The Nominal Price Premium[†]

Justin Birru* and Baolian Wang**

March 2016

Abstract

Motivated by the evidence that investors tend to be overly optimistic about low-priced stocks, we examine how nominal price affects the cross section of stock returns. To circumvent the mechanical inverse relationship between price and expected return, we construct a novel way of examining the effect of nominal price on the cross section of stock returns. In the cross-section, a portfolio exploiting this strategy generates a value-weighted (equal-weighted) four-factor alpha of 85 (88) basis points per month, while raw price does not predict return robustly. Consistent with a mispricing-based explanation, the results are stronger for hard-to-arbitrage stocks and following high sentiment periods, and strategy returns are highly correlated with contemporaneous changes in sentiment. Using stock splits as an exogenous change in price level, we find that the post-split return dynamics mimic those predicted by our hypothesis. Evidence from earnings surprises and analyst price target forecasts confirms that beliefs are overly optimistic for low-priced stocks. Providing further evidence that the results reflect a belief-based rather than purely a preference-based channel, we find that the effect is distinct from other gambling related proxies that have been used in the past such as extreme returns, idiosyncratic volatility, and skewness.

[†]The authors are grateful for valuable comments received from Yakov Amihud, Nicholas Barberis, Utpal Bhattacharya, Nusret Cakici, Zhi Da, Bing Han, Kewei Hou, Lawrence Jin, Weikai Li, Jianan Liu, Abhiroop Mukherjee, Mark Seasholes, K.C. John Wei, and seminar participants at Fordham University. All errors are the responsibility of the authors.

*Assistant Professor, Fisher College of Business, The Ohio State University. Email: birru.2@fisher.osu.edu.

**Assistant Professor, Gabelli School of Business, Fordham University. Email: bwang46@fordham.edu.

1. Introduction

Anecdotal evidence suggests that investors possess an irrational belief that stocks with lower nominal prices have greater upside potential.[1] Recent studies also speculate that irrational beliefs induced by nominal price are likely to be a primary explanation for other observed price-related phenomena, such as the observed preference of individual investors for low-priced stocks (Kumar (2009)), comovement of stocks with similar price levels (Green and Hwang (2009)), and time-variation in premiums for low-priced stocks (Baker, Greenwood, and Wurgler (2009)). Using option pricing data to extract investors' skewness expectations, Birru and Wang (2015) find direct evidence that investors perceive lower priced stocks to have greater upside potential. In this paper we test whether nominal price also has predictive power for the cross-section of stock returns. Overly optimistic investor expectations for low-priced stocks predict that low-priced stocks will likely be overpriced relative to high-priced stocks, thereby delivering lower future risk-adjusted stock returns. In this paper, we find strong evidence in support of a nominal price premium for low-priced stocks.

The cross-sectional relationship between raw nominal prices and future returns is likely to underestimate the real economic magnitude of the nominal price premium. This is because a sort on raw nominal price is confounded by the mechanical relationship between raw nominal price and expected returns. Any model of prices (e.g., the Gordon growth model) inversely links prices and expected returns. Stocks with higher risk will have higher expected returns, causing future cash flows to be discounted at a higher rate when determining price, and therefore leading

[1] For example, a number of mutual fund families offer "low-priced" stock funds in an effort to appeal to investor psychology. These funds primarily invest in stocks trading below a specified price per share (the definition varies by fund, but is typically in the $15-$35 range). The notion that low-priced stocks have more upside potential is often reinforced by these funds in their prospectuses. Fidelity, Perritt, RS Funds, and Royce are examples of fund families that have previously launched low-priced funds. See Birru and Wang (2015) for further discussion.

to a lower price today.[2] It is therefore not surprising that past research has not documented a relationship between nominal price and future returns, as a sort on raw nominal price combines two countervailing forces – a nominal price premium (predicting that low-priced stocks should exhibit low future returns) and a mechanical discount-rate effect (predicting that low-priced stocks should exhibit high future returns). To the extent that existing asset pricing models (e.g., Fama and French (1993) three-factor model) cannot perfectly adjust for risk, using raw nominal price as a sorting variable will underestimate the nominal price premium.[3] For this reason, using raw nominal price is problematic. Table A1 of the Appendix illustrates this point by using Fama-MacBeth regressions to examine the cross-sectional relationship between raw price and future excess returns. As the results in Column 1 show, in the cross-section, raw price has no predictive ability for future excess returns. The remaining columns confirm that this conclusion persists with the introduction of various controls.

We navigate this problem by using a fitted price variable estimated by capitalizing on the strong cross-sectional relationship between price and a set of nominal variables from accounting statements: assets per share, book value per share, earnings per share, and dividends per share. Importantly, the fitted price variable is highly correlated with raw nominal price, but at the same time, is unlikely to suffer from the mechanical relationship with expected returns discussed above.

A strategy that holds a long position in high fitted price stocks and a short position in low fitted price stocks generates a value-weighted (equal-weighted) four-factor alpha of over 85 (88)

[2] Miller and Scholes (1982) actually use the reciprocal of price per share as a measure of risk.

[3] This argument is similar to that given in Berk (1995) to explain the size premium. Consistent with this logic, in Table A1, we find that the excess return of the long-short portfolio sorted by raw price per share is insignificantly different from zero. However, after controlling for risk via the Fama-French factors or the Fama-French-Carhart factors, long-short portfolios exhibit economically and statistically significant alphas.

basis points per month. Consistent with overpricing of low-priced stocks, we find that most of the abnormal returns accrue to the short leg of the strategy rather than the long leg that is invested in high-priced stocks. Further consistent with a mispricing story, we also find that the results are stronger in the presence of greater limits to arbitrage, and that low-priced stocks are most overpriced relative to high-priced stocks during high sentiment periods – that is, the bulk of the strategy returns occur following times of high sentiment and further, as sentiment decreases, high-priced stocks attain high returns relative to low-priced stocks.

Using stock splits as an exogenous change in price level (Green and Hwang (2009), Baker, Greenwood, and Wurgler (2009)), we find that the return dynamics observed in the post-split period mimic those predicted by our hypothesis. Specifically, we find that after splitting to a lower price level, stocks exhibit positive abnormal returns in the short run, followed by negative abnormal returns in the long-run. This is consistent with investors bidding up the prices of low-priced stocks to overvalued levels, and this being followed by the slow correction of mispricing.

The results are distinct from studies examining the relationship between lottery-like stock attributes and returns, both conceptually and empirically. Empirically, our results are robust to controls for idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)), max daily return of the past month (Bali, Cakici, and Whitelaw (2011)), expected idiosyncratic skewness (Boyer, Mitton, and Vorkink (2010)), the TK prospect theory variable of Barberis, Mukherjee, and Wang (2015), and coskewness (Harvey and Siddique (2000)). Conceptually, past studies have examined the relationship between lottery-like stock attributes and returns from purely a preference for skew channel, while we document an effect arising from a belief-based channel. Consistent with a belief-based channel, we provide direct evidence in support of the view that market participants have overly optimistic expectations regarding low-priced stocks. Consistent with over-optimism toward low-priced stocks, we find that fitted price strongly predicts earnings surprises. Low-priced stocks have systematically negative earnings surprises, while high-priced stocks experience systematically positive earnings surprises. We find similar evidence when examining analyst price forecasts. Low-priced stocks have substantially higher analyst price appreciation expectations than high-priced stocks. These findings on investors' expectational errors cannot be explained by purely a preference for skew channel (Barberis and Huang (2008)), and therefore provide supporting evidence that the results are (at least partially) driven by a belief-based channel.

While the evidence we present strongly supports the errors in beliefs channel, it is likely that a second channel also contributes to the predictability of price-sorted returns. In particular, Birru and Wang (2015) find that while there exists no empirical relationship between nominal price and skewness after one controls for other firm characteristics, investors nevertheless incorrectly perceive low-priced stocks to have greater upside potential. This error in beliefs regarding the skewness of low-priced stocks, coupled with investor preference for skew is a further potential cause of overpricing among low-priced stocks, and likely strengthens the asset pricing outcomes we observe.

Our paper is also related to the literature on nominal price. Baker, Greenwood and Wurgler (2009), Green and Hwang (2009), and Kumar (2009) all speculate that investors' expectations may depend on nominal price, but do not test this hypothesis. Birru and Wang (2015) provide direct evidence by using option data to back out investor expectations. However, they do not examine how nominal price affects the cross section of stock returns.[4]

[4] Kumar (2009) defines lottery-type stocks as those with high idiosyncratic skewness, high idiosyncratic volatility, and low raw nominal price and finds that lottery-like stocks earn negative risk-adjusted returns. However, Kumar (2009) does not use price per share as a separate return predictor. More importantly, as discussed, a sort on raw

The paper proceeds as follows. Section 2 discusses the fitted price variable and introduces the data. Section 3 examines portfolio returns and explores hypotheses related to limits to arbitrage. Section 4 examines price dynamics following stock splits. Section 5 tests whether nominal prices induce expectational errors. Section 6 concludes.

2. Data

Nominal price and expected return are mechanically linked, as riskier firms will require higher returns and thus have lower prices. To the extent that existing asset pricing models (e.g., Fama and French (1993) three-factor model) cannot perfectly adjust for risk, using raw nominal price as a sorting variable will underestimate the nominal price premium. To circumvent this issue we use a fitted price variable. The fitted value comes from the following cross-sectional regression

$$Price_{i,t} = Constant_t + \beta_1 BPS_{i,t} + \beta_2 EPS_{i,t} + \beta_3 APS_{i,t} + \beta_4 DPS_{i,t} + \varepsilon_{i,t.} \quad (1)$$

where *Price* is the market price per share at the end of the fiscal year, *BPS* is book value per share, *EPS* is earnings per share, *APS* is total assets per share, and *DPS* is dividend per share.[5] Table 1 defines these and the other main variables used throughout the study. Each of the variables in the fitted regression is measured as a per share variable. The fitted variable from

---

nominal price combines two countervailing forces – a nominal price premium (predicting that low-priced stocks should exhibit low future returns) and a mechanical discount-rate effect (predicting that low-priced stocks should exhibit high future returns). Disentangling these two forces is the key of this study. However, Kumar (2009) does not do this.

[5] *Price* is Compustat item PRCC_F. *BPS* is CEQ/CSHO. *EPS* is (Sale-COGS-XSGA+XRD)/CSHO. *APS* is (AT/CSHO), and *DPS* is (DVC/CSHO). In Compustat, the selling, general & administrative expenses (Compustat item XSGA) is the sum of firms' actual reported selling, general & administrative expenses and their research & development expenditures (Compustat item XRD). Conservative accounting rules expense research & development expenditures as they are incurred, even though they are incurred largely to generate future rather than current expense. Ball, Gerakos, Linnainmaa, and Nikolaev (2015) find that undoing Compustat's adjustments (subtracting XRD from XSGA) can better align expenses and revenue, and therefore they suggest measuring operating profitability as Sale-COGS-XSGA+RD. In unreported analysis, we find that profitability calculated in this way predicts price level better than the gross profit variable (Sale-COGS) proposed by Novy-Marx (2013).

equation (1) therefore circumvents the mechanical relationship between raw price and future stock returns.

All the variables are measured at the same fiscal year end. The choice of these variables is largely based on the accounting valuation literature, which shows that these variables are important for stock price (e.g., Ohlson (1995)). We use accounting data starting in December of 1967. We include observations for which firm market capitalization is at least $10 million and for which there are positive values for book equity per share, and for which total assets per share, earnings per share, and dividends per share are not missing. All accounting variables are winsorized at 1% and 99%. We also exclude observations where price is less than $1 or greater than $1,000. We use the natural logarithm of the fitted value (denoted as *Price**) as our main variable of interest in much of the analysis that follows.

Table 2 shows regression coefficient estimates for the cross-sectional price regressions. Columns 1-4 display coefficients of univariate regressions. As expected, in a univariate setting, each of the four variables has a positive and statistically significant relationship with price. Column 5 displays coefficient estimates for the multivariate specification where all variables are included together. When all variables are included together, the sign on assets per share flips, while the remaining variables continue to display positive coefficients. The fitted regression in Column 5 has a rather high adjusted R^2 of 55.2%. The correlation coefficient between *Price** and raw *Price* is 72.4%, suggesting that *Price** and raw price are closely related. Therefore it is not surprising that in our later analysis, portfolios sorted by *Price** also have very large cross-sectional spreads in raw price. Unless otherwise specified, we use *Price** from the specification in Column 5 in the remainder of the analysis.

Table 3 examines the summary statistics of a number of variables by *Price** decile. For all deciles, the mean of *Price** is very similar to the mean of raw price. Not surprisingly, size increases with *Price**. It is also the case that book-to-market increases with *Price**, while beta and momentum both decrease with *Price**. Finally, illiquidity exhibits a strongly decreasing relationship with *Price**. While stocks with lower values of *Price** are more illiquid, we show later that they actually earn lower risk-adjusted returns.

3. Portfolio Return Analysis

Table 4 shows results of univariate portfolio sorts on *Price**. Data on stock returns is from CRSP. We focus on stocks with share code of 10 or 11 and stocks listed on NYSE, Amex or NASDAQ. We exclude stocks with price below $1 or higher than $1,000 at the end of last month, and also stocks with market capitalization lower than $10 million. The portfolios are rebalanced annually at the end of each June. Both value-weighted and equal-weighted returns for decile portfolios are shown. Because we use accounting data starting in December of 1967, our return sample period begins in July 1968 and extends through December 2013.[6]

Table 4 shows excess returns, alpha from the Fama-French three-factor model, and alpha from the three-factor model along with the Carhart (1997) momentum factor.[7] In each of the models, returns are generally increasing in *Price** decile. Consistent with low-priced firms being overpriced, the majority of the spread in alphas comes from the short side of the portfolio. For example, the four-factor alpha for the value-weighted strategy is 85.4 basis points per month,

---

[6] We follow the convention of Fama and French (1992) to match *Price** and stock returns.

[7] Returns throughout the paper are adjusted for delisting. Following Shumway (1997), in the case of delisting we set observations with delisting code of 500,520, 551-573, 574, 580, and 584 to -30%. Otherwise, if the CRSP return is available, we aggregate the return and delisting return as the last return. If the monthly return on CRSP is not available, we use the delisting return as the last return of the stock. Results are similar without the delisting return adjustment.

with the short leg earning -77.9 basis points and the long leg of the strategy earning a statistically insignificant 7.5 basis points.

Table 5 displays the portfolio factor loadings for the long-short portfolios displayed in Table 4. The loadings from the strategy suggest that relative to high-priced stocks, low-priced stocks have higher betas, resemble small firms, and tend to resemble growth rather than value.

Table 6 displays results of Fama-MacBeth regressions of returns on *Price** and controls. Column 1 shows the univariate specification. Consistent with the earlier portfolio sorts, *Price** is positively related to future returns. Column 2 includes beta, size, and book-to-market. The inclusion of these variables decreases the magnitude of the coefficient on *Price** by about 25%, but nevertheless *Price** remains economically and statistically significant in predicting returns. In Column 3, controls are included for momentum, long-term reversal, illiquidity, the liquidity shock variable from Bali, Peng, Shen, and Tang (2014), and idiosyncratic volatility. The inclusion of these variables does not alter the interpretation of the relationship between *Price** and returns. The inclusion of these variables reduces the coefficient of *Price** by nearly 50% relative to the univariate specification, however, *Price** still continues to be significant at the 1% level. Finally, Column 4 includes operating profitability from Ball, Gerakos, Linnainmaa, and Nikolaev (2015), asset growth from Cooper, Gulen, and Schill (2008), and the Altman Z-score. Relative to the specification in Column 3, the inclusion of these additional variables has virtually no effect on the coefficient of *Price**.

3.1 Robustness

Kumar (2009) hypothesizes that investors treat stocks with low nominal price as a “cheap bet,” and that individual investors have excess demand for these lottery-like assets. To the extent that *Price** is correlated with other variables that capture lottery-like attributes of a stock, we may be overstating the influence of price on returns. To examine whether this is the case, we add a number of gambling proxies to the Fama-MacBeth regression specification. Table 7 examines the relationship between returns and *Price** after controlling for these gambling proxies.

In Column 1 of Table 7 we include the maximum and minimum daily return variables measured in month *t*-1 from Bali, Cakici, and Whitelaw (2011). In Column 2 we include past skewness. Past skewness is negatively related to returns, consistent with investor preference for skewness, but does not strongly affect the magnitude or statistical significance of the relationship between *Price** and returns. In Column 3 we include the expected idiosyncratic skewness measure of Boyer, Mitton, and Vorkink (2010). Consistent with a preference for skewness, expected idiosyncratic skewness is negatively related to returns, but does little to affect the magnitude of the coefficient on *Price**. Column 4 includes the Tversky and Kahneman prospect theory variable (denoted as *TK*) from Barberis, Mukherjee, and Wang (2015). Consistent with prospect theory preferences, the coefficient is negative and significant on *TK*, but does not affect the relationship between *Price** and returns. Column 5 shows that the inclusion of the coskewness measure of Harvey and Siddique (2000) does little to affect the point estimate on *Price**.

In the remaining columns we show that the results are robust to the inclusion of raw price, and to the inclusion of the Kumar (2009) variables used to capture the lottery status of a stock. Column 6 again confirms that raw price does not predict returns, and shows that the inclusion of raw price does not diminish the predictive power of *Price**. Kumar (2009) defines lottery (non-lottery) stocks as those with below (above) median price, and above (below) median levels of idiosyncratic volatility and idiosyncratic skewness. The inclusion of these variables in Column 7 does not alter the economic or statistical significance of *Price**. Finally, in Column 8 we include raw price along with the lottery variables and again show that the coefficient estimate and statistical significance of *Price** are not affected.[8] To further show that the effect we pick up is distinct from the Kumar (2009) lottery variable, we show double sorts of the Kumar (2009) lottery variable and *Price** in the Appendix. We first classify stocks as lottery, non-lottery, and others according to Kumar (2009) and then within each lottery classification we further sort stocks into quintiles based on *Price**. Our main effect persists within each lottery classification. Table A2 shows that high *Price** stocks experience higher alphas than low *Price** stocks. The difference is statistically significant in each of the three lottery classifications for equal-weighted returns, and significant for all but non-lottery stocks for value-weighted returns. The analysis again confirms that the predictive power of *Price** is distinct from that of the Kumar (2009) lottery variable.

A further concern is that one of the regressors of the fitted price regression might be somehow driving the portfolio results. Of particular concern, past work has documented a relationship between profitability and returns in the cross-section (Novy-Marx (2013); Ball, Gerakos, Linnainmaa, and Nikolaev (2015)). To the extent that earnings per share is correlated with profitability, perhaps our results are somehow related to the profitability anomaly. Table 8 shows that this is not the case.

[8] Kumar (2009) find that lottery stocks deliver negative alpha and non-lottery stocks deliver positive alpha. Consistent with Kumar (2009), in unreported results, we find that the coefficient of Lottery (Non-Lottery) in Fama-MacBeth regression is negative (positive). However, neither the coefficient of Lottery nor Non-Lottery in Column (7) and Column (8) of Table 7 is significant. We find that this is mainly because, in these two models, we control for idiosyncratic volatility which is one component of the lottery variable of Kumar (2009) and has been used as a lottery variable on its own (Han and Kumar, 2013).

Table 8 performs conditional sorts on profitability and *Price**. We first sort stocks into quintiles based on the operating profitability measure of Ball, Gerakos, Linnainmaa, and Nikolaev (2015), and then within each profitability quintile we sort stocks into quintiles based on *Price**.[9] Panel A displays equal-weighted portfolio four-factor alphas, while Panel B displays four-factor alphas for value-weighted portfolios. Within each profitability quintile, both equal-weighted and value-weighted returns are generally increasing in *Price**, and the difference in top minus bottom *Price** quintiles is statistically significant at the 5% or better level in seven out of the ten profitability quintiles and significant at the 10% level in another. The exception is the highest profitability quintile. We would expect stocks in this quintile to be the least speculative and have the fewest limits to arbitrage (Baker and Wurgler (2006)), therefore suggesting that these stocks should exhibit very little effect of price-based investor demand. Consistent with this, *Price** does not exhibit strong predictability for returns within this quintile. On the other hand, the magnitude of the difference in top and bottom *Price** quintile is the largest in the lowest profitability quintile. This is also consistent with a mispricing story, as investors demanding low-priced stocks due to speculative motives will likely find unprofitable stocks to be particularly speculative due to their highly subjective valuations, suggesting the portfolio returns from a *Price** based strategy should be particularly large in magnitude for stocks of the lowest profitability quintile. Furthermore, these stocks are also likely to have the greatest limits to arbitrage, again suggesting that we should expect to find the largest portfolio return magnitudes in this quintile. In unreported analysis, we have also confirmed that ability of *Price** to predict returns within profitability quintiles is not simply due to *Price** serving as a further sort on profitability. The results show that *Price** has strong predictive ability for returns even after

[9] Results are very similar if we use other profitability measure, such as the gross profitability measure of Novy-Marx (2013) or ROE.

controlling for profitability, eliminating the concern that a sort on profitability is somehow driving our observed results.

Eliciting further comfort that our results are distinct from profitability, in unreported results we find that the correlation of *Price** with profitability is actually lower than the correlation of the raw nominal price variable with profitability (0.269 vs 0.331). In Table 9 we also report four-factor alphas for long-short portfolios that are sorted based on *Price** fitted using only book price per share in the fitted regression (i.e., not including earnings, assets, or dividends per share variables). The top row of Table 9 displays the portfolio alphas and shows that the main results are not dependent on using a version of *Price** that incorporates earnings per share. The second panel of the table shows that the results hold in both the first and second half of the sample, and the third panel shows that the results hold when excluding stocks priced below $5. Both value-weighted and equal-weighted alphas become smaller once we exclude stock priced below $5. This is not surprising, given that this shrinks the spread of our sorting variable, while also eliminating the stocks for which individual investors are more important, and the stocks most difficult to arbitrage. Nevertheless, the results are not driven by extremely low priced stocks as the removal of stocks under $5 only decreases the VW (EW) four-factor alpha by about 32% (23%).

Blume and Stambaugh (1983) show that microstructure noise induces (due to Jensen's inequality) upward bias in measured stock returns, with the bias approximately proportional to the variance of the noise. Asparouhova, Bessembinder, and Kalcheva (2010, 2013) argue that this can lead to bias in empirical asset pricing studies, particularly when security-level explanatory variables are cross-sectionally correlated with the amount of noise. *Price** is likely to be correlated with the noise. Following Asparouhova, Bessembinder, and Kalcheva (2010, 2013), we use "return-weighted" portfolio returns, where the weights are (1+the stock's lagged monthly return). This is similar to equal weighting but with correction for potential bias due to market microstructure noise. Using this methodology, the four-factor alpha increases from 0.877% to 1.010%.[10] Finally, the last row shows that the results are robust to also including the Pastor-Stambaugh (2003) liquidity factor along with the Fama-French and Carhart factors.

3.2. Limits to Arbitrage

If the spread in returns between high and low price portfolios is driven by mispricing, then we should expect the spread in return to be largest (the mispricing to be greatest) for those stocks that are the most difficult or riskiest to arbitrage. We explore this hypothesis next. Table 10 explores how long-short *Price** portfolio returns vary with various limits to arbitrage proxies used previously in the literature.

We use idiosyncratic volatility, institutional ownership, illiquidity, and size as proxies for limits to arbitrage. Pontiff (1996) and Wurgler and Zhuravskaya (2002), show that stocks with greater idiosyncratic volatility are more risky to arbitrage. Stocks with less institutional ownership are also more likely to be affected by irrational demand of individual investors. Nagel (2005) uses institutional ownership as a proxy for difficulty of shorting. We expect that stocks with less institutional ownership will have greater limits to arbitrage as these stocks are more difficult to short. Illiquidity is the Amihud (2002) measure of illiquidity, which captures the impact of order flow on stock price – another concern for arbitrageurs. Higher illiquidity is

[10] The increase in alpha is not surprising. Low priced stocks' returns are more likely to have larger variance of microstructure noise than high priced stocks. Therefore low priced stocks tend to have larger upward bias in their measured stock returns. Correcting this leads to an even larger nominal price premium.

therefore associated with greater limits to arbitrage. Finally, small stocks have greater limits to arbitrage as they are typically more difficult to short, have less institutional ownership, and greater illiquidity and idiosyncratic volatility.

Table 10 sorts stocks into quintiles by each of the limits to arbitrage proxies, and then examines the four-factor alphas for a long-short *Price** portfolio for each quintile. Consistent with a mispricing story, for each limit to arbitrage proxy, the magnitude of the return to the long-short portfolios is greatest in the highest limit to arbitrage quintile. The long-short portfolio return is greatest for the smallest quintile of stocks, the most illiquid quintile of stocks, the highest idiosyncratic volatility quintile of stocks, and the lowest institutional ownership quintile of stocks.

While the effect is monotonic in size, with the largest spread appearing in the smallest quintile of stocks, the size sorts also provide reassurance that the results are not purely driven by small stocks, as the sort on size is based on NYSE breakpoints, and a sort on *Price** still produces a statistically and economically significant spread in returns within the fourth size quintile. Even for the largest size quintile the spreads in returns exhibit the correct sign, albeit not statistically significantly.

Table 11 uses cross-sectional Fama-MacBeth regressions to confirm the portfolio sort results. In Table 11 we include the limits to arbitrage variables alone and interacted with *Price** in order to ascertain the extent to which portfolio returns are dependent on limits to arbitrage. The interaction term between *Price** and size in Column 1 is negative, showing that *Price** portfolio returns are decreasing in size, consistent with limits to arbitrage being greatest for small stocks. Column 2 finds that portfolio returns are increasing in illiquidity, consistent with the most illiquid stocks having the greatest limits to arbitrage. Column 3 shows that portfolio returns are increasing in idiosyncratic volatility, consistent with high idiosyncratic volatility stocks facing the greatest limits to arbitrage. Finally, Column 4 shows that portfolio returns are decreasing in institutional ownership, consistent with low institutional ownership stocks having the greatest limits to arbitrage. The limits to arbitrage results are consistent with a mispricing-based explanation for the results.

3.3. Sentiment and Nominal Price Premium

If the cross-sectional predictability of *Price** is attributable to mispricing, then additional implications for returns emerge when conditioning on times of high or low sentiment. Specifically, our story suggests that low *Price** stocks are more speculative than high *Price** stocks. Therefore, if investors believe that low-priced stocks have more upside potential, then they will be particularly likely to believe this when sentiment is high or when sentiment increases. Times of increasing sentiment and overpricing should therefore be associated with high returns for low-priced stocks relative to high-priced stocks, conversely times of decreasing sentiment should be associated with high returns for high-priced stocks relative to low-priced stocks. The implication is that returns on a portfolio long high *Price** stocks and short low *Price** stocks should be negatively related to contemporaneous changes in sentiment.

Table 12 examines the time-series relationship between Fama-French-Carhart four factor alphas for long, short, and long-short portfolios of stocks sorted on *Price** and the contemporaneous change in the Baker-Wurgler (2006) sentiment index orthogonalized to macroeconomic variables, along with the lagged level of the orthogonalized sentiment index. Controls for the excess market return, small minus big size factor, high-minus-low book-to-market factor, and the up-minus-down momentum factor are also included. Panel A reports the results for EW portfolios and Panel B reports the results for VW portfolios. The first three columns of Table 12 test the hypothesis related to contemporaneous changes in sentiment. Consistent with the hypothesis that returns on a portfolio long high *Price** stocks and short low *Price** stocks should be negatively related to contemporaneous changes in sentiment, change in sentiment enters with a negative and significant coefficient in the regression of long minus short portfolio alphas in Column 3. Consistent with times of increasing sentiment being associated with high returns for low-priced stocks and lower returns for high-priced stocks, the coefficient on the contemporaneous sentiment change is positive and significant for the short leg of the portfolio in Column 2, and negative and significant for the long leg of the portfolio in column 1. Consistent with Stambaugh, Yu, and Yuan (2012) most of the mispricing is driven by the short leg, as the coefficient for the short leg in Column 2 is about four times as large in absolute magnitude as the coefficient for the long leg in Column 1.

Columns 3-6 specifically test the Stambaugh, Yu, Yuan (2012) hypothesis that the profitability of the long-short strategy should occur primarily following periods of high sentiment, and more specifically that the long-short portfolio return should be driven primarily by the short leg. The positive and significant coefficient on one-period lagged sentiment in Column 6 shows that higher long-short portfolio returns occur following periods of high sentiment. Consistent with Stambaugh, Yu, and Yuan (2012), Column 4 shows that the alpha for the long portfolio is slightly higher following periods of high sentiment. Most importantly, consistent with the effect being driven primarily by the short leg following times of high sentiment, the large negative and significant coefficient on lagged sentiment in Column 5 shows that the short portfolio performs particularly poorly following periods of high sentiment. This is consistent with the idea that short-sale impediments should cause returns to mispricing strategies to primarily be driven by the short leg of the strategy, and specifically to accrue to the short leg of the strategy following periods of high sentiment.

Columns 6-9 include both changes in contemporaneous sentiment and the lagged sentiment level together. Regardless of the specification, returns to the long-short *Price** sorted portfolio are negatively related to contemporaneous changes in sentiment, and positively related to lagged sentiment. The results are consistent with times of increasing sentiment coinciding with increases in returns for low-priced stocks relative to high-priced stocks, and times of decreasing sentiment coinciding with decreases in returns for low-priced stocks relative to high-priced stocks. The evidence is again consistent with a mispricing-based explanation for the observed nominal price premium.

4. Stock Splits

Next, we examine the behavior of returns following stock splits. Stock splits provide a relatively clean setting to examine the response of returns to an exogenous change in price. The prevailing view in the literature is that stock splits are motivated by a desire to return prices to a normal trading range (Baker and Gallagher (1980), Lakonishok and Lev (1987), Conroy and Harris (1999), Dyl and Elliot (2006), and Weld, Michaely, Thaler, and Benartzi (2009)).[11] Furthermore, the stock split analysis does not rely on fitted price, and as such serves as a complement to the fitted price analysis.

In particular, stock splits allow us to explore whether the return dynamics predicted by

[11] Recent papers by Green and Hwang (2009) and Baker, Greenwood, and Wurgler (2009) also use stock splits as an instrument to test behavioral theories, arguing that the lack of a relationship between splits and firm fundamentals allows for a particularly clean experimental setting.

our hypothesis are consistent with the data. Specifically, our hypothesis predicts an initial increase in returns following a stock split as investor demand for low-priced stocks leads to overvaluation. This will be followed by low returns for these stocks in the long-run as the mispricing is slowly corrected.

Table 13 shows short-run (1-12 month) and long-run (13-36 month) returns in the period after the stock split date. Following Baker, Greenwood, and Wurgler (2009), we define stock splits as events with CRSP distribution code of 5523 and split ratio of at least 1.25 to 1. We employ a calendar-time portfolio methodology. Namely, all stocks are aligned based on calendar time and equal and value-weighted portfolio returns are calculated. For value-weighted returns, the weight is the market capitalization of the splitting stocks at the end of the last month. We show both adjusted and unadjusted returns. Unadjusted returns are the excess returns over the risk-free rate, and adjusted returns are the returns to splitting stocks minus the returns to matched stocks. Matched stocks are stocks with similar characteristics that have not recently split. We match stocks on the dimensions of size, book-to-market, momentum, and past skewness. Specifically, we require matched stocks to be in the same quintile of size, book-to-market, momentum, and skewness. If more than one stock satisfies these criteria, we choose the one with the smallest difference in pre-split *Price**. To make sure that the split stock and the matched stock are comparable, we also require that the matched stock's *Price** value is between 80% and 125% of the pre-split value of *Price** for the split stock.[12] Relative to raw returns, adjusted returns can better control for the effects of other factors on returns.

Table 13 shows that split stocks exhibit exactly the predicted pattern. The adjusted returns

[12] The results are robust to the various matching methodology, such as matching by size, B/M, momentum and skewness deciles or terciles, or choosing all the stocks with *Price** value between 80% and 125% of the pre-split *Price** for the split stock.

(also its Fama-French-Carhart four-factor alpha) in Panel A show that splitting stocks earn higher returns than matched stocks in the 12 months after splitting. This is consistent with increased demand from investors in the period after the split pushing up the prices of these stocks. However, in the 24 month period following the first 12 months, adjusted returns are significantly negative, indicating that splitting stocks substantially underperform the matched sample, consistent with the recently split stocks becoming overvalued, and this overvaluation slowly correcting over the future.

Along with the adjusted returns, Table 13 also reports the analysis based on unadjusted returns and the Fama-French-Carhart four-factor alphas. Four-factor alphas of split stocks continue to be significantly positive in the five years after the split date. This is consistent with Ikenberry, Rankine, and Stice (1996). The comparison between the adjusted returns and unadjusted returns reveals an important observation. The average "abnormally" high returns of stocks in the 5 years post-split period are shared by other stocks with similar characteristics that did not split. Even for the first year post-split, the four-factor alphas of unadjusted returns are 0.757% and 0.718% per month for equal-weighted and value-weighted portfolios, respectively, but the four-factor alphas of adjusted returns are only 0.190% and 0.011% for equal-weighted and value-weighted portfolios, respectively. This suggests that even for the first year post-split, most of the previously documented abnormal returns are not caused by stock splitting.

5. Expectational Errors

The results thus far are consistent with overly optimistic expectations for low-priced stocks leading to overpricing of low-priced stocks. In this section, we formally test the hypothesis that market participants are overly optimistic about low-priced stocks. We show that nominal price levels induce expectational errors, causing market participants to be overly optimistic regarding low-priced stocks.

We test for biases in beliefs in two ways. First, we examine earnings surprises and find that investors have overly optimistic expectations of earnings for stocks with low values of *Price**, and overly pessimistic expectations of earnings for stocks with high values of *Price**. Second, we directly examine expectations of price appreciation by examining analyst target price forecasts. We find that forecasts of price appreciation are substantially higher for stocks with low values of *Price** relative to stocks with high values of *Price**.

Table 14 analyzes earnings surprises. We examine the market reaction to earnings in the three days around the announcement (t-1, t+1). Earnings dates are from both Compustat and IBES. DellaVigna and Pollet (2009) find that dates listed in Compustat and IBES are less accurate prior to 1995. Following DellaVigna and Pollet (2009), we keep the earlier of the two dates in the instance where dates from Compustat and IBES are not in accordance. We show results both for the entire 1983-2013 sample period and also for only the later 1995-2013 time period where dates are found to be most accurate. We also require that the stock price is between $1 and $1,000 at the beginning of the quarter, and that the market capitalization is at least $10 million.

The results in Table 14 show a quite clear pattern, as stocks with low values of *Price** on average experience large negative return reactions to earnings, while stocks with high values of *Price** on average experience large positive return reactions to earnings. Over the entire sample period, the three-day market-adjusted abnormal return is -79 basis points for the lowest decile of *Price**, while for the highest decile of *Price** the three-day market-adjusted abnormal return is 23 basis points. Both numbers are significant at the 1% level. The difference between top and bottom decile is a statistically significant 101 basis points. The magnitudes are even larger in the 1995-2013 sample period, with the lowest *Price** decile earning abnormal returns of over -121 basis points, as compared to three-day abnormal returns of 31 basis points for the top decile. The difference in top and bottom deciles for the 1995-2013 period is slightly larger than 152 basis points and significant at the 1% level. In the 1983-2013 period and the 1995-2013 period, the EW (VW) alphas for the long-short trading strategy in Table 4 are 0.988% (0.966%) and 0.871% (1.158%), respectively. On average, earnings announcements occur four times a year. This means that, on average, roughly 30-60% of the abnormal returns of the long-short trading strategy are realized around earnings announcement. The results lend strong support to the hypothesis that investors are overly optimistic regarding low-priced stocks and overly pessimistic regarding high-priced stocks.[13]

Next, we examine whether analyst price target forecasts reflect similar overoptimism for low-priced stocks. Price target data is from the IBES unadjusted detail history dataset. We focus on 12-month analyst price target forecasts, as these are by far the most common. We define expected price appreciation as

$$\textit{Expected Price Appreciation}_t = (\textit{Forecast}_t/\textit{Price}_{t-1}) - 1,$$

where $\textit{Forecast}_t$ is the 12-month price target forecast and $\textit{Price}_{t-1}$ is the stock price on the day *prior* to the price target forecast. In the case that there are multiple forecasts in the same month, we take the average of the expected price appreciation variable.

Table 15 displays the values of *Expected Price Appreciation* and *Forecast Error* for decile portfolios constructed from univariate sorts on *Price**. *Forecast Error* is defined as the difference between *Expected Price Appreciation* and the ex-post realized price appreciation

[13] The results are also robust to starting the sample in 1973 using only Compustat data. However, using only Compustat data comes at the cost of using earnings dates that are far less precisely measured.

measured as the cumulative ex-dividend return from the announcement date through 365 calendar days after the announcement date.[14] We use the ex-dividend return rather than the cum-dividend return because analysts forecast target prices rather than the total expected return (Dechow and You (2013)). The sorts display extremely large differences in analysts' forecasts of price appreciation for stocks of different nominal price levels. The average analyst price appreciation forecast for a stock in the bottom decile of *Price** is nearly 96%, compared to an expected 12-month price appreciation of only 3% for stocks in the top decile of *Price**. The second column displaying *Forecast Error* shows that analyst forecasts are certainly not in line with the observed ex-post price appreciation, as they overestimate price appreciation by 87.6% for stocks in the bottom decile of *Price** and underestimate price appreciation by nearly 8% for stocks in the top decile of *Price**.

Table 15, Panel B shows results of cross-sectional regressions of expected price appreciation on *Price** and a number of controls motivated by Dechow and You (2013). Regardless of the controls included, *Price** is economically and statistically significantly negatively related to expected price appreciation. The results are consistent with market participants having more optimistic expectations for stocks with low nominal prices. In Panel C, we replicate the analysis from Panel B using *Forecast Error* in place of *Expected Price Appreciation*. The results using *Forecast Error* are consistent with those using *Expected Price Appreciation*, and show that the high expected price appreciation that analysts expect for low-priced stocks is not consistent with the future realized price appreciation of these stocks.

[14] The results are virtually identical if we instead use the slightly different adjustment technique of Dechow and You (2013).

6. Conclusion

We document a substantial nominal price effect in the cross-section of returns. Stocks with low nominal prices have higher risk-adjusted returns than high-priced stocks. Low-priced stocks also experience systematically negative earnings surprises, while high-priced stocks experience systematically positive earnings surprise. The observed evidence is consistent with overly optimistic investor expectations for low-priced stocks resulting in overpricing. Post-split return dynamics are also consistent with this interpretation as we observe initially high returns in the post-split period, consistent with low nominal prices inducing overvaluation, followed by negative abnormal returns in the long-run, consistent with a correction of the overpricing. In sum, the evidence suggests that expectational errors of investors cause the overpricing of low nominal price stocks relative to stocks with high nominal prices.

References

Altman, Edward I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance* 23 (4): 589-609.

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-series Effects, *Journal of Financial Markets* 5 (1): 31-56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61 (1): 259-299.

Asparouhova, Elena, Hendrik Bessembinder, and Ivalina Kalcheva, 2010, Liquidity Biases in Asset Pricing Tests, *Journal of Financial Economics* 96 (2): 215-237.

Asparouhova, Elena, Hendrik Bessembinder, and Ivalina Kalcheva, 2013, Noisy Prices and Inference Regarding Returns, *Journal of Finance* 68 (2): 665-714.

Baker, H. Kent, and Patricia L. Gallagher, 1980, Management's View of Stock Splits, *Financial Management* 9 (2): 73-77.

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2009, Catering through Nominal Share Price, *Journal of Finance* 64 (6): 2559-2590.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance* 61 (4): 1645-1680.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns, *Journal of Financial Economics* 99 (2): 427-446.

Bali, Turan G., Lin Peng, Yannan Shen, and Yi Tang, 2014, Liquidity Shocks and Stock Market Reactions, *Review of Financial Studies* 27 (5): 1434-1485.

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri Nikolaev, 2015, Deflating Profitability, *Journal of Financial Economics* forthcoming.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as Lotteries: The Implications of Probability Weighting for Security Prices, *American Economic Review* 98 (5): 2066-2100.

Barberis, Nicholas, Abhiroop Mukherjee, and Baolian Wang, 2015, Prospect Theory and Stock Returns: An Empirical Test, working paper.

Berk, Jonathan, 1995, A Critique of Size-Related Anomalies, *Review of Financial Studies* 8 (2): 275-286.

Birru, Justin, and Baolian Wang, 2015, Nominal Price Illusion, *Journal of Financial Economics* forthcoming.

Blume, Marshall E., and Robert F. Stambaugh, 1983, Biases in Computed Returns: An Application to the Size Effect, *Journal of Financial Economics* 12 (3): 387-404.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected Idiosyncratic Skewness, *Review of Financial Studies* 23 (1): 169-202.

Bradshaw, Mark, Scott Richardson, and Richard Sloan, 2006, The Relation between Corporate Financing Activities, Analysts' Forecasts and Stock Returns, *Journal of Accounting and Economics* 42 (1-2): 53-85.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52 (1): 57-82.

Conroy, Robert, and Robert Harris, 1999, Stock Splits and Information: The Role of Share Price, *Financial Management* 28 (3): 28-40.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset Growth and the Cross-Section of Stock Returns, *Journal of Finance* 63 (4): 1609-1651.

Dechow, Patricia, and Haifeng You, 2013, Understanding and Predicting Target Price Valuation Errors, working paper.

DellaVigna, Stefano, and Joshua M. Pollet, 2009, Investor Inattention and Friday Earnings Announcements, *Journal of Finance* 64 (2): 709-749.

Dyl, Edward, and William Elliot, 2006, The Share Price Puzzle, *Journal of Business* 79(4): 2045-2066.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47 (2): 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33 (1): 3-56.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63 (4): 1653-1678.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81 (3): 607-636.

Green, T. Clifton, and Byoung-Hyoun Hwang, 2009, Price-Based Return Comovement, *Journal of Financial Economics* 93 (1): 37-50.

Green, T. Clifton, and Byoung-Hyoun Hwang, 2012, Initial Public Offerings as Lotteries: Skewness Preference and First-Day Returns, *Management Science* 58 (2): 432-444.

Han, Bing, and Alok Kumar, 2013, Speculative Retail Trading and Asset Prices, *Journal of Financial and Quantitative Analysis* 48 (2): 377-404.

Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional Skewness in Asset Pricing Tests, *Journal of Finance* 55 (3): 1263-1295.

Ikenberry, David, Graeme Rankine, and Eral Stice, 1996, What Do Stock Splits Really Signal? *Journal of Financial and Quantitative Analysis* 31(3): 357-375.

Kumar, Alok, 2009, Who Gambles in the Stock Market? *Journal of Finance* 64 (4): 1889-1933.

Lakonishok, Josef, and Baruch Lev, 1987, Stock Splits and Stock Dividends: Why, Who, and When, *Journal of Finance* 42 (4): 913-932.

Miller, Merton H., and Myron S. Scholes, 1982, Dividends and Taxes: Some Empirical Evidence, *Journal of Political Economy* 90 (6): 1118-1141.

Nagel, Stefan, 2005, Short Sales, Institutional Investors and the Cross-Section of Stock Returns, *Journal of Financial Economics* 78 (2): 277-309.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55 (3): 703-708.

Novy-Marx, Robert, 2013, The Other Side of Value: The Gross Profitability Premium, *Journal of Financial Economics* 108 (1): 1-28.

Ohlson, James, 1995, Earnings, Book Values, and Dividends in Equity Valuation, *Contemporary Accounting Research* 11 (2): 661-687.

Pastor, Lubos, and Robert Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111 (3): 642-685.

Pontiff, Jeffrey, 1996, Costly Arbitrage: Evidence from Closed-End Funds, *Quarterly Journal of Economics* 111 (4): 1135-1151.

Shumway, Tyler, 1997, The Delisting Bias in CRSP Data, *Journal of Finance* 52(1): 327-340.

Stambaugh, Robert, Jianfeng Yu, and Yu Yuan, 2012, The Short of It: Investor Sentiment and Anomalies, *Journal of Financial Economics* 104 (2): 288-302.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in Prospect Theory: Cumulative Representation of Uncertainty, *Journal of Risk and Uncertainty* 5 (4): 297-323.

Weld, William, Roni Michaely, Richard Thaler, and Shlomo Benartzi, 2009, The Nominal Share Price Puzzle, *Journal of Economic Perspectives* 23(2):121-142.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, Does Arbitrage Flatten Demand Curves for Stocks? Journal of Business 75 (4): 583-608.

Table 1. Definition of variables

This table discusses the definitions of the main variables used in the paper.

Variable	Description
BPS	Book value per share, measured as total book equity (Compustat item CEQ) divided by total number of shares outstanding (Compustat item CSHO).
Price	Market price per share (Compustat item PRCC_F).
EPS	Earnings per share, calculated as gross profit minus selling, general and administrative expenses (excluding research and development expenditures) divided by total number of shares outstanding: (Sale-COGS-XSGA+XRD)/CSHO.
APS	Total asset per share, calculated as total assets divided by total number of shares outstanding: AT/CSHO.
DPS	Dividend per share, calculated as total dividends divided by total number of shares outstanding: DVC/CSHO.
Beta	Following Fama and French (1992), we estimate betas from the past five year's monthly data, with the requirement that at least 24 months' data is available.
B/M	The ratio of total book value of equity to total market capitalization. Book value is measured as in Fama and French (2008), and is measured in natural logarithm.
Size	Market capitalization at the end of last month, measured in natural logarithm.
MOM	Cumulative return from month *t*-12 to month *t*-2.
REV	Short term reversal. Return of month *t*-1.
LTREV	Long term reversal. Cumulative return from month *t*-60 to month *t*-13.
ILLIQ	Illiquidity measure as in Amihud (2002), measured based on daily data over month *t*-1.
Liquidity Shock	Liquidity shock variable, adapted from Bali, Peng, Shen, and Tang (2014). In Bali, Peng, Shen, and Tang (2014), liquidity shock is measured as $-ILLIQ_{t-1} + (\sum_{k=2}^{13} ILLIQ_{t-k}/12)$. In this paper, we calculate the natural logarithm difference: $-Log(ILLIQ_{t-1}) + Log(\frac{\sum_{k=2}^{13} ILLIQ_{t-k}}{12})$.
IVOL	Idiosyncratic volatility, calculated as in Ang, Hodrick, Xing, and Zhang (2006).
MAX	The maximum daily return over month *t*-1, as in Bali, Cakici, and Whitelaw (2011).
MIN	The negative of the minimum daily return over month *t*-1, as in Bali, Cakici, and Whitelaw (2011).
SKEW	Skewness calculated from monthly returns over month *t*-60 to month *t*-1.
EISKEW	Expected idiosyncratic skewness, calculated as in Boyer, Mitton, and Vorkink (2010).
TK	The prospect theory variable as in Barberis, Mukherjee, and Wang (2015). TK stands for Tversky and Khaneman (1992).
COSKEW	Coskewness, calculated using monthly returns over the previous five years in the manner described by Harvey and Siddique (2000), namely as $E(\epsilon_{i,t}\epsilon_{M,t}^2)/(E(\epsilon_{M,t}^2)\sqrt{E(\epsilon_{i,t}^2)})$, where $\epsilon_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{M,t}$ are residuals in a regression of excess stock returns $R_{i,t}$ on excess market returns $R_{M,t}$ and where $\varepsilon_{M,t} = R_{M,t} - \mu_M$ are the residuals after de-meaning the market returns.
OP	Operating profitability, calculated as (REVT-COGS-XSGA+XRD)/Total Assets, as in Ball, Gerakos, Linnainmaa, and Nikolaev (2015).
AG	Asset growth is the percentage growth rate of total assets, as measured in Cooper, Gulen, and Schill (2008).
ZSCORE	ZSCORE=(3.3*PI+SALE+1.4*RE+1.2*(ACT-LCT))/AT, as measure in Altman (1968).
IO	Institutional ownership is the total number of shares held by Thomson Reuters 13f institutions divided by the total number of shares outstanding.

Table 2. Fitting stock price per share

This table reports regression results for Fama-MacBeth cross-sectional regressions that use book variables to predict stock price per share. The regressions are run for each calendar year. The coefficients and *t-statistics* are calculated from the time series estimates. Adj-R^2 is the average Adj-R^2 of yearly regressions. The sample is from 1967 to 2012, 46 years in total. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
BPS: Book Per Share	0.939***				0.511***
	(12.95)				(7.40)
EPS: Earnings Per Share		2.862***			2.054***
		(12.27)			(11.27)
APS: Total Assets Per Share			0.067***		-0.028***
			(9.07)		(-7.39)
DPS: Dividend Per Share				11.810***	5.027***
				(12.79)	(8.56)
Constant	8.418***	8.622***	15.913***	14.200***	5.920***
	(11.17)	(12.49)	(23.72)	(20.67)	(11.53)
Adj-R^2	0.373	0.418	0.084	0.206	0.552
Number of years	46	46	46	46	46

Table 3. Summary statistics by *Price deciles**

This table reports the characteristics of *Price** sorted portfolios. For each month, we sort all stocks into deciles based on *Price**. We first calculate the mean of each variable for each decile each month, and then calculate the time series means of cross-sectional averages. The sample period is from July 1968 to December 2013.

Portfolio	*Price**	Log (Price)	Beta	Log(Size)	B/M	MOM	LTREV	REV	ILLIQ	IVOL
1	1.727	1.582	1.471	10.719	-1.128	0.222	0.408	0.025	11.340	0.038
2	2.138	1.910	1.422	10.888	-0.696	0.215	0.621	0.020	10.599	0.033
3	2.368	2.219	1.361	11.177	-0.595	0.185	0.820	0.016	8.694	0.029
4	2.550	2.443	1.279	11.446	-0.551	0.159	0.897	0.014	6.715	0.027
5	2.718	2.613	1.215	11.717	-0.517	0.149	0.901	0.013	4.097	0.024
6	2.879	2.782	1.149	11.998	-0.477	0.151	0.890	0.013	3.258	0.022
7	3.040	2.969	1.076	12.301	-0.455	0.147	0.905	0.013	2.429	0.020
8	3.216	3.155	1.014	12.613	-0.424	0.144	0.860	0.012	1.554	0.018
9	3.435	3.367	0.977	13.025	-0.380	0.142	0.831	0.013	0.895	0.016
10	3.835	3.754	0.952	13.727	-0.310	0.143	0.831	0.012	0.454	0.015

Table 4. Portfolio performance

This table reports excess return, Fama and French (1993) three factor alpha, and Fama and French (1993) and Carhart (1997) four-factor alpha for each of the ten decile portfolios, and the long-short portfolio (High-Low). Excess return is the raw return minus the risk free rate. EW and VW stand for equal-weighted portfolios and value-weighted portfolios, respectively. In total, there are 546 months from July 1968 to December 2013.

	Excess returns		FF (93)		FF (93)+Carhart(97)	
Portfolio	EW	VW	EW	VW	EW	VW
Low 1	-0.087	-0.119	-0.812	-0.793	-0.687	-0.779
	(-0.24)	(-0.32)	(-5.38)	(-4.91)	(-4.52)	(-4.72)
2	0.446	0.276	-0.231	-0.274	-0.115	-0.192
	(1.37)	(0.76)	(-2.24)	(-1.79)	(-1.13)	(-1.24)
3	0.584	0.317	-0.110	-0.170	0.018	-0.135
	(1.98)	(0.97)	(-1.39)	(-1.54)	(0.23)	(-1.20)
4	0.609	0.389	-0.109	-0.113	0.013	-0.020
	(2.21)	(1.32)	(-1.54)	(-1.07)	(0.19)	(-0.19)
5	0.671	0.362	-0.042	-0.133	0.089	-0.083
	(2.58)	(1.34)	(-0.61)	(-1.43)	(1.38)	(-0.87)
6	0.699	0.441	-0.012	-0.000	0.086	0.047
	(2.88)	(1.83)	(-0.20)	(-0.00)	(1.50)	(0.58)
7	0.746	0.500	0.047	0.052	0.152	0.066
	(3.24)	(2.20)	(0.78)	(0.70)	(2.64)	(0.88)
8	0.769	0.537	0.062	0.034	0.163	0.046
	(3.49)	(2.57)	(1.01)	(0.54)	(2.73)	(0.71)
9	0.810	0.510	0.102	0.040	0.210	0.061
	(3.74)	(2.53)	(1.62)	(0.70)	(3.47)	(1.05)
High 10	0.790	0.548	0.105	0.100	0.192	0.075
	(3.81)	(3.04)	(1.62)	(2.04)	(3.01)	(1.49)
High-Low	0.877	0.667	0.917	0.893	0.879	0.854
	(3.55)	(2.43)	(5.37)	(5.07)	(5.04)	(4.75)

Table 5. Portfolio factor loadings

This table reports the factor loadings of different models. Mktrf, SMB, HML, and UMD stand for the market factor, size factor, value factor, and the momentum factor, respectively.

	FF (93)		FF (93)+Carhart(97)	
Portfolio	EW	VW	EW	VW
Mktrf	-0.130	-0.340	-0.122	-0.332
	(-3.31)	(-8.39)	(-3.04)	(-8.03)
SMB	-1.061	-1.219	-1.060	-1.217
	(-18.67)	(-20.80)	(-18.64)	(-20.76)
HML	0.525	0.369	0.539	0.383
	(8.74)	(5.96)	(8.77)	(6.06)
UMD			0.043	0.044
			(1.08)	(1.08)
Adj-R^2	0.542	0.605	0.542	0.605
N	546	546	546	546

Table 6. Fama-MacBeth regressions

This table reports Fama-MacBeth monthly regression results. Variable definitions can be found in Table 1. The dependent variable is excess return, measured in percent.

	(1)	(2)	(3)	(4)
Log (*Price**)	0.434	0.331	0.222	0.220
	(3.06)	(3.47)	(2.89)	(2.97)
Beta		0.024	0.142	0.148
		(0.21)	(1.46)	(1.58)
Log (Size)		-0.048	-0.109	-0.168
		(-1.69)	(-4.04)	(-4.67)
B/M		0.180	0.202	0.157
		(3.11)	(4.05)	(3.21)
MOM			0.572	0.468
			(5.08)	(4.25)
LTREV			-0.073	-0.055
			(-3.54)	(-2.85)
REV			-4.423	-4.437
			(-12.77)	(-13.05)
ILLIQ			0.031	0.030
			(2.45)	(2.43)
Liquidity shock			0.344	0.371
			(12.31)	(12.49)
IVOL (*100)			-0.275	-0.265
			(-10.27)	(-10.27)
OP				0.012
				(1.98)
Asset Growth				-0.510
				(-7.52)
ZSCORE				0.051
				(2.26)
Intercept	-0.250	0.744	2.158	2.798
	(-0.42)	(1.41)	(4.57)	(5.08)
R^2	0.015	0.041	0.065	0.069
Number of months	546	546	546	546

Table 7. Fama-MacBeth regressions: horse-race with other gambling/skewness measures
This table reports Fama-MacBeth regression results. Variable definitions can be found in Table 1. The dependent variable is excess return, measured in percent.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (*Price**)	0.216	0.199	0.210	0.249	0.213	0.291	0.211	0.287
	(2.93)	(2.69)	(2.82)	(3.44)	(2.86)	(2.79)	(2.66)	(2.77)
Beta	0.168	0.163	0.155	0.163	0.178	0.145	0.147	0.145
	(1.82)	(1.72)	(1.66)	(1.72)	(1.87)	(1.46)	(1.47)	(1.47)
Log (Size)	-0.165	-0.182	-0.175	-0.169	-0.164	-0.150	-0.172	-0.153
	(-4.63)	(-5.20)	(-4.92)	(-4.68)	(-4.55)	(-4.40)	(-4.93)	(-4.55)
B/M	0.151	0.161	0.164	0.109	0.163	0.144	0.162	0.146
	(3.10)	(3.28)	(3.35)	(2.27)	(3.36)	(2.77)	(2.93)	(2.81)
MOM	0.484	0.501	0.500	0.538	0.483	0.436	0.471	0.440
	(4.43)	(4.56)	(4.45)	(5.12)	(4.47)	(3.63)	(3.93)	(3.65)
LTREV	-0.053	-0.051	-0.054	-0.033	-0.054	-0.049	-0.055	-0.050
	(-2.78)	(-2.66)	(-2.78)	(-1.71)	(-2.84)	(-2.44)	(-2.73)	(-2.46)
REV	-5.317	-4.402	-4.377	-4.325	-4.401	-4.477	-4.427	-4.463
	(-14.53)	(-12.98)	(-12.85)	(-13.04)	(-12.89)	(-12.11)	(-11.93)	(-12.06)
ILLIQ	0.029	0.030	0.030	0.031	0.030	0.030	0.031	0.031
	(2.33)	(2.47)	(2.46)	(2.49)	(2.46)	(2.39)	(2.37)	(2.39)
Liquidity shock	0.377	0.376	0.376	0.380	0.373	0.362	0.370	0.362
	(12.91)	(12.68)	(12.62)	(12.88)	(12.75)	(12.33)	(12.70)	(12.39)
IVOL (*100)	-0.128	-0.262	-0.263	-0.271	-0.265	-0.267	-0.258	-0.259
	(-2.52)	(-10.20)	(-10.15)	(-10.78)	(-10.35)	(-10.15)	(-9.98)	(-10.15)
OP	0.012	0.013	0.012	0.011	0.012	0.010	0.013	0.011
	(2.00)	(2.24)	(2.08)	(1.90)	(2.05)	(1.75)	(2.14)	(1.96)
AG	-0.496	-0.510	-0.519	-0.473	-0.518	-0.493	-0.513	-0.495
	(-7.30)	(-7.56)	(-7.70)	(-6.83)	(-7.71)	(-7.03)	(-7.23)	(-7.03)
ZSCORE	0.052	0.046	0.049	0.053	0.052	0.052	0.050	0.051
	(2.28)	(2.07)	(2.18)	(2.35)	(2.32)	(2.07)	(1.96)	(2.03)
MAX	0.374							
	(0.37)							
MIN	-8.148							
	(-7.24)							
SKEW		-0.112						
		(-3.97)						
EISKEW			-0.061					
			(-3.02)					
TK				-3.928				
				(-4.63)				
Coskew					-0.154			
					(-1.53)			
Log (*Price*)						-0.089		-0.100
						(-1.26)		(-1.41)
Lottery							-0.063	-0.086
							(-1.08)	(-1.48)
Non-Lottery							-0.016	-0.005
							(-0.44)	(-0.13)
Intercept	2.809	3.061	2.930	2.444	2.741	2.622	2.876	2.717
	(5.12)	(5.68)	(5.36)	(4.48)	(4.97)	(4.68)	(5.26)	(5.00)
R^2	0.072	0.070	0.071	0.071	0.071	0.071	0.071	0.073
Number of months	546	546	546	546	546	546	546	546

Table 8. Double sort with profitability

This table examines whether profitability can explain the observed return results. Each month, we first sort all stocks into quintiles based on the operating profitability measure of Ball, Gerakos, Linnainmaa, and Nikolaev (2015). Then, within each profitability quintile, we sort stocks into quintiles based on *Price**. The table reports the four-factor (Fama and French (1993) and Carhart (1997)) alpha of the 25 portfolios, and the High-Low *Price** portfolios for each profitability quintile. Panel A reports the results for equal-weighted portfolios and Panel B reports results for value-weighted portfolios.

	Least profitable	2	3	4	Most profitable
Panel A. EW					
Low 1	-1.077	-0.237	-0.154	-0.096	0.189
	(-6.04)	(-1.94)	(-1.28)	(-0.84)	(1.81)
2	-0.374	0.050	0.037	0.216	0.229
	(-2.35)	(0.48)	(0.40)	(2.68)	(2.90)
3	-0.365	0.079	0.073	0.191	0.254
	(-2.96)	(0.80)	(0.87)	(2.48)	(3.77)
4	-0.142	0.104	0.114	0.113	0.261
	(-1.23)	(1.13)	(1.41)	(1.53)	(3.99)
High 5	0.132	0.160	0.154	0.211	0.175
	(1.33)	(1.97)	(1.98)	(2.55)	(2.43)
High-Low	1.208	0.397	0.308	0.306	-0.015
	(5.69)	(2.78)	(2.10)	(2.08)	(-0.12)
Panel B. VW					
Low 1	-1.033	-0.521	-0.410	-0.201	-0.016
	(-4.91)	(-3.30)	(-3.08)	(-1.56)	(-0.13)
2	-0.564	-0.167	-0.138	0.024	0.096
	(-2.52)	(-1.35)	(-1.22)	(0.22)	(1.14)
3	-0.638	-0.243	-0.106	0.018	0.106
	(-3.71)	(-2.17)	(-1.06)	(0.22)	(1.49)
4	-0.337	-0.030	-0.133	-0.017	0.063
	(-2.02)	(-0.26)	(-1.44)	(-0.21)	(1.04)
High 5	0.043	-0.021	0.018	0.078	0.084
	(0.31)	(-0.20)	(0.19)	(0.93)	(1.54)
High-Low	1.077	0.500	0.428	0.279	0.100
	(4.18)	(2.50)	(2.45)	(1.75)	(0.68)

Table 9. Robustness

This table reports four-factor alphas for five sets of robustness tests. In the first set, we examine the measure of *Price** using only BPS (book value of equity per share) as the independent variable to estimate fitted stock price per share (model (1) in Table 2). The second set of robustness tests shows the results of subperiods. In the third set of analysis, we exclude stocks with price lower than $5. In the fourth set of robustness tests, we report the four-factor alpha of return-weighted portfolio returns, where the weights are (1+the stock's lagged monthly return). The last set of robustness tests shows alphas when the Pastor-Stambaugh (2003) liquidity factor is included with the Fama-French factors and the momentum factor.

		EW	VW
Different measures	BPS	0.782	0.515
		(4.98)	(2.97)
Subperiods	1968/07-1990/12	1.005	0.843
		(5.13)	(4.69)
	1991/01-2013/12	0.936	1.108
		(3.41)	(3.82)
Exclude price < $5		0.681	0.584
		(5.17)	(3.32)
Return-weighted portfolio returns		1.010	N/A
		(5.88)	
FF + Carhart + PS Factor		0.861	0.817
		(4.90)	(4.52)

Table 10. Limits to arbitrage – portfolio performance

This table reports the results of double sorts with various limits to arbitrage variables. Each month we first sort stocks into quintiles by the specified limits to arbitrage variable, then within each quintile we sort stocks based on *Price**. Size breakpoints are based on the NYSE breakpoints, while others are based on the whole sample. This table reports the four factor (FF(93) + Carhart(97)) alphas of long-short portfolios within each limits to arbitrage variable sorted quintile. The Most-Least portfolio alpha in the last row of the table reports the difference between the long-short portfolio in quintile 5 of the limits to arbitrage variable and the long-short portfolio in quintile 1 of the limits to arbitrage variable. The sample period is from July 1968 to December 2013. For IO, the sample period is from January 1980 to December 2013.

	Size		ILLIQ		IVOL		IO	
	EW	VW	EW	VW	EW	VW	EW	VW
Most constrained 1	0.897	0.917	0.257	0.053	0.274	0.057	1.274	1.592
	(5.11)	(5.21)	(1.92)	(0.38)	(2.68)	(0.35)	(5.14)	(5.76)
2	0.577	0.535	0.355	0.442	0.214	0.199	1.036	1.362
	(3.65)	(3.34)	(2.28)	(2.83)	(2.01)	(1.91)	(4.29)	(4.75)
3	0.517	0.531	0.667	0.779	0.317	0.431	0.170	0.133
	(3.66)	(3.73)	(3.48)	(4.21)	(2.74)	(1.97)	(0.95)	(0.48)
4	0.372	0.371	0.697	0.754	0.456	0.499	0.308	0.027
	(2.59)	(2.54)	(3.63)	(4.00)	(3.04)	(1.78)	(2.21)	(0.13)
Least constrained 5	0.118	0.048	0.952	1.057	1.039	1.178	-0.019	-0.014
	(0.95)	(0.36)	(5.63)	(5.97)	(5.17)	(4.90)	(-0.14)	(-0.08)
Most-Least	-0.778	-0.869	0.695	1.003	0.765	1.121	-1.287	-1.578
	(-4.10)	(-4.07)	(3.56)	(4.60)	(3.65)	(3.81)	(-5.00)	(-5.21)

Table 11. Limits to arbitrage – Fama-MacBeth regressions

This table reports limits to arbitrage results for Fama-MacBeth regressions. We include each limit to arbitrage variable, along with an interaction term between *Price** and the limit to arbitrage variable. The sample period is from July 1968 to December 2013. For IO, the sample period is from January 1980 to December 2013.

	(1)	(2)	(3)	(4)
	Size	ILLIQ	IVOL	IO
Log (*Price**)	1.067	0.364	-0.151	0.590
	(2.83)	(3.63)	(-1.70)	(4.82)
Beta	0.075	0.007	0.138	0.111
	(0.71)	(0.07)	(1.39)	(0.89)
Size	0.138	-0.174	-0.089	-0.072
	(1.33)	(-3.60)	(-3.24)	(-2.49)
B/M	0.207	0.218	0.198	0.198
	(4.19)	(4.33)	(4.08)	(3.85)
MOM	0.914	0.885	0.865	0.880
	(7.67)	(7.31)	(7.57)	(7.52)
LTREV	-0.082	-0.084	-0.084	-0.052
	(-4.07)	(-4.23)	(-4.20)	(-3.31)
REV	-4.450	-4.436	-4.020	-3.481
	(-13.40)	(-13.42)	(-11.70)	(-9.66)
Size * Log (*Price**)	-0.059			
	(-2.07)			
ILLIQ		-0.188		
		(-3.00)		
ILLIQ * Log (*Price**)		0.034		
		(1.86)		
IVOL (*100)			-0.650	
			(-6.42)	
IVOL (*100) * Log (*Price**)			0.155	
			(4.70)	
IO				3.372
				(2.92)
IO * Log (*Price**)				-0.957
				(-4.66)
Intercept	-1.649	2.012	2.916	0.111
	(-1.22)	(2.45)	(6.61)	(0.19)
R^2	0.073	0.075	0.074	0.065

Table 12. Sentiment

This table reports the results of regressions of excess returns for the long leg, short leg, and the long-short portfolios (denoted as Dif in the Table) on the change in sentiment and the level of sentiment. Panel A reports the results for EW portfolios, and Panel B reports the results for VW portfolios. The data on sentiment is from Baker and Wurgler (2006) and is downloaded from Jeffrey Wurgler's website. We use the sentiment variable orthogonal to macroeconomic variables (the $SENT^{\perp}$) and also the change in sentiment variable orthogonal to macroeconomic variables (the $\Delta SENT^{\perp}$) . The sample is from July 1968 to December 2010, 510 months in total. The loss of the data for 2011-2013 is due to availability of the sentiment data.

Panel A. EW

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Long	Short	Dif	Long	Short	Dif	Long	Short	Dif
$\Delta SENT^{\perp}$	-0.221	0.704	-0.925				-0.211	0.675	-0.885
	(-3.01)	(4.06)	(-4.71)				(-2.86)	(3.89)	(-4.52)
$SENT^{\perp}$				0.132	-0.367	0.499	0.116	-0.318	0.435
				(2.00)	(-2.36)	(2.82)	(1.78)	(-2.07)	(2.50)
Mktrf	0.971	1.077	-0.106	0.968	1.089	-0.121	0.972	1.075	-0.103
	(63.51)	(29.88)	(-2.60)	(63.26)	(30.02)	(-2.95)	(63.67)	(29.90)	(-2.54)
SMB	0.268	1.258	-0.991	0.248	1.321	-1.072	0.269	1.256	-0.988
	(11.94)	(23.81)	(-16.54)	(11.61)	(26.06)	(-18.61)	(12.00)	(23.84)	(-16.57)
HML	0.400	-0.079	0.479	0.413	-0.120	0.532	0.400	-0.078	0.477
	(17.00)	(-1.42)	(7.61)	(17.79)	(-2.17)	(8.51)	(17.01)	(-1.40)	(7.63)
UMD	-0.092	-0.135	0.043	-0.094	-0.130	0.036	-0.093	-0.133	0.041
	(-6.24)	(-3.87)	(1.08)	(-6.32)	(-3.69)	(0.91)	(-6.29)	(-3.85)	(1.04)
Constant	0.636	-0.242	0.877	0.634	-0.240	0.875	0.628	-0.221	0.848
	(9.51)	(-1.53)	(4.91)	(9.42)	(-1.51)	(4.82)	(9.39)	(-1.40)	(4.76)
Adj-R^2	0.911	0.839	0.574	0.910	0.836	0.562	0.911	0.840	0.579

Panel B. VW

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Long	Short	Dif	Long	Short	Dif	Long	Short	Dif
$\Delta SENT^{\perp}$	-0.194	0.970	-1.164				-0.187	0.937	-1.124
	(-3.38)	(5.21)	(-5.82)				(-3.25)	(5.03)	(-5.63)
$SENT^{\perp}$				0.092	-0.427	0.520	0.079	-0.360	0.439
				(1.80)	(-2.53)	(2.85)	(1.54)	(-2.17)	(2.47)
Mktrf	0.931	1.245	-0.313	0.928	1.262	-0.333	0.932	1.242	-0.310
	(78.04)	(32.13)	(-7.53)	(77.49)	(32.06)	(-7.85)	(78.16)	(32.16)	(-7.48)
SMB	-0.172	0.928	-1.100	-0.190	1.015	-1.205	-0.172	0.925	-1.097
	(-9.85)	(16.33)	(-18.02)	(-11.34)	(18.46)	(-20.30)	(-9.83)	(16.34)	(-18.06)
HML	0.099	-0.216	0.316	0.111	-0.273	0.384	0.099	-0.215	0.314
	(5.40)	(-3.62)	(4.92)	(6.09)	(-4.58)	(5.96)	(5.39)	(-3.61)	(4.92)
UMD	0.032	-0.011	0.042	0.031	-0.004	0.035	0.032	-0.009	0.041
	(2.76)	(-0.28)	(1.06)	(2.63)	(-0.11)	(0.84)	(2.74)	(-0.25)	(1.02)
Constant	0.520	-0.318	0.837	0.520	-0.322	0.841	0.514	-0.294	0.808
	(9.95)	(-1.87)	(4.60)	(9.87)	(-1.86)	(4.50)	(9.85)	(-1.74)	(4.45)
Adj-R^2	0.929	0.824	0.636	0.928	0.817	0.617	0.929	0.826	0.639

Table 13. Stock splits

This table reports the stock return analysis of splitting stocks in the period after stock splitting. We employ a calendar-time portfolio methodology. Namely, all stocks are aligned based on calendar time and equal and value-weighted portfolio returns are calculated. For value-weighted returns, the weight is the market capitalization of the splitting stocks at the end of the last month.

Different panels report results for different periods after stock splitting. For example, Panel A reports the stock returns of splitting stocks in the period from the month after the ex-date to 12 months after the ex-date. *t+1* is the first whole calendar month after the ex-date. Other windows are defined accordingly.

For each panel, we report unadjusted returns and adjusted returns. Unadjusted returns are excess returns (raw returns over the risk free interest rate). Adjusted returns are the difference between the returns of the splitting stock and the returns of the matched stocks. For each splitting stock, we require the matched stock and the split stock to be in the same size quintile, BM quintile, momentum quintile and skewness quintile. If more than one stock satisfies the above criteria, we choose the one with the smallest difference in *Price**. We also require that the matched stock's pre-split *Price** is not greater than 125% of the split stock's pre-split *Price**, and also not smaller than 80% of the split stock's pre-split *Price**. In total, we have 9,924 stock splits for which we can find matched stock. The sample period is from July 1968 to December 2013, in total 546 months.

	Excess returns		FF (93)+Carhart(97) alpha	
	EW	VW	EW	VW
Panel A. [t+1, t+12]				
Unadjusted	1.283	1.121	0.757	0.718
	(4.77)	(4.44)	(8.68)	(7.28)
Adjusted	0.230	0.045	0.190	0.011
	(2.70)	(0.36)	(2.43)	(0.09)
Panel B. [t+13, t+36]				
Unadjusted	0.936	0.760	0.498	0.441
	(3.58)	(3.21)	(7.01)	(6.50)
Adjusted	-0.157	-0.298	-0.102	-0.221
	(-3.13)	(-3.10)	(-2.08)	(-2.54)
Panel C. [t+37, t+60]				
Unadjusted	1.087	0.967	0.503	0.548
	(4.33)	(4.17)	(7.48)	(7.86)
Adjusted	-0.079	-0.151	-0.086	-0.127
	(-1.47)	(-1.43)	(-1.57)	(-1.30)
Panel D. [t+13, t+60]				
Unadjusted	1.003	0.845	0.484	0.474
	(3.96)	(3.65)	(8.40)	(8.57)
Adjusted	-0.124	-0.227	-0.101	-0.178
	(-3.67)	(-2.91)	(-3.11)	(-2.71)

Table 14. Earnings announcements

This table reports stock performance around earnings announcements for different *Price**deciles. At the beginning of each quarter, we sort stocks into deciles based on the beginning period *Price**. For each stock, we calculate the cumulative returns from one trading day before earnings announcement to one trading day after earnings announcement. We calculate both raw cumulative returns and market-adjusted cumulative returns. Market-adjusted returns are the difference between raw return and the contemporaneous market return. For each quarter, we calculate the average of all cumulative returns for each portfolio. The table reports the time series average of quarterly cumulative returns for each decile. We also report the difference between the highest *Price** decile and the lowest *Price** decile.

There are two sources of data on earnings announcements, the Compustat Quarterly file and I/B/E/S. I/B/E/S data starts from July 1983 and ends in December 2013. DellaVigna and Pollet (2009) find that data on earnings announcement dates contains errors in both sources before January 1995. We therefore also show results for only the more precisely measured post-January 1995 time period from January 1995 to December 2013.

*Price** Deciles	198307-201312		199501-201312	
	Raw	Raw-Mkt	Raw	Raw-Mkt
Low 1	-0.663	-0.790	-1.087	-1.213
	(-5.21)	(-7.86)	(-6.27)	(-9.62)
2	-0.205	-0.328	-0.461	-0.579
	(-1.54)	(-3.13)	(-2.51)	(-4.10)
3	0.110	-0.033	0.058	-0.102
	(1.04)	(-0.42)	(0.40)	(-0.99)
4	0.164	0.023	0.289	0.142
	(1.44)	(0.29)	(1.82)	(1.30)
5	0.319	0.201	0.399	0.267
	(3.11)	(3.01)	(2.96)	(3.09)
6	0.354	0.225	0.449	0.307
	(3.81)	(4.39)	(3.65)	(4.45)
7	0.456	0.331	0.554	0.419
	(4.84)	(5.75)	(4.10)	(5.17)
8	0.335	0.226	0.542	0.408
	(3.28)	(3.66)	(4.12)	(4.91)
9	0.362	0.259	0.491	0.377
	(3.96)	(5.31)	(4.11)	(5.69)
High 10	0.324	0.219	0.424	0.310
	(3.72)	(4.41)	(3.78)	(4.75)
High-Low	0.987	1.009	1.511	1.523
	(7.82)	(8.49)	(9.85)	(10.45)
N (Quarters)	122	122	76	76

Table 15. Analysts price target projection

This table reports the results for analyst price target projections. Panel A shows expected price appreciation and forecast error sorted by *Price**. Panel B and Panel C report results for Fama-MacBeth regressions for expected price appreciation and forecast error. In Panel B, the dependent variable is expected price appreciation based on analysts' projected future stock price, i.e., price target. It is calculated as the 12-month target price forecast divided by the stock price on the day prior to forecast, minus one. In Panel C, the dependent variable is the expected price appreciation minus the observed ex-post stock price appreciation measured as the cumulative ex-dividend return from the announcement date through 365 calendar days after the announcement date. In the case that multiple analysts' price target forecasts are announced in a month for a stock, we take the average of the expected price appreciation and forecast error. In order to mitigate the effect of outliers, we winsorize price target based returns at the 1% level for both tails. In addition to the previously defined variables, we define external finance following Bradshaw, Richardson, and Sloan (2006), as the sum of net equity financing and net debt financing. Net equity financing is measured as the proceeds from the sale of common and preferred stock (SSTK) less cash payments for the purchase of common and preferred stock (PRSTKC) less cash payments for dividends (DV). Net debt financing is measured as the cash proceeds from the issuance of long term debt (DLTIS) less cash payments for long-term reductions (DLTR) less the net changes in current debt (DLCCH). We use the average daily turnover over the most recent month to measure trading volume. Dividend yield is the dividend divided by beginning of period stock price. We adjust the standard errors by Newey and West (1987) using 12 lags. Analysts' price target data starts from March 1999. In order to be able to measure realized future stock returns, we end the sample at December 2012. In total, from April 1999 to December 2012, there are 165 months.

Panel A: Univariate Sorts

*Price** Decile	Expected Price Appreciation (%)	Forecast Error (%)
Low 1	95.948	87.589
	(42.85)	(21.06)
2	51.835	42.352
	(29.24)	(12.83)
3	37.347	26.001
	(32.35)	(11.68)
4	24.811	13.613
	(26.37)	(6.25)
5	24.347	12.475
	(27.96)	(5.95)
6	17.946	6.234
	(26.67)	(3.09)
7	17.820	6.339
	(24.69)	(3.47)
8	11.333	-0.037
	(15.98)	(-0.02)
9	7.841	-4.117
	(11.10)	(-2.21)
High 10	3.015	-7.868
	(3.26)	(-4.00)
High-Low	92.933	95.457
	(37.54)	(27.23)

Panel B. Dependent variable: Expected Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log (*Price**)	-1.104	-0.767	-0.787	-0.727	-0.476	-0.251	-0.248	-0.248	-0.202	-0.232	-0.251
	(-4.41)	(-7.90)	(-7.68)	(-7.66)	(-6.73)	(-4.63)	(-4.59)	(-4.41)	(-4.19)	(-4.65)	(-4.58)
Beta		0.254	0.190	0.144	0.107	0.074	0.072	0.076	0.081	0.091	0.079
		(2.61)	(2.60)	(2.33)	(2.10)	(2.73)	(2.92)	(3.21)	(3.29)	(3.09)	(2.94)
Log (Size)		-0.047	-0.042	-0.016	-0.103	-0.049	-0.046	-0.051	-0.062	-0.066	-0.050
		(-2.38)	(-2.09)	(-0.85)	(-3.58)	(-1.99)	(-1.91)	(-2.25)	(-2.73)	(-2.52)	(-1.98)
B/M		0.158	0.144	0.144	0.097	0.033	0.032	0.031	0.006	0.010	0.032
		(2.89)	(3.24)	(3.39)	(2.66)	(1.15)	(1.09)	(1.08)	(0.25)	(0.39)	(1.09)
MOM			-0.243	-0.244	-0.185	-0.218	-0.213	-0.217	-0.215	-0.213	-0.225
			(-4.02)	(-3.96)	(-3.58)	(-3.94)	(-3.90)	(-4.03)	(-4.39)	(-4.24)	(-3.99)
UMD			-0.015	-0.018	-0.008	-0.016	-0.016	-0.014	-0.017	-0.017	-0.016
			(-1.34)	(-1.54)	(-0.65)	(-1.72)	(-1.73)	(-1.57)	(-1.80)	(-1.81)	(-1.72)
REV			-0.824	-0.938	-0.825	-0.851	-1.039	-0.859	-0.847	-0.834	-0.846
			(-7.44)	(-7.77)	(-6.91)	(-7.13)	(-7.58)	(-7.08)	(-7.50)	(-7.39)	(-6.91)
ILLIQ			-0.009	-0.013	-0.023	-0.098	-0.099	-0.097	-0.089	-0.092	-0.099
			(-1.03)	(-1.43)	(-1.20)	(-3.35)	(-3.43)	(-3.38)	(-3.38)	(-3.38)	(-3.37)
Liquidity Shock			-0.055	-0.052	-0.079	-0.119	-0.120	-0.122	-0.119	-0.114	-0.119
			(-1.27)	(-1.29)	(-1.91)	(-2.90)	(-2.91)	(-2.90)	(-2.73)	(-2.71)	(-2.89)
IVOL				13.717	11.801	7.802	12.779	7.767	7.728	7.909	7.775
				(8.06)	(6.79)	(6.10)	(4.79)	(6.06)	(5.94)	(6.04)	(6.16)
OP					0.004	0.001	0.001	0.001	0.002	0.002	0.001
					(3.86)	(1.85)	(1.84)	(1.93)	(2.16)	(2.19)	(1.86)
AG					0.118	-0.027	-0.027	-0.024	-0.019	-0.023	-0.022
					(3.94)	(-0.72)	(-0.71)	(-0.62)	(-0.48)	(-0.59)	(-0.60)
ZSCORE					-0.171	-0.127	-0.125	-0.125	-0.126	-0.126	-0.127
					(-4.86)	(-4.58)	(-4.59)	(-4.76)	(-4.56)	(-4.38)	(-4.54)
IO						-2.027	-2.023	-2.029	-1.996	-2.007	-2.026
						(-7.25)	(-7.20)	(-7.30)	(-7.14)	(-7.14)	(-7.24)
External Finance						0.522	0.524	0.528	0.516	0.525	0.498
						(3.21)	(3.22)	(3.23)	(3.14)	(3.28)	(3.08)
Turnover						0.005	0.004	0.004	0.004	0.004	0.005
						(2.44)	(2.44)	(2.43)	(2.27)	(2.29)	(2.46)
Dividend Yield						0.002	0.002	0.002	0.002	0.003	0.002
						(1.08)	(1.04)	(1.03)	(0.92)	(1.16)	(1.08)
MAX							-0.316				
							(-0.71)				
MIN							-1.542				
							(-2.82)				
SKEW								0.005			
								(0.17)			
EISKEW									0.029		
									(1.38)		
TK										-0.006	
										(-0.12)	
Coskew											-0.061
											(-1.21)
Intercept	3.919	3.375	3.440	2.663	3.292	3.051	2.979	3.058	3.012	3.214	3.052
	(4.65)	(7.96)	(7.29)	(6.73)	(6.76)	(7.97)	(8.17)	(8.53)	(8.14)	(6.46)	(7.86)
R^2	0.058	0.076	0.094	0.103	0.138	0.202	0.206	0.203	0.202	0.202	0.202
N	165	165	165	165	165	165	165	165	165	165	165

Panel C. Dependent variable: Forecast Error

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log (*Price**)	-1.133	-0.788	-0.809	-0.748	-0.505	-0.273	-0.270	-0.268	-0.221	-0.248	-0.272
	(-4.15)	(-7.90)	(-7.75)	(-7.70)	(-6.75)	(-4.82)	(-4.74)	(-4.56)	(-4.39)	(-4.72)	(-4.72)
Beta		0.237	0.176	0.129	0.101	0.064	0.061	0.066	0.071	0.079	0.069
		(2.00)	(1.90)	(1.61)	(1.57)	(1.60)	(1.66)	(1.81)	(1.90)	(1.92)	(1.77)
Log (Size)		-0.035	-0.029	-0.002	-0.086	-0.032	-0.029	-0.033	-0.045	-0.047	-0.032
		(-1.83)	(-1.58)	(-0.10)	(-3.41)	(-1.46)	(-1.34)	(-1.69)	(-2.19)	(-2.20)	(-1.45)
B/M		0.149	0.141	0.142	0.092	0.027	0.026	0.025	-0.001	0.004	0.026
		(2.46)	(2.87)	(3.03)	(2.37)	(0.85)	(0.80)	(0.77)	(-0.03)	(0.13)	(0.78)
MOM			-0.239	-0.242	-0.174	-0.209	-0.203	-0.211	-0.212	-0.202	-0.214
			(-3.60)	(-3.58)	(-3.14)	(-3.47)	(-3.45)	(-3.65)	(-3.91)	(-3.59)	(-3.51)
UMD			-0.009	-0.012	-0.004	-0.015	-0.015	-0.013	-0.015	-0.016	-0.015
			(-0.79)	(-1.04)	(-0.33)	(-1.48)	(-1.49)	(-1.33)	(-1.54)	(-1.62)	(-1.51)
REV			-0.873	-1.003	-0.873	-0.889	-1.121	-0.906	-0.895	-0.867	-0.887
			(-6.55)	(-7.02)	(-6.12)	(-6.20)	(-6.95)	(-6.28)	(-6.52)	(-6.34)	(-6.08)
ILLIQ			-0.013	-0.017	-0.031	-0.105	-0.107	-0.104	-0.097	-0.099	-0.107
			(-1.34)	(-1.72)	(-1.42)	(-3.41)	(-3.49)	(-3.44)	(-3.43)	(-3.44)	(-3.45)
Liquidity Shock			-0.043	-0.041	-0.070	-0.109	-0.109	-0.112	-0.110	-0.103	-0.109
			(-1.00)	(-1.02)	(-1.66)	(-2.62)	(-2.61)	(-2.64)	(-2.50)	(-2.43)	(-2.62)
IVOL				14.290	12.293	7.909	12.881	7.877	7.819	7.993	7.895
				(7.44)	(6.62)	(5.71)	(4.71)	(5.69)	(5.66)	(5.83)	(5.77)
OP					0.003	0.001	0.001	0.001	0.001	0.001	0.001
					(3.98)	(1.73)	(1.71)	(1.81)	(2.05)	(2.06)	(1.73)
AG					0.143	-0.014	-0.014	-0.010	-0.005	-0.011	-0.009
					(5.04)	(-0.33)	(-0.32)	(-0.24)	(-0.12)	(-0.26)	(-0.21)
ZSCORE					-0.174	-0.128	-0.126	-0.125	-0.126	-0.127	-0.127
					(-4.65)	(-4.28)	(-4.29)	(-4.45)	(-4.27)	(-4.12)	(-4.24)
IO						-2.092	-2.088	-2.092	-2.059	-2.071	-2.090
						(-7.41)	(-7.37)	(-7.48)	(-7.31)	(-7.34)	(-7.40)
External Finance						0.572	0.574	0.579	0.565	0.577	0.548
						(3.42)	(3.44)	(3.44)	(3.34)	(3.50)	(3.28)
Turnover						0.005	0.005	0.005	0.005	0.005	0.005
						(2.75)	(2.77)	(2.73)	(2.56)	(2.61)	(2.76)
Dividend Yield						0.003	0.003	0.003	0.003	0.003	0.003
						(1.24)	(1.19)	(1.19)	(1.11)	(1.29)	(1.24)
MAX							-0.172				
							(-0.37)				
MIN							-1.721				
							(-3.06)				
SKEW								0.015			
								(0.39)			
EISKEW									0.041		
									(1.74)		
TK										0.013	
										(0.27)	
Coskew											-0.073
											(-1.52)
Intercept	3.901	3.180	3.240	2.439	3.035	2.809	2.738	2.799	2.751	2.905	2.799
	(4.18)	(7.03)	(6.71)	(6.11)	(6.47)	(7.54)	(7.66)	(8.02)	(7.59)	(7.12)	(7.42)
R^2	0.049	0.066	0.084	0.093	0.123	0.184	0.189	0.186	0.184	0.184	0.185
N	165	165	165	165	165	165	165	165	165	165	165

Table A1. Fama-MacBeth regressions

This table reports Fama-MacBeth monthly regression results. Variable definitions can be found in Table 1. The dependent variable is excess return, measured in percent.

	(1)	(2)	(3)	(4)
Log (*Price*)	-0.009	0.006	-0.020	0.026
	(-0.11)	(0.08)	(-0.34)	(0.48)
Beta		-0.028	0.118	0.133
		(-0.23)	(1.09)	(1.28)
Log (Size)		0.020	-0.069	-0.137
		(0.71)	(-2.61)	(-3.89)
B/M		0.268	0.246	0.200
		(4.14)	(4.22)	(3.62)
MOM			0.541	0.452
			(4.41)	(3.71)
LTREV			-0.059	-0.049
			(-2.71)	(-2.36)
REV			-4.406	-4.439
			(-11.75)	(-11.93)
ILLIQ			0.029	0.029
			(2.36)	(2.38)
Liquidity shock			0.327	0.360
			(11.77)	(12.36)
IVOL (*100)			-0.292	-0.275
			(-10.25)	(-10.15)
OP				0.011
				(1.88)
Asset Growth				-0.515
				(-7.22)
ZSCORE				0.058
				(2.28)
Intercept	1.016	0.744	2.465	3.029
	(2.32)	(1.41)	(5.61)	(5.96)
R^2	0.012	0.041	0.065	0.069
Number of months	546	546	546	546

Table A2. Double sorts with Lottery variable of Kumar (2009)

In this table, we do double sort on the lottery variable of Kumar (2009) and *Price**. For each month, we first sort all stocks into three groups (i.e., Lottery, Non-Lottery, and Others) based on Kumar (2009). Then within each group, we sort stocks into equal-sized quintiles based on *Price**. This table reports the Fama and French (1993) and Carhart (1997) four-factor alphas of the 15 portfolios, and also High-Low (High *Price** minus Low *Price**) portfolio alpha for Lottery, Non-Lottery, and Others group. The sample period is from July 1968 to December 2013.

	Non-Lottery	Others	Lottery
Panel A. EW			
Low Price* 1	-0.042	-0.404	-0.704
	(-0.48)	(-3.64)	(-3.52)
2	0.091	-0.03	-0.231
	(1.23)	(-0.45)	(-1.61)
3	0.130	0.082	0.193
	(1.85)	(1.36)	(1.68)
4	0.189	0.156	0.181
	(2.76)	(2.70)	(1.70)
High Price* 5	0.211	0.184	0.346
	(2.92)	(3.03)	(3.50)
High-Low	0.253	0.588	1.049
	(2.77)	(4.42)	(5.34)
Panel B. VW			
Low Price* 1	0.032	-0.286	-1.012
	(0.29)	(-1.97)	(-4.78)
2	0.163	-0.043	-0.491
	(1.83)	(-0.42)	(-2.92)
3	-0.002	0.041	-0.071
	(-0.02)	(0.48)	(-0.46)
4	0.125	0.007	0.235
	(1.58)	(0.10)	(1.66)
High Price* 5	0.136	0.021	0.432
	(1.90)	(0.38)	(2.95)
High-Low	0.104	0.306	1.444
	(0.77)	(1.91)	(6.11)