysts covering large price stocks. Industry fixed effects are included to control for differences in price range across industries. Adding such fixed effects in the regression does not change the results. The coefficients in Models 1 and 2, specifically the coefficients associated with the interactions between *NegativeIR* and the price dummies, also show that our findings are distinct from the “more room to grow” argument developed by Birru and Wang (2016) and Green and Hwang (2009). To facilitate the comparison between Model 2 and Model 3, we also perform the analysis of Model 2 on the reduced sample of Model 3 (490,733 observations).

In Model 3, the sample is reduced because we add firm-level control variables to control for differences in firm characteristics, among which the (total) skewness of returns, and Kumar et al. (2016) LIDX index which combines the three main features of lottery-type stocks.[17] Introducing these control variables does not change the structure of the coefficients of the price-based dummy variables and interaction variables (compared to Model 2). In fact, the presence of control variables slightly mitigates the effect on optimistic target prices but does not change the effect on pessimistic ones. The coefficient associated with the small price dummy (<$10) remains approximately 10% while the coefficient of the interaction between *NegativeIR* and the small price dummy reaches −20%.

4.4. Rounding

We also consider the possibility that the small price bias could 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 nearest higher 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 (to $31.90) is almost negligible, representing 0.3% of the initial target price. The reverse reasoning can also be valid for pessimistic forecasts. Hence, rounding may be an alternative explanation for the small price bias. Thus, it is possible that the results obtained above are driven by target prices being systematically rounded in an optimistic or pessimistic way depending on the sign of the implied return.

The preference for rounded numbers (called “heaping”) is documented in various fields including 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 et al. (2013). For example, Herrmann and Thomas (2005) find 55% of EPS forecasts ending in 0 or 5 in the penny location, when the average percentage should be 20% because the convention is to forecast EPS in dollars and cents. Clarkson et al. (2013) show that rounding is significant in explaining the formation of target prices.

In our sample, 92% of target prices are rounded to the dollar and the rounding magnitude varies across price categories.[18] Not surprisingly, rounding to the nearest dollar is less frequent for small prices (70%). More precisely, among the 82,330 target prices in the small price category ($0-$10), 57,619 are rounded to the dollar, 14,357 to the half-dollar, 4,378 to the quarter, 3863 to the dime, and 862 to the nearest nickel.

We consider the four worst-case scenarios corresponding to the above types of rounding (we group nickel and dime rounding) to take into account the way optimistic (pessimistic) financial analysts may round target prices. We performed the relevant correction in the regression corresponding to Model 3 of Table 3. The (untabulated) results show that the small price bias is not explained by the rounding process.[19] The price-based dummies remain significant in our worst case scenarios.

[17] If the lottery-type stock argument was a convincing explanation for the small price bias, the LIDX index and the skewness of returns would be more important determinants of implied returns than our small price dummies. Table A1, in the appendix, indicates that this is not the case; in Model 3, deleting the price dummy variables reduces the average adjusted R-squared of the regression by 9%. In an unreported result, we find that if only Fama–French factors, the LIDX index and the skewness of returns are considered, the adjusted R-squared of the regression is 9.68% (23 percentage points smaller than the adjusted R-squared in Model 1 of Table 3).

[18] Clarkson et al. (2013) report an average of 87% of target prices rounded to the dollar for the 1999–2007 period.

[19] Results available upon request.

Table 4
Proportion of recommendations – Double sort on market capitalization and nominal stock prices.

	Strong Buy	Buy	Hold	Underperform	Sell
Panel A: Small-capitalization stocks					
Small price stocks (≤$10)	0.2480	0.2854	0.3866	0.0543	0.0257
$10 to $20 category	0.2613	0.2641	0.4084	0.0444	0.0218
$20 to $30 category	0.2568	0.2581	0.4261	0.0397	0.0193
$30 to $40 category	0.2430	0.2461	0.4518	0.0401	0.0190
Large price stocks (> $40)	0.2321	0.2570	0.4544	0.0370	0.0195
Panel B: Medium-capitalization stocks					
Small price stocks (≤$10)	0.1647	0.2488	0.4631	0.0941	0.0294
$10 to $20 category	0.1952	0.2629	0.4487	0.0666	0.0265
$20 to $30 category	0.2100	0.2695	0.4367	0.0608	0.0230
$30 to $40 category	0.2257	0.2635	0.4349	0.0566	0.0193
Large price stocks (> $40)	0.2287	0.2694	0.4331	0.0496	0.0192
Panel C: Large-capitalization stocks					
Small price stocks (≤$10)	0.1349	0.2322	0.4662	0.1143	0.0525
$10 to $20 category	0.1819	0.2634	0.4548	0.0724	0.0276
$20 to $30 category	0.1904	0.2791	0.4433	0.0627	0.0246
$30 to $40 category	0.1927	0.2867	0.4403	0.0592	0.0211
Large price stocks (> $40)	0.2091	0.3018	0.4193	0.0512	0.0185

This table presents the proportion of Strong buy, Buy, Hold, Underperform and Sell recommendations with respect to market capitalization and nominal stock price. The size terciles are obtained by taking NYSE capitalization breakpoints for each year. The price categories are: $0–$10, $10–$20, $20–$30, $30–$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.

5. Additional results

5.1. Stock prices and recommendations

Our previous results support the idea that analysts issue more optimistic target prices on small price stocks than on large price stocks. Although we controlled for risk factors and a number of firm and analyst characteristics, we want to make sure that our results are not driven by an omitted variable. We thus analyze stock recommendations. If analysts issue more optimistic target prices on small price stocks than on large price stocks[20] because of differences in unobserved economic factors, we should find that these analysts issue more favorable recommendations on small price stocks than on large price stocks. On the contrary, if the differences in implied return result from a differential processing of small and large numbers, we should not observe any difference in stock recommendations.

Table 4 reports recommendations double-sorted on market capitalization and on stock prices.[21] There are five categories of recommendations: Strong Buy, Buy, Hold, Underperform, and Sell. Table 4 shows that analysts do not issue more favorable recommendations for small price stocks. On the contrary, the proportion of Strong Buy and Buy recommendations is higher for large price stocks than for small price stocks. Symmetrically, the proportion of Hold, Underperform and Sell recommendations is higher for small price stocks than for large 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 with the exception of the Strong Buy and Sell recommendations for small-capitalization stocks. This additional analysis supports the idea that our previous results are driven by the differential processing of small and large numbers and not by differences in unobservable economic factors.

5.2. Stock splits

Finally, we follow Birru and Wang (2016) and investigate the impact of stock splits on implied returns. A forward (reverse) split consists of increasing (decreasing) the number of shares while decreasing (increasing) the price per share. A stock split is therefore an interesting event for our study, because it generates a large price change while having no impact on fundamentals (He and Wang, 2012). If analysts are prone to the small price bias, we expect target prices to be more optimistic following forward stock splits.[22]

[20] At the aggregate level, optimism is greatest on small price stocks than on large price stocks because the vast majority of forecasts are optimistic.
[21] We use terciles of capitalization with NYSE breakpoints. Results are unchanged with quintiles of capitalization.
[22] Since 90% of target prices are optimistic for this subsample, we aggregate all target prices in a single analysis.

Table 5
Implied returns and signed forecast errors before and after stock splits.

	Average implied return	Signed forecast errors
Panel A: All analysts		
Split ratio between 1.25 and 2		
Before splits	0.1578	0.0217
After splits	0.2030	0.1291
Difference	0.0453***	0.1074***
Split ratio greater or equal to 2		
Before splits	0.1683	0.0968
After splits	0.2281	0.2002
Difference	0.0598***	0.1034***
Panel B: Controlling for coverage initiation and termination		
Split ratio between 1.25 and 2		
Before splits	0.1571	0.0150
After splits	0.2051	0.1257
Difference	0.0479***	0.1107***
Split ratio greater or equal to 2		
Before splits	0.1679	0.0903
After splits	0.2234	0.1882
Difference	0.0555***	0.0980***

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. Panel A provides the results based on all the analysts in our sample. Panel B gives the results for a subsample of analysts who issue target prices both before and after the split. In Panel A, there are 532 splits with a split ratio between 1.25 and 2, and 869 splits with a ratio larger or equal to 2. In Panel B, there are 503 splits with a split ratio between 1.25 and 2, and 825 splits with a ratio larger or equal to 2. The first column presents average implied returns. The second column provides signed forecast errors (target price bias). Signed forecast errors are defined as the difference between implied returns and realized returns.

Since the publication of the seminal paper of Fama et al. (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 et al., 1989; Ikenberry et al., 1996). For example, Ikenberry et al. (1996) find a 3.8% abnormal return on the announcement date, and Lin et al. (2009) find more than 3%. Devos et al. (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. Thus, if analysts also consider that a stock split provides new information about future cash flows, then they should become more optimistic before, 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 will already have occurred.

More recently, Baker et al. (2009) proposed an alternative approach for the motivation of splits. Their catering theory of nominal share prices is based on the idea that firms decide to split their stocks to reach a smaller share price when investors are ready to pay a premium for small price stocks. If financial analysts are rational, they should perceive the overvaluation of stocks that split 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 small price bias.

5.2.1. Implied returns and forecast errors before and after stock splits

We start by looking at implied returns and forecast errors before and after stock splits. We distinguish two categories of splits.[23] 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 the average implied return of the target prices issued in the quarter[24] preceding (following) the split. We then take the average of the results for each type of split.

Our sample contains 1401 stock splits, 532 type-1 splits and 869 type-2 splits. Panel A of Table 5 gives the results based on all the target prices in the sample. In Panel B, we control for possible initiation or termination coverage effects due to stock splits by taking only the subsample of analysts who issue target prices both before and after the split.

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. Since 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 5 provides the results for forecast errors. Signed forecast errors increase from 2.17% to 12.91% for a split ratio between 1.25 and 2 and from 9.68% to 20.02% for a split ratio greater or equal to 2. The difference in forecast errors is statistically significant at the

[23] 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.

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

Table 6
Implied returns and signed forecast errors before and after stock splits – Difference-in-differences analysis.

	Average implied return			Target price bias (Signed forecast errors)		
	Splitting firms	Control firms	Difference	Splitting firms	Control firms	Difference
Split ratio between 1.25 and 2						
Before splits	0.1447	0.1845	−0.0398	0.0173	0.0986	−0.0813
After splits	0.1853	0.1927	−0.0074	0.1303	0.1121	0.0182
Difference	0.0406	0.0082	0.0324***	0.1131	0.0136	0.0995***
Split ratio greater or equal to 2						
Before splits	0.1565	0.1879	−0.0314	0.0770	0.1742	−0.0972
After splits	0.2031	0.2019	0.0013	0.1555	0.1561	−0.0007
Difference	0.0466	0.0140	0.0326***	0.0784	−0.0181	0.0965***

This table provides the results of the difference-in-differences analysis. Our first sample is composed of firms that split their stock during the 2000–2013 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 (320 observations), and splits with a ratio greater or equal to 2 (349 observations). Columns 1 to 3 provide average implied returns. Columns 4 to 6 report signed forecast errors (target price bias). Signed forecast errors are defined as the differences between implied returns and realized returns.

1% level. The levels of significance are the same in Panel B, where target prices (for a given firm) are issued by the same set of analysts, before and after splits. Since firms' fundamentals are unchanged after splits, we conclude that these results support the existence of a small price bias.

5.2.2. Propensity score matching

One could argue that endogeneity affects our previous results, because the decision to split a firm's stock is not random. To deal with this endogeneity issue, we implement propensity score matching (Rosenbaum and Rubin, 1983). The purpose of this approach is to control for the specific characteristics of splitting firms and potential time-period effects by selecting a sample of control firms that do not split, but share a number of significant characteristics with firms that split.[25] We calculate propensity scores using probit regressions where independent variables (Baker et al., 2009) are the logarithm of the stock price at the end of 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 months of year $t-1$.[26]

For each stock split in year *t*, we select (with replacement) a matching firm from the same year that belongs to the same industry[27] 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 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 et al. (2009), together with pre-split analysts' implied returns. Table A2 in the Appendix reports the results of the probit regressions before and after matching. The after matching regression contains both firms that split and matching firms, ending in 1336 observations. Before matching (first column of Table A2), all the determinants are significant. As expected, the last column of Table A2 indicates that none of the determinants remains significant after matching. In addition, Table A3 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 difference-in-differences analysis.

The results of the difference-in-differences analysis are reported in Table 6. For type-1 (type-2) splits, the difference-in-differences of average implied returns is equal to 3.24% (3.26%). This difference is highly significant. Thus, the increase in implied returns following stock splits is not the result of 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 from non-splitting firms. The last three columns of Table 6 show that signed forecast errors also increase following stock splits. Our difference-in-differences analysis thus confirms our previous findings. Following stock splits, financial analysts issue more optimistic target prices. These results provide additional indications that analysts do not process small and large numbers in the same way.

[25] 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).

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

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

6. Conclusion

In this paper, we offer strong empirical evidence of the existence of a small price bias. We show that financial analysts process small stock prices and large stock prices differently, when issuing target prices. Specifically, optimistic (pessimistic) analysts consistently issue more optimistic (pessimistic) target prices on small price stocks than on large price stocks. This result is consistent with research in neuropsychology that shows deviations 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 also subject to this bias.

We show that the small price bias is not driven by the usual risk factors, namely size, book-to-market and momentum. Moreover, the small price bias is distinct from other explanations such as the tendency of analysts to round numbers, the 52-week high bias, the following of distressed firms, or the preference for lottery-type stocks and positive skewness. We also investigate the relationship between stock prices and recommendations, and highlight that analysts do not recommend small price stocks more strongly than large price stocks. Finally, we find that analysts become more optimistic after stock splits, which cannot be explained by changes in the sensitivity to risk factors.

Overall, our findings point in the direction of a deeply rooted behavioral bias in number processing among financial analysts. This paper suggest directions for future research. In particular, it would be interesting to investigate if other market participants are also subject to the small price bias.

Appendix

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, that belongs to the same industry[28] 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's 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 a common support on both splitting and control firms (Rosenbaum and Rubin, 1983). For each year from 2000 to 2013, we estimate

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

Table A1
Fama–MacBeth regression analysis of target price implied returns without price dummy variables.

	Regression of target prices' implied returns on firm characteristics					
	Model 1		Model 2		Model 3	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Intercept	0.7811***	0.0578				
Size	−0.0273***	0.0021	−0.0153***	0.0024	0.0035***	0.0017
Log book-to-market	−0.0213***	0.0042	−0.0026***	0.0026	−0.0040***	0.0022
Momentum	−0.0213***	0.0081	−0.0273***	0.0063	0.0160***	0.0038
Operating profitability					−0.0028***	0.0013
Investment					0.0041***	0.0014
Dividend Yield					−1.0018***	0.1230
External financing					0.0547***	0.0073
Earnings management					0.0004***	0.0021
Negative earnings dummy					0.0375***	0.0055
52 week high ratio					−0.2615***	0.0205
LIDX					0.1140***	0.014
Skewness					−0.0104***	0.0018
Industry fixed effects	NO		YES		YES	
Analyst fixed effects	NO		YES		YES	
Average adjusted R^2	5.87%		59.94%		66.01%	
Number of observations	761,271		761,271		490,733	

This table presents the time-series averages of 168 slopes from monthly regressions of
$IR_{i,j,t} = \alpha_t + \beta_{1,t}SIZE_{j,t} + \beta_{2,t}BTM_{j,t} + \beta_{3,t}MOM_{j,t} + \zeta_{i,t}AFE_{i,t} + \eta_{j,t}IFE_{j,t} + \delta_t Firm\text{-}Controls_{j,t} + \epsilon_{i,j,t}$
where $IR_{i,j,t}$ is the return implied by the target price issued by analyst i on stock j during month t, $SIZE_{j,t}$ is the logarithm of the market capitalization of firm j at the end of month $t-1$, $BTM_{j,t}$ is the logarithm of the book-to-market ratio for firm j as of the end of the fiscal year preceding month t, $MOM_{j,t}$ is the buy-and-hold return on firm j for the 11-month period ending one month prior to month t, $AFE_{i,t}$ are analyst fixed effects and $IFE_{j,t}$ are industry fixed effects. Finally, $Firm\text{-}Controls_{j,t}$ is a set of variables that control for firm characteristics. These controls are: (1) operating profitability, (2) investment, (3) dividend yield, (4) external financing, (5) the absolute value of discretionary accruals from the Modified Jones Model, (6) a negative earnings dummy, (7) the 52-week high ratio, (8) the LIDX of Kumar et al. (2016), and (9) past skewness of returns . The regression 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 sample period. Standard errors are adjusted using the Newey–West procedure.

Table A2
Probit regression of stock split on the determinants.

	Before matching	After matching
Intercept	−4.4501***	−3.2849***
Intercept	(0.2472)	(2.5407)
Log-price$_{t-1}$	0.8788***	0.7688***
Log-price$_{t-1}$	(0.0658)	(0.6244)
Capitalization$_{t-1}$	−0.0196***	−0.0615***
Capitalization$_{t-1}$	(0.0058)	(0.0500)
Return$_{t-1}$	0.9822***	1.6813***
Return$_{t-1}$	(0.0969)	(1.2244)
Volatility$_{t-1}$	−1.1890***	−3.4547***
Volatility$_{t-1}$	(0.3841)	(2.8897)
Book-to-Market$_{t-1}$	−0.4184***	0.0036***
Book-to-Market$_{t-1}$	(0.0623)	(0.0030)
Implied Return$_{t-1}$	0.4381***	4.3938***
Implied Return$_{t-1}$	(0.1573)	(3.0844)
Number of observations	49,864	1,336
Pseudo R^2	7.99%	

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

Table A3
Mean values of determinants and propensity scores for splitting firms and control firms.

	Splitting firms	Control firms	Difference
Propensity score	0.1202	0.1202	0.0000
Log price	3.6569	3.6789	−0.0220
Capitalization	5.9411	5.7674	0.1737
Return	0.4196	0.3911	0.0285
Volatility	0.4139	0.4033	0.0106
Book-to-market	0.4633	0.4595	3.8150
Implied Return	0.1913	0.1786	0.0127

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

propensity scores with the following probit regression. We include known determinants of stock splits (Baker et al., 2009) and analysts' implied returns in our set of independent variables.

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

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 (Capitalization$_{t-1}$), the one-year return (Return$_{t-1}$), the one-year total volatility (Volatility$_{t-1}$), the book-to-market (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 $t-1$.

To evaluate the quality of our matching, we follow a diagnostic approach similar to that of Lemmon and Roberts (2010). Table A2 reports the results of the probit regressions, before and after matching. Before matching, all the determinants significantly predict the probability of a stock split.

If our matching is correct, the determinants should no longer explain stock splits after matching. The last column in Table A2 indicates that none of the determinants are significant. Table A3 shows the balancing test results after matching. We find that the difference in characteristics between splitting firms and control firms is 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 cannot be attributed to differences in firm characteristics.

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